A Cognitive Human Behaviour Model for Pedestrian Behaviour Simulation

Claudia Hollmann

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Declaration

"I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy being studied at the University of Greenwich. I also declare that this work is the result of my own investigations except where otherwise identified by references and that I have not plagiarised the work of others."

Claudia Hollmann (PhD student)

Dr Peter Lawrence (First Supervisor)

Professor Ed Galea (Second Supervisor)

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Abstract

Pedestrian behaviour simulation models are being developed with the intention to simulate human behaviour in various environments in both non-emergency and emergency situations. These models are applied with the objective to understand the underlying causes and dynamics of pedestrian behaviour and how the environment or the environment's intrinsic procedures can be adjusted in order to provide an improvement of human comfort and safety.

In order to realistically model pedestrian behaviour in complex environments, the specific human behaviour patterns which govern their behaviour need to be represented. It is thereby of importance to understand the causal chains between the surrounding conditions and the pedestrians' behaviours: The impact of the environment's purpose and facilities as well as the pedestrians' individual goals on the pedestrians' planning and route choice behaviour; the influence of emergent stimuli on the pedestrians' plans and environment usage; the influence of the pedestrians' environment usage under normal usage conditions on the pedestrians' behaviour in response to a potential alarm event. In this thesis, a framework is developed for modelling advanced individual pedestrian behaviours and especially purpose-driven environment usage. The framework thereby aims to assist building and facility planners in improving a building's layout in terms of pedestrian experience and walking routes.

In this thesis, a comprehensive review on how individual pedestrian behaviour and the pedestrians' environment usage are realised in current pedestrian behaviour simulation models has been undertaken. In addition, current theories on human decision making, goal-driven behaviour and emotion modelling have been surveyed from the research fields of artificial intelligence, virtual reality simulation, human psychology and human behavioural sciences. From this survey, theories suitable for this thesis' cause have been identified and combined for the proposed Cognitive Pedestrian Agent Framework (CPAF). The proposed framework contains a sophisticated human decision making model, a multi-faceted individual knowledge representation, a model to realise situational and contextual awareness, and a novel realisation of a human path planning heuristic. The proposed framework has been demonstrated in the simulation of a building usage-cycle use case. Further, it has been outlined how the proposed framework could be used to model experiential alarm response behaviour.

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Acronyms

AGS	Agent Goal Set	110
ATL	Agent Task List	113
CMPE	complex multi-purpose environment	
CPAF	Cognitive Pedestrian Agent Framework	306
CPAF-SSG	Cognitive Pedestrian Agent Framework Scenario Specification Generator	327
C-R-CP	Cluster Route Choice Problem	161
DO-GLR-CP	Distance-Optimal Goal Location Route Choice Problem	167
DO-SR-CP	Distance-Optimal Spatial Route Choice Problem	158
GGS	Global Goal Set	103
GIS	Geo-Information System	
GLS	Goal Location Set	166
GS-PO-GLS-CP	Goal Set's Preference-Optimal Goal Location Set Choice Problem	155
IT-IA	Imposed-Time Imposed-Activities	
IT-PA	Imposed-Time Predicted-Activities	
IC-R-CP	Intra-Cluster Route Choice Problem	164
MCOP	Multi-Criteria Optimisation Problem	
MGLS-CP	Minimal Goal Location Set Choice Problem	154
OEK	Occupant Exit Knowledge	
OIL	Occupant Itinerary List	
PBS	pedestrian behaviour simulation	xv
PDM	Planned Decision Making	118
PGLR-CP	Planned Goal Location Route Choice Problem	168
PO-GL-CP	Preference-Optimal Goal Location Choice Problem	
PO-GLS-CP	Preference-Optimal Goal Location Set Choice Problem	153
SCOP	Single-Criteria Optimisation Problem	

SMS Spatial Memory Set 110

SSF Scenario Specification File

STS-ADM Short Time Span Adaptive Decision Making 123

TtB Take-the-Best 120

UDG Behaviour Unsatisfied Desired Goal Behaviour

WPS Way Point Set 108

Nomenclature

Symbols for buildingEXODUS and Cognitive Pedestrian Agent Framework (CPAF) Features

Simulation Features

$\mathbf{T}^{\text{TimeStep}}$	Length of a Time Step (buildingEXODUS)	79
τ	Simulation time (buildingEXODUS)	79
τ_i	Simulation time after i time steps (buildingEXODUS)	79

Environment Representation

∂	Walking distance metric (CPAF)	102
$\mathbb{E}$	Environment Space (buildingEXODUS) $\mathbb{E} \subset \mathbb{R}^2 \times \mathbb{N}$	100
$\Lambda(l)$	Spatial area occupied by a goal location l	104
λ	Environmental Location Function (CPAF) $\lambda : \text{GLS} \to \mathbb{R}_0^+$	104

Special Indices

π_0	Index of the currently ongoing task on the agent's Occupant Itinerary List	85
π_{cr}	Index of the next highest critical time task on the agent's Occupant Itinerary List: $\pi_{cr} \geq \pi_0$	86

Agent Attributes

C	Perceived Crowd Attribute (CPAF)	139
D	Drive Attribute (buildingEXODUS)	82
P	Patience Attribute (buildingEXODUS)	82
U	Urgency Attribute (buildingEXODUS)	82
T_{resp}	Response Time (buildingEXODUS)	82
v	Walk Speed Attribute (buildingEXODUS)	82
$x_{current}$	the agent's current spatial location, $x_{current} \in \mathbb{E}$ (buildingEXODUS)	102

Symbols for Cognitive Pedestrian Agent Framework Features

Special Sets in the Cognitive Pedestrian Agent Framework

$\mathfrak{L}(\widehat{g})$	Set of all goal locations where the goal $\widehat{g} \in$ GGS can be achieved, $\mathfrak{L}(\widehat{g}) \subseteq$ GLS	104
$\mathfrak{L}(g)$	Set of all goal locations where the agent goal $g \in$ AGS can be achieved: $\mathfrak{L}(g) := \mathfrak{L}(\widehat{g})$ for $g \lhd \widehat{g}$	111
$\mathfrak{L}(\mathfrak{G})$	Set of all goal locations where all (agent) goals in the goal set $\mathfrak{G} \subseteq$ GGS or $\mathfrak{G} \subseteq$ AGS can be achieved	129
$\mathfrak{L}^{\mathrm{M}}(g)$	Set of all memorised active goal locations where the agent goal $g \in$ AGS can be achieved, $\mathfrak{L}^{\mathrm{M}}(g) := \{l \in \mathfrak{L}(g) \cap \mathrm{SMS} \mid l \text{ is active}\}$	112
$\mathfrak{G}(l)$	Set of all goals associated with the goal location $l \in$ GLS	104
$\mathfrak{G}(t)$	Set of all agent goals associated with the task $t \in$ OIL	113

Special Functions in the Cognitive Pedestrian Agent Framework

$I(g)$	Relative importance of the agent goal $g \in$ AGS	110
$g \lhd \widehat{g}$	The agent goal $g \in$ AGS is derived from the (global) goal $\widehat{g} \in$ GGS	110

Constants used in the Cognitive Pedestrian Agent Framework

$\mathbf{M}_{low}$	Lower motivation threshold	127
$\mathbf{M}_{up}$	Upper motivation threshold	127
$\mathbf{I}_{up}(\widehat{g})$	Lower relative importance bound of the goal $\widehat{g} \in$ GGS	103
$\mathbf{I}_{up}(\widehat{g})$	Upper relative importance bound of the goal $\widehat{g} \in$ GGS	103
$\mathbf{T}_{min}(\widehat{g})$	Minimum completion time bound of the goal $\widehat{g} \in$ GGS	103
$\mathbf{T}_{min}(g)$	Minimum completion time bound of the agent goal $g \in$ AGS: $\mathbf{T}_{min}(g) = \mathbf{T}_{min}(\widehat{g})$ for $g \lhd \widehat{g}$	
$\mathbf{T}_{max}(\widehat{g})$	Maximum completion time bound of the goal $\widehat{g} \in$ GGS	103
$\mathbf{T}_{max}(g)$	Maximum completion time bound of the agent goal $g \in$ AGS: $\mathbf{T}_{max}(g) = \mathbf{T}_{max}(\widehat{g})$ for $g \lhd \widehat{g}$	
$\mathbf{T}_{min}(l)$	Minimum service time bound of the goal location $l \in$ GLS	106
$\mathbf{T}_{max}(l)$	Maximum service time bound of the goal location $l \in$ GLS	106

Mathematical Symbols

Set Notation

$\mathbb{R}$	The set of real numbers
$\mathbb{R}^m$	The m-dimensional vector space of real numbers
$\mathbb{R}^+$	The set of positive real numbers: $x \in \mathbb{R}^+ \Leftrightarrow x \in \mathbb{R},\ x > 0$
$\mathbb{R}_0^+$	The set of non-negative real numbers: $x \in \mathbb{R}_0^+ \Leftrightarrow x \in \mathbb{R},\ x \leq 0$
$\mathbb{N}$	The set of natural numbers: $\mathbb{N} = \{1, 2, 3, \ldots\}$
$\mathbb{N}_0$	The set of the natural numbers including zero: $\mathbb{N}_0 = \{0\} \cup \mathbb{N}$

Common Mathematical Notations

$\mathbb{1}_{\mathfrak{X}}$	Identity function on the set $\mathfrak{X}$	321
$\lVert.\rVert_p$	p-Norm	321

Optimisation Theory

$(\mathfrak{X}, f)$	Multi-Criteria Optimisation Problem	63
$\mathfrak{P}_{(\mathfrak{X},f)}$	The set of all optimal solutions with regard to f of the Multi-Criteria Optimisation Problem $(\mathfrak{X}, f)$	64

Mathematical Notations defined in this Thesis

$(\zeta, \mathfrak{P})$	Choice Rule	115
ζ_{min}	Minimum Choice Function	116
ζ_{max}	Maximum Choice Function	116
ζ_{rand}	Random Choice Function	116
$\mathfrak{S}(\mathfrak{X})$	Sequence Set of the set $\mathfrak{X}$	321
$\omega_<$	Smaller Comparison Function	123
$\omega_>$	Greater Comparison Function	123

Chapter 1: Introduction

In this chapter, the research topic of this doctoral thesis is motivated. From the motivation, research questions are collated which then lead to the formulation of this thesis' research objectives. Subsequently, the contribution and outline of this doctoral thesis are described.

1.1. Motivation

Analysing and understanding pedestrian behaviour and the pedestrians' environment usage has become an important research field over the past decades. Under the aspect of safety engineering, one major issue is to analyse the usage rate of travelling routes during gatherings of huge crowd events as has, for example, been studied for the Hajj [15, 16]. Publicly noticed crowd catastrophes such as the tragedy at the Love Parade 2010 in Duisburg, Germany [17–19], also clearly highlight the necessity to understand pedestrian behaviour in complex environments.

The study of pedestrian behaviour is however not only of interest in the analysis of catastrophes or when organising and conducting exceptional events. Everyday pedestrian behaviour in public environments such as traffic facilities, shopping malls, sport stadiums or even entire urban districts is also an important field of research. Potential insights can be used to understand and predict pedestrian behaviour in both emergency scenarios as well as the pedestrians' normal usage of the environment. The researchers aim to understand the walking routes of pedestrians in order to predict local pedestrian population densities and waiting times. By better understanding the causes of congestion, architects and designers can improve the building's layout to ensure safe egress in emergency situations. In the same way, they can use this information to improve the pedestrians' experience in visiting the environment in question by reducing unnecessary waiting times and congestion. This can be achieved by ensuring that a sufficient number of stairs, escalators or lifts are available for vertical transport and are located in appropriate places [20]; or by ensuring well measured and unobstructed entry and exit points at optimal locations within the environment [21].

In addition to these structural design decisions, site and facility planners need to decide on the optimal locations for the environment's facilities. Especially in more complex environments such as large traffic facilities or shopping malls, deciding on the arrangement of further facilities (shops, restrooms, etc.) in relation to the given structural features (entrance points, stairs, railway tracks, bus stations, etc.) is a difficult task to achieve. Pedestrian behaviour research can aid the site and facility planners by indicating which walking routes between certain facilities might be preferred by the pedestrians given some assumptions on the pedestrian population. Such information might result in reducing both the planning costs and the time required for the facility planning. At the same time, detailed information on likely pedestrian walking routes will lead to environments with an optimal internal layout for pedestrian comfort and efficient pedestrian usage. A negative public image and costly restructurings that had to be undertaken for example at Heathrow airport in 2007 as a reaction to long passenger waiting times and queues [22, 23] could thereby be avoided.

1.2. Pedestrian Behaviour Simulation

Pedestrian behaviour simulation tools have become an important instrument to improve the understanding of pedestrian behaviour in various environments. Pedestrian behaviour simulation models are being developed with the intention to simulate human behaviour in various environments in non-emergency and emergency situations. These tools allow for the analysis of past events as well as the safety assessment of new buildings and other structures. The results obtained can be used to identify and assess possible risks and safety threats implied by building design, or to gain insights into the possible usage and the actual pedestrian behaviour in the environment. With the help of pedestrian behaviour simulation tools, these assessments can be conducted in every building design stage, from the planning stage to the actual finished environment.

Pedestrian behaviour simulation models are used for the evaluation of past incidents as well as for case studies addressing what-if scenarios. Such case studies are undertaken with the objective to understand the underlying causes and dynamics of human behaviour and how the environment or the intrinsic procedures can be adjusted in order to provide an improvement of human comfort and safety. By comparing the outcomes of simulations to data from trial evacuations and real incidents, pedestrian behaviour simulation models provide a very useful tool in understanding the incident's causes. By altering the parameters representing the incident's circumstances, pedestrian behaviour simulation models can help to find possible improvements to the environment's structure, the implemented procedures or the evacuation strategy, thereby helping to prevent future incidents under similar circumstances.

With the increasing need for evaluating more complex and large environments for their design and safety performance, pedestrian behaviour simulation models have received greater attention over the last decades. With the help of these simulation tools, it is possible to understand the interplay of the many inter-related factors involved in complex and large environments such as for example the evacuation of the World Trade Center [24].

Over the last decades, a broad variety of pedestrian behaviour simulation models have been developed [11, 13, 25], the main approaches for pedestrian behaviour representation used being agent-based (e.g. [26]), cellular automata (e.g. [27]) and physical force-based (e.g. [28]) modelling paradigms. All paradigms have their strengths and weaknesses, which will be further discussed in Chapter 2. Depending on the specific model in question, the model's focus on the actual pedestrian behaviour to be simulated varies from being concentrated on locomotion, space usage, queuing and congestion and pedestrian planning. However, with more focus being drawn to the analysis of advanced pedestrian behaviour such as cognition and decision making in the context of a given environment and its intrinsic purpose and facilities, agent-based models appear as being the most appropriate measure.

1.2.1. Modelling Human Behaviour in Complex Multi-Purpose Environments

With the help of pedestrian behaviour simulation tools, the study of pedestrian behaviour in large and complex environments has become possible. Environments of interest are for example cruise ships, high-rise buildings, amusement parks, airport terminals or shopping malls. What these environments have in common is that they are usually occupied by a large number of pedestrians and that the pedestrians within these environments normally have quite heterogeneous agendas. Therefore, these environments are in the following referred to as complex multi-purpose environments.

In order to use pedestrian behaviour simulation models to realistically represent pedestrian behaviour in complex multi-purpose environments, the main specific human behaviour patterns which govern the pedestrians' behaviour need to be reproduced. Since these behaviour patterns are usually the consequence of the surrounding conditions, it is of importance to understand the causal chains between the surrounding conditions and the pedestrians' behaviours. Amongst others, important issues to study are:

- The impact of the environment's purpose and facilities as well as the pedestrians' individual goals on the pedestrians' planning and route choice behaviour under normal usage conditions.
- The influence of emergent stimuli on the pedestrians' plans and environment usage under normal usage conditions.
- The influence of the pedestrians' environment usage under normal usage conditions on the pedestrians' behaviour in response to a potential alarm event.

It would however be too simplistic to treat the pedestrians as a uniform mass which reacts to the surrounding conditions as a whole. Instead, the observable pedestrian behaviour in an environment is the sum of the individual behaviours of each individual pedestrian. It is on this level, that pedestrian behaviour and the influencing factors on each individual pedestrian need to be understood in order to realistically reproduce the global observable pedestrian crowd behaviour. Currently, human behaviour in pedestrian behaviour simulation models is mostly simulated by explicit user inputs or probabilistic models, disregarding the cognitive abilities of the individual. Only very few pedestrian behaviour simulation models have addressed the simulation the pedestrian's individual cognitive abilities, and if then only to a basic degree.

1.2.2. The Influence of the Environment on Pedestrian Behaviour

The factors that influence the individual pedestrian's behaviour in a given environment are intrinsic to the pedestrian themselves or to the environment which the pedestrian occupies. On the side of the environment, the pedestrians are influenced by the environment's design and layout, as well as the purpose and processes that the pedestrians associate with the environment. On the side of the pedestrian, their usage of the environment depends on their current goals and their previous history with the environment. The pedestrian's current goals are however related to the occupied environment and the facilities and possibilities represented within.

In general, the pedestrian's current goals can be grouped in two categories. The pedestrian will have *primary goals* which represent their main motivation in visiting the environment itself. In addition, the pedestrian will have *secondary goals* which represent minor goals that the pedestrian would like to achieve but which neither are the main motivation for the pedestrian being in the studied environment nor are essential to the pedestrian. With this universal distinction between primary and secondary goals, it can in general be postulated that pedestrians will aim to achieve all of their current primary goals within an environment, even if that implicates that some or all of their desired secondary goals might not be achieved.

As an example, a railway station environment is considered. A railway station environment is designed such that it encompasses platforms and railway tracks for the arrival and departure of trains. In addition, a railway station environment encompasses ticket offices, because tickets are required for the pedestrians to travel by train. Commonly, railway station environments also comprise a number of retail outlets, where the pedestrians can make purchases or simply pass their time.

The pedestrians visiting a railway station environment will follow certain goals. In general, it can be distinguished between five main types of pedestrians in a railway station environment, depending on their primary goals in visiting the environment:

- *Foot Passengers:* The primary goal of foot passengers is to take a train from the station to a desired destination.

- *Train Passengers:* The primary goal of train passengers is to simply leave the station after they have arrived at the station by train.

- *Transfer Passengers:* The primary goal of transfer passengers is to change their trains at the station after they have arrived by train.
- *Pick-up Visitors:* The primary goal of pick-up visitors is to collect other pedestrians, for example their friends or relatives, that have arrived at the station by train.
- *Retail Visitors:* The primary goal of retail visitors is to partake in the railway station's retail environment.

Depending on their individual primary goal in visiting the railway station, the pedestrians will make use of the station's facilities in different ways. The foot passenger who intends to take a train from the station might need to acquire a ticket prior to boarding their train in order to achieve their primary goal. On the other hand, the foot passenger might want to purchase some food for their journey. However, if they for example are running late for catching their desired train, the foot passenger will probably decide not to purchase any food and instead make sure that they will not miss their train. In this case, the foot passenger's experienced time pressure will lead to the foot passenger dismissing their secondary goal in favour of meeting their primary goal. If the foot passenger has arrived well in time at the railway station environment, they will be able to purchase some food before their train's departure. In addition, they might even want to pass the remaining time until their train's scheduled departure by exploring other available retail outlets, thereby satisfying other secondary goals.

A similar behaviour holds also likely for the transfer passenger who wants to change trains at the station. Depending on whether they have got enough time at their disposal until their connecting train's departure, they might also be able to satisfy other secondary goals in the environment. The same behaviour pattern holds true for the pick-up visitor.

In contrast, the primary goals of the retail visitor are to purchase one or multiple desired products in the station's retail environment. They will not be influenced by the railway station's train timetable but rather by the product ranges of the retail outlets within the railway station. The retail visitor might satisfy their primary goals also in a different environment such as a shopping mall. The primary goals of the retail visitor are therefore not connected to the main purpose of the railway station environment.

Aside from the pedestrians' goals and motivations, the pedestrians' usage of the facilities available in the railway station environment also depends on the individual pedestrian's knowledge of the available facilities within the environment. If the pedestrian has been to the same railway station before, they will be aware of some or all available facilities in the station environment. For example, if the pedestrian might want to purchase some food and they have previously been to the station, they will probably know where they can go to accomplish their goal. On the other hand, if the hungry pedestrian has not been to the station beforehand, they might decide to explore the environment in order to find a place where they can purchase the desired food.

In summary, pedestrian behaviour in a given environment depends on the environment's purpose and the purposes of the comprised facilities. On the other hand, pedestrian behaviour in a given environment depends on the individual pedestrian's goals and their previous history with the environment. These influence factors don't stand independently of each other but are connected such that the pedestrian's goals in using the environment correspond to the environment's and comprised facilities' purpose and their knowledge of the environment, see Figure 1.1.

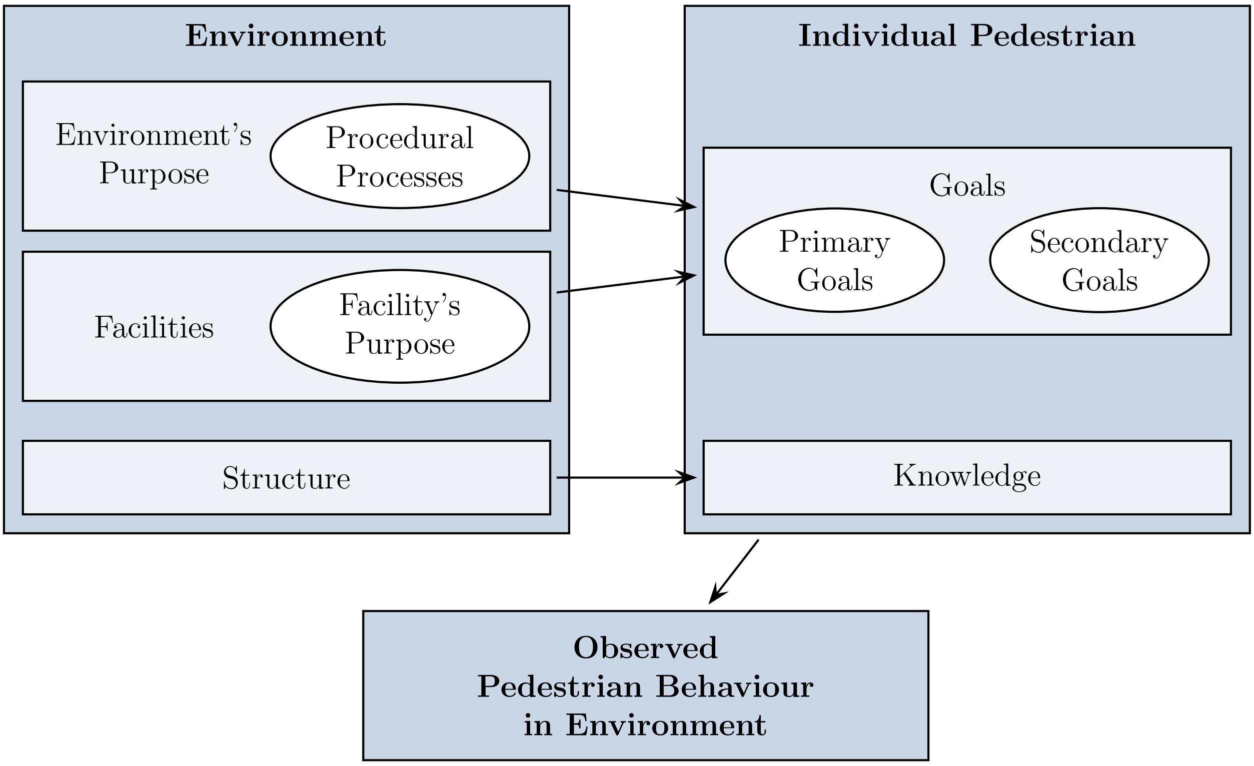


Figure 1.1.: An overview of how the environment influences the pedestrians' behaviour.

It has to be noted, that pedestrians in general have more goals, needs and desires than those that can be accomplished in the environment in question. For example, a pedestrian might have the need to acquire a certain book, but the traffic facility to be studied does not include any book shops. However, for the purpose of studying pedestrian behaviour in a given environment, mainly those goals are of interest that relate to the purposes and facilities available in the given environment. Other needs and desires will simply not be satisfiable in the given context and can therefore be disregarded.

1.2.3. The Impact of prior Normal Usage Behaviour on Evacuation Behaviour

The initial conditions of an evacuation have a crucial impact on the evacuation's outcome. When simulating an evacuation with a pedestrian behaviour simulation tool, the initial conditions need to be chosen realistically in order to provide a valid starting point for the evacuation simulation. Any outcome of an evacuation simulation needs to be assessed specifically with regard to the chosen initial conditions. The information required to inform an evacuation simulation comprise:

- the spatial distribution of the pedestrians within the environment at the time of the alarm event
- the familiarity of the individual pedestrian with the environment, especially with the exits and exit routes within the environment
- the pedestrians' activities at the time of the alarm event
- the amount of time that the individual pedestrian takes from the alarm event until they initiate their evacuation

These initial conditions of an evacuation depend on the pedestrians' prior usage of the environment, their familiarity with the environment and on the goals that the pedestrians try to satisfy during their sojourn in the environment. In current evacuation simulations, these initial conditions are either set explicitly by the user for a given scenario or are assigned based on probability distributions. The probability distributions thereby are often obtained from evacuation trials or studies of past incidents. As such, the observed behaviour might not be representative for the environment in question or might have been generalised from a different but similar environment.

If advanced human cognitive behaviour and the impact of the environment on the pedestrian behaviour will be represented in a pedestrian behaviour simulation tool on an individual motivational, stimulative and knowledge level, these features could be used to inform evacuation simulations of complex multi-purpose environments. In order to determine realistic starting locations of the pedestrians within the environment at the time of an alarm event, the pedestrians' prior usage of the environment in question under normal conditions could be simulated. Since each individual pedestrian would make use of the environment according to their goals and knowledge, a reasonable usage of the environment space will justify from the emergent pedestrian population behaviour. In the same way, the activities that the pedestrians might be following at the time of the alarm event would be a natural result of a prior usage simulation under normal conditions. If also the abilities of pedestrians to both have previous experience with the environment in question but also learn new spatial information whilst following their route are represented in a pedestrian behaviour simulation tool, the individual pedestrian's familiarity with the environment at the time of an alarm event can also be obtained from a prior pedestrian usage simulation.

To conclude, three of the four required initial conditions of an evacuation simulation could be directly obtained from simulating a normal pedestrian usage behaviour in the same environment which takes into account the individual pedestrian's goals and experience. From this information, an estimation of the amount of time that the pedestrian will be occupied with other activities after the alarm event occurred and prior to initiating their evacuation might also be possible. If such motivational and experiential information is available on an individual level, different models for estimating this individual alarm response time can be devised and compared to empirically obtained data or the outcome of current evacuation simulation approaches.

1.2.4. Research Questions

Currently, only very few pedestrian behaviour simulation models have addressed the simulation of the influencing factors and individual pedestrian behaviours outlined in Sections 1.2.1 and 1.2.2, and if then only to a basic degree. Instead, human behaviour in pedestrian behaviour simulation models is mostly pre-determined by user inputs and probabilistic models, disregarding the cognitive abilities of the individual. Therefore, it would be desirable to represent the cognitive human behaviour by reactive or even proactive behaving software agents. This doctoral thesis will address this aspect of pedestrian modelling, the representation of cognitive human behaviour within agent-based pedestrian behaviour modelling. The specific research questions addressed by this thesis are:

Research Question 1 (Purposeful and Goal-Directed Pedestrian Behaviour)
In the context of complex multi-purpose environments, how can purposeful and goal-directed pedestrian behaviour be represented in a pedestrian behaviour simulation?

a) How can the environment's main purpose be represented?

b) What effect does the environment's purpose have on the occupying pedestrians?

c) In a complex multi-purpose environment, how can several other purposes available in the environment be represented?

d) How are the environment's purposes reflected in the individual pedestrian?

e) How does the complex multi-purpose environment lead to goal-driven pedestrian behaviour?

Research Question 2 (Individual Pedestrian Decision Making)
In the context of complex multi-purpose environments, how can the individual pedestrian's decision processes be represented in a pedestrian behaviour simulation?

a) How do humans draw decisions?

b) What characteristics does a decision making model require in order to enable the simulated individual pedestrian to draw informed decisions?

c) What triggers the individual pedestrian's decision making process?

d) How are the individual pedestrian's decisions related to the purposes of the complex multi-purpose environment?

Research Question 3 (Experience and Knowledge)
In the context of complex multi-purpose environments, how can individual knowledge and different levels of experience be represented in a pedestrian behaviour simulation?

a) What environmental and situational information needs to be taken into account in a pedestrian behaviour simulation in order to represent an individual pedestrian's knowledge and experience of the environment?

b) How can the process of gaining environmental knowledge and experience be represented in a pedestrian behaviour simulation?

c) How does the individual pedestrian make use of their acquired experience and knowledge and how can this be represented in a pedestrian behaviour simulation?

Research Question 4 (Situational Awareness and Contextual Behaviour)
In the context of complex multi-purpose environments, how can the individual pedestrian's situational and contextual awareness be represented in a pedestrian behaviour simulation?

a) What is needed to reflect the individual agent's current situation in the individual agent in a pedestrian behaviour simulation?

b) How do humans evaluate a given situation and context?

c) How can adaptive behaviour be represented in a pedestrian behaviour simulation?

Once these questions on the level of the individual pedestrian's behaviour have been addressed, it is also of interest how these insights can be used to simulate the global pedestrian usage behaviour patterns in a given environment:

Research Question 5 (Pedestrian Circulation Modelling)
In the context of complex multi-purpose environments, how can the normal usage behaviour of pedestrians be represented?

a) How and on what basis do pedestrians choose their targeted facilities within complex multi-purpose environment? How can this be represented in a pedestrian behaviour simulation?

b) How and on what basis do pedestrians choose their path within a complex multi-purpose environment? How can this be represented in a pedestrian behaviour simulation?

c) How can the process of a pedestrian planning their itinerary in a normal usage scenario with multiple target locations be represented in a pedestrian behaviour simulation model?

Research Question 6 (Alarm Response Behaviour Modelling)
How can the influence of the individual pedestrian's previous environment usage onto the individual pedestrian's behaviour in response to an emergent alarm event be represented in a pedestrian behaviour simulation model?

a) How can the simulation of previous environment usage under normal usage conditions help to improve the representation of the individual pedestrian's initial conditions at the time of an emergent alarm event?

b) How can the simulation of previous environment usage under normal usage conditions help to improve the representation of the individual pedestrian's decision processes and activities after an occurred alarm event?

1.3. Research Objectives

In order to address the research questions listed in Section 1.2.4, the following list of research objectives for this doctoral thesis has been compiled.

Research Objective 1 (Pedestrian Behaviour Simulation Models)
Determine the current state of research in pedestrian behaviour simulation modelling. Review the currently available pedestrian behaviour simulation modelling tools with specific focus on the modelling of

- the influence of the environment on pedestrian behaviour,
- purposeful and cognitive human behaviour,
- procedural processes and stimuli,
- experiential alarm response.

Research Objective 2 (Survey of Relevant Research)
Determine and review the models and methods used in relevant research disciplines with which the pedestrian behaviours in focus of Research Objective 1 can be modelled in a pedestrian behaviour simulation model. Identify suitable models and methods to enhance

the currently used techniques in pedestrian behaviour simulation modelling with the specific focus on purpose-related, deliberate and contextual behaviour modelling, see Research Questions 1, 2, 3 and 4. In order to prepare the definition of a model, identify

- the dominant features of purpose-driven human behaviour,
- the main characteristics of how pedestrians choose their actions and behaviours in complex multi-purpose environments
- a suitable representation of human knowledge

Research Objective 3 (Comprehensive Model)
Using the gathered knowledge from the review and analysis of the relevant research areas, devise a model that enhances the currently used techniques in pedestrian behaviour simulation with the specific focus on purpose-related, deliberate and contextual behaviour modelling, see Research Questions 1, 2, 3 and 4. This model needs to contain components to

- represent complex multi-purpose environments,
- simulate individual cognitive pedestrian behaviour in the context of a complex multi-purpose environment,
- simulate pedestrian knowledge in the context of a complex multi-purpose environment,
- simulate pedestrian-environment interaction
  - motivations to initiate, maintain or complete tasks,
  - the handling of dynamic and emergent surrounding events including event perception, event interpretation, event evaluation and reaction to the event.

Research Objective 4 (Pedestrian Behaviour)
Apply the postulated model to address Research Question 5. Demonstrate the model's capabilities in simulating pedestrian behaviours in complex multi-purpose environments. These behaviours shall include the pedestrian usage-cycle of an environment including pedestrian path planning and target choice. Further, the pedestrians' capability to exhibit contextual and situational aware behaviour.

Research Objective 5 (Alarm Response Behaviour)
Apply the postulated model to address Research Question 6. Demonstrate the model's capabilities to simulate the influence of acquired experience before a potential evacuation initiation on the actual initial evacuation response phase, in particular in terms of the pedestrians' spatial knowledge and their planning behaviours.

1.4. Thesis Contribution

This thesis presents the development of a Cognitive Pedestrian Agent Framework, which incorporates and combines insights from various different research domains including mathematical optimisation, artificial intelligence, computer game development as well as sociological and behavioural science theories. The Cognitive Pedestrian Agent Framework especially comprises:

- An advanced agent decision making entity which adopts behavioural science theories on human decision making. The model provides a deliberate and planning decision making component based on the Unbounded Rationality theory. Furthermore, the model enhances reactive and adaptive human behaviour modelling including contextual situational awareness by implementing a lexicographic decision making heuristic from the Fast-and-Frugal Heuristics Toolbox. No other pedestrian behaviour simulation model to date comprises a similar complex decision making entity which is based on concrete findings in human behaviour research.

- An algorithm for optimal route choice based on the information available to the individual, their experience and their personal preferences. The algorithm makes use of a regional-grouping observation in studies on human path planning [7] and mathematical optimisation techniques. This is the first implementation of the observed human behaviours [7] with a computational algorithm in a pedestrian behaviour simulation model.

- An approach for knowledge representation which couples working memory, long-term goals memory and short-term spatial memory as distinct, but interacting representations of human knowledge required for pedestrian behaviour simulation models. Especially the time- and repetition-dependency of acquired spatial knowledge hasn't been addressed in a pedestrian behaviour simulation model up to the present day.

- A stimuli model for reactive behaviour modelling including personal preferences; motivations and emotions; and goals. These elements have been used especially in computer game design and human-computer interaction modelling, and so far only scarcely in pedestrian behaviour simulation models.

An implementation of the proposed framework has been integrated in the existing pedestrian behaviour simulation model buildingEXODUS [14] as a buildingEXODUS plug-in.

By employing the proposed Cognitive Pedestrian Agent Framework in a pedestrian behaviour simulation model, the model would be of direct benefit to site and facility planners as motivated in Section 1.1. The Cognitive Pedestrian Agent Framework would enable the planners to study different scenarios of their planned building layout in terms of the facilities to be placed in the environment. The Cognitive Pedestrian Agent Framework will simulate the route choice of each individual pedestrian by taking into account the impact of the environment and included facilities on the pedestrian's goals and plans. It further allows for the modelling of emergent stimuli which could directly affect the pedestrians' route choice. The resulting emergent pedestrian population behaviour simulation can then be used to improve the planned building layout and to detect potential bottlenecks prior to the actual building and usage stage of the environment. The Cognitive Pedestrian Agent Framework therefore provides means to assist the site and facility planners in improving the pedestrians' experience when making use of the environment and at the same time enhance the environment's safety design. Such complex analyses of a building's layout on the level of producing plausible individual pedestrian walking routes is not possible with current pedestrian behaviour simulation models.

1.5. Outline of the thesis

The thesis is outlined as follows: Chapter 2 comprises a literature review of the currently available pedestrian behaviour simulation models in industry and research. Furthermore, Chapter 2 outlines recently motivated research suggestions for the specific context of pedestrian behaviour simulation such as for example the ICE concept [9]. Subsequently, Chapter 3 presents a survey of relevant research concepts from various research disciplines such as cognitive architectures, human decision making, emotion modelling and motivational action selection. In Chapter 4, a detailed description of the pedestrian behaviour simulation model buildingEXODUS and the comprised features is given. The generic Cognitive Pedestrian Agent Framework and its components are described in detail in Chapter 5. Chapter 6 describes the application of the theoretical framework in the modelling of pedestrian circulation behaviour and especially modelling the building usage cycle. Further, the possible application of the Cognitive Pedestrian Agent Framework in simulating the alarm response phase between a normal environment usage and an emergent evacuation it presented in Chapter 7.

In order to demonstrate the developed generic framework, a version of the framework has been integrated in the existing pedestrian behaviour simulation tool buildingEXODUS as a plug-in. With this buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in, the capabilities of the generic Cognitive Pedestrian Agent Framework framework have been demonstrated. Chapter 8 comprehends the results from the functional verification cases which highlight the individual components' capabilities and prove their functional integrity. The benefit of the model's combined capabilities are demonstrated in Chapter 9 by the simulation of a railway station environment as an example of a complex multi-purpose environment.

Finally, the contribution of the proposed Cognitive Pedestrian Agent Framework in addressing the posed research questions is discussed in Chapter 10. In addition, some areas for future research inspired by this thesis' are suggested.

Chapter 2:

Literature Review on Pedestrian Behaviour Simulation Models

Pedestrian behaviour simulation software tools have been developed for approximately 35 years and a broad variety of different models are available at present [13, 25, 29]. The models differ not only in terms of their main application areas, but they also fundamentally differ in the approaches used to model human behaviour.

Pedestrian behaviour simulation models have been developed with the intention to understand, replicate and study human movement and behaviour in various enclosures and under varying conditions. Situations involving simple and small environments and a small number of people can be studied "by hand". On the other hand, large and complex environments inhabited by a large number of people do pose a challenge for analysts, because of the various inter-dependent and correlated factors involved. Pedestrian behaviour simulation models try to assist the analyst in the comprehension of these complex scenarios.

Pedestrian behaviour simulation models are being designed for a diverse range of application areas:

- to support the analysis of pedestrian shopping behaviour in shopping malls (e.g. Borgers and Timmermans [30]),
- to assist in the organisation and monitoring of massive crowd events such as the hajj (e.g. Al Bosta [15]),
- to study public transport facilities and the intrinsic procedures (e.g. Rindsfüser and Klügl [31]),
- or to evaluate specific environment layouts and designs for usage and security such as in procedural fire safety engineering (e.g. Tavares and Galea [21]).

By employing pedestrian behaviour simulation tools, analysts can assess a given environment in every stage of the building design process. The analyst can study multiple "what-if"-scenarios and can evaluate the environment's layout under various circumstances. These circumstances include the study of buildings still in the building design stage, before they have been built. Or the study of the impact of extreme conditions, which would not be possible by conducting e.g. life evacuation trials, because of cost and time limitations and the risk of harming the participants. Pedestrian behaviour simulation models therefore provide a wide range of beneficial capabilities for architects, regulators and designers.

In this chapter, the currently available pedestrian behaviour simulation models will be reviewed under consideration of requirements to model advanced human behaviour. Section 2.1 briefly introduces the concepts used in pedestrian behaviour simulation models. In Section 2.2, several reviews of fire safety and crowd engineering researchers about the current state of the art of modelling advanced human behaviours within pedestrian behaviour simulation models is discussed. To sum up, Section 2.3 lists requirements for the modelling of advanced and sophisticated individual human behaviour. Based on this list of desirable features, a set of relevant pedestrian behaviour simulation models is surveyed in Section 2.4 and a review of the selected pedestrian behaviour simulation models with regard to the suggestions summarised in Section 2.3 is presented in Section 2.5.

2.1. General Modelling Approaches

Pedestrian behaviour simulation models mostly have a common application procedure. At first, the environment to be studied is modelled. Hereby, the environment can be any enclosure or fixed spatial area including buildings, ships, aircrafts or urban districts. A representation of typical occupants and constraints representing procedural processes are then introduced into the environment. Depending on the nature of the study, it is then assessed either how the occupants make use of the environment under normal circulation conditions, or how the occupants' egress strategies might be or might have been under emergency conditions.

According to Papadimitriou et al. [13], Kuligowski et al. [25], Kuligowski and Peacock [29], Gwynne et al. [32], pedestrian behaviour simulation models can be generally categorised and compared based on a set of criteria depicted in Table 2.1. For this thesis, the most important criteria in a pedestrian behaviour simulation model are the model's main application area, the way a pedestrian is represented and the intrinsic behaviour and knowledge models.

As pointed out in this chapter's introduction, pedestrian behaviour simulation models can be used in a wide range of applications and to model different kinds of scenarios. It is common to distinguish between pedestrian behaviour simulation models which can simulate the behaviour of the pedestrians during normal usage conditions and emergency conditions. Pedestrian behaviour simulation models which represent normal usage conditions of a given environment, such as the modelling of a shopping trip in a shopping environment or the modelling of sports fans entering and leaving a sport stadium, are commonly referred to as *circulation models*. These circulation models therefore simulate pedestrian movement within

Table 2.1.: Criteria for the comparison of pedestrian behaviour simulation models [13, 25, 29, 32].

Criterion	Possible Realisations
Main Application Area	circulation, evacuation, circulation and evacuation
Pedestrian Representation	global (macroscopic), individual (microscopic)
Structural Representation	continuous, fine-grid, coarse-grid
Movement Model	density, user's choice, inter-person distance, potential, emptiness of next grid cell, conditional, acquired knowledge, unimpeded flow, CA
Behaviour Model	no behavioural representation, functional analogy behaviour, implicit behaviour, rule based behaviour, artificial intelligence based behaviour
Knowledge Model	individual knowledge, global or complete knowledge, no knowledge model
Validation	against codes, trials, literature on past experiments, other models, third-party validation, no documented validation

a structure, comprising the simulation of pedestrians entering of the environment, walking around in the environment and finally leaving the environment in a planned manner. On the other hand, certain pedestrian behaviour simulation models simulate the evacuation of pedestrians from a structure under stress and emergency conditions and are therefore referred to as *evacuation models*. With the help of evacuation models it is possible to analyse past incidents and assess structures for their safety requirements. Evacuation models therefore simulate pedestrians reacting to an incident, leaving the environment and possibly interacting with complications caused by the modelled incident. Some pedestrian behaviour simulation models are capable of modelling both kinds of scenarios. An overview of relevant pedestrian behaviour simulation models and their respective application areas is presented an Table 2.4, Section 2.4.

Aside from their application area, pedestrian behaviour simulation models differ mainly regarding the manner in which pedestrians are simulated. It is thereby distinguished between two modelling methods: a macroscopic pedestrian representation and a microscopic pedestrian representation. A macroscopic pedestrian behaviour simulation model represents pedestrians as a dynamic feature of the global simulation. Examples include the flow of pedestrians along a network graph or the indirect representation of pedestrians as occupancy levels of the environment using cellular automata. Conversely, pedestrians in microscopic pedestrian behaviour simulation models are represented by individual model entities. The complexity and the degree of individuality of these entities however vary to a high extent amongst different pedestrian behaviour simulation models. Some models use approaches equivalent to modelling particles within a physical fluid which are governed by global sets of equations. The most common microscopic modelling approach in pedestrian behaviour simulation models is to employ software agent entities for the modelling of pedestrians. This approach offers a great flexibility in the extent to which individualised pedestrian behaviour is represented.

As a natural consequence of the different ways of representing pedestrians within a pedestrian behaviour simulation model, the range of pedestrian behaviours that are simulated varies significantly. The range of realised behaviour models has been categorised by Gwynne et al. [32]: Pedestrian behaviour simulation models which specialise on the modelling of the pedestrians' locomotion in order to predict pedestrian flows are categorised as implementing no behavioural rules. If the behaviours of the agents are governed by a uniform set of equations, the pedestrian behaviour simulation models is categorised as modelling the functional analogy of pedestrian behaviour. In the case that a complex set of interdependent and individualised equations is used to govern the behaviour modelling of single agents, Gwynne et al. categorise the pedestrian behaviour simulation model as implicitly modelling the pedestrians' behaviour. Pedestrian behaviour simulation models with a rule-based behaviour model simulate pedestrian behaviour by evaluating potentially complex if-then-else decision trees. The last category of pedestrian behaviour simulation models according to Gwynne et al. contains all those pedestrian behaviour simulation models, which behaviour model is inspired by artificial intelligence research. Since this doctoral thesis is concerned with the simulation of advanced cognitive pedestrian behaviour, those pedestrian behaviour simulation models which incorporate a rule-based or an artificial intelligence based behaviour model are of the main interest.

As for the pedestrian behaviour simulation models' intrinsic pedestrian behaviour models, the implemented knowledge models also varies to a high degree within the range of available pedestrian behaviour simulation models. It is therefore in general distinguished between the cases that each individual agent is assigned an individual knowledge, or whether the agents have got access to a global simulation knowledge pool or whether in general no access to knowledge is simulated. Since this doctoral thesis is concerned with the realistic simulation of individualised pedestrian behaviour, those pedestrian behaviour simulation models which simulate individualised knowledge are of the main interest.

2.2. Human Behaviour Representation in Pedestrian Behaviour Simulation Models

As can be seen by the discussion of possible realisations of the fundamental parts of each pedestrian behaviour simulation model in the previous Section 2.1, the field of simulating pedestrian behaviour under both normal and emergency conditions is multifaceted. Over the recent years, several researchers from the area of pedestrian behaviour simulation have taken the opportunity to review the development of pedestrian behaviour simulation modelling tools and to suggest further directions of research and potential improvements based on their review and on the needs from potential users. In this section, the most recent reviews of expert researchers in the field of pedestrian behaviour simulation are introduced and summarised.

"Key Recommendations" for the development of evacuation simulation models by Santos and Aguirre

In 2004, Santos and Aguirre [11] presented a critical review of 15 evacuation simulation models with the main focus on the simulation of psychological and social behaviour. Based on this review, the authors have compiled a set of key recommendations "from a social science perspective" [11] for the future development of evacuation simulation models. Santos and Aguirre recommend for pedestrian behaviour simulation models to concentrate on the development of models with an individual or microscopic pedestrian representation.

> "From a social science perspective, the ideal simulation modeling approach should seek the development of sub-models that posit an active, 'investigative' socially embedded agent that assesses the state of other persons and forms a definition of the situation in cooperation with others. Furthermore, these agent-centered calculations should be placed in an on-going interaction between the properties of a particular fire and other hazard and the physical surroundings in which the evacuation takes place. Moreover, it would recognize that individuals evacuate in groups, and thus that group dynamics is an essential dimension that must be considered."
>
> *Santos and Aguirre [11]*

Santos and Aguirre therefore express the need to develop agent-based evacuation simulation models where the agents are capable of actively inquiring and evaluating their surrounding conditions and the state of other agents, while also being aware of social bonds with other agents. The model's agents should therefore have a sense of awareness and an understanding of their situation and should be capable to align their behaviour with other agents.

"Lessons for modelling crowd behaviour" by Challenger et al.

In 2009, the Centre for Socio-Technical Systems Design (CSTSD) and the Centre for Organisational Strategy, Learning and Change (COSLAC) at Leeds University Business School produced a report for the UK Cabinet Office on the "Understanding of Crowd Behaviour" [12]. The research aims of the report [12] were:

- "To review – and identify gaps in – existing research, theoretical literatures, and available knowledge on crowds and their behaviour, in both normal and emergency situations."
- "To review how the leading simulation software tools accommodate crowd behaviours, and consider how approaches to modelling and simulating crowd behaviours might be enhanced for the future, incorporating both psychological and technical concerns."
- "To identify ways forward for the field of crowd management, particularly in relation to planning for very large scale crowd events, which will take place over consecutive days and across multiple locations."
- "To produce a set of professional guidelines for emergency planners and responders, specifying reasonable assumptions which can be made with regard to crowd behaviours in normal and emergency situations, against which current assumptions can be tested, and with which future planning can be informed."

In order to accomplish their research aims, the authors compiled a literature review on crowd behaviours, reviewed three well known pedestrian behaviour simulation tools, analysed issues arising from past events, and conducted expert interviews with pedestrian behaviour simulation model developers and experts in the field of the studying and modelling of crowds. This report produced a wide range of interesting outcomes, including good practice guidelines in both emergency and non-emergency crowd handling, and an overview of identified lessons and research suggestions for crowd behaviour research and pedestrian behaviour simulation models.

Regarding the future development of pedestrian behaviour simulation models, the report's authors suggest several crowd behaviours which aren't currently included in pedestrian behaviour simulation models to a satisfactory degree. Amongst these suggested behaviours [12] are the propositions to

- "Include more psychological aspects of human behaviour, such as memory, emotions and stress"
- "Realistically simulate communication between crowd members and the impact this has on crowd behaviours"
- "Design simulations which acknowledge that crowd members are unlikely to have complete information about, or a complete understanding of, their environment and, therefore, may choose to explore."
- "Simulate how groups, e.g., families or groups of friends, behave in a given environment, incorporating the role of psychological 'groupness', i.e., a strong sense of shared social identity."

- "Include multi-purpose behaviours, i.e., behaviours undertaken during a crowd event – such as stopping to look in a shop window or taking a rest – which have purposes additional to the primary purpose of attending the event itself."

"The Need for an Integrated Approach" by Papadimitriou et al.

Also in 2009, Papadimitriou et al. [13] have compiled an extensive review of pedestrian behaviour models. The review consists of two parts, the first focusing on pedestrian behaviour simulation models which incorporate pedestrian route or itinerary choice behaviour, the second part focusing on those pedestrian behaviour simulation models which incorporate pedestrian crossing behaviour. The first category of pedestrian behaviour modelling tools …

> "... concern pedestrians decision making process as regards the optimal path between an origin and a (fixed or not) destination, among a number of alternatives, under some constraints. The problems examined mainly concern crowd and evacuation dynamics, with particular emphasis on congestion, bi-directional flow and bottleneck situations."
>
> *Papadimitriou et al. [13]*

The authors argue, that in most pedestrian behaviour models the agents' route choice and their crossing behaviour are treated independently. However, Papadimitriou et al. suggest, that an "integrated approach" which could account for both typical pedestrian behaviours would be beneficial. For this "integrated approach" the authors suggest a hierarchical pedestrian behaviour structure, based on ideas by e.g. Hoogendoorn and Bovy [33].

The proposed hierarchy of pedestrian behaviour comprises three levels: strategic behaviour, tactical behaviour and operational behaviour. According to Papadimitriou et al. [13], the strategic behavioural level should include planning pedestrian decision making such as departure time choice or activity planning. This behavioural level would simulate pedestrian behaviour and decision making taking place prior to their sojourn in the given environment. The strategic behaviour level should then provide the prerequisites for the tactical behavioural level. The tactical behaviour level therefore is concerned with e.g. activity scheduling decisions, activity area choice and route choice. The tactical behavioural level then informs the operational behaviour level, both of which are concerned with the pedestrians' behaviour during their sojourn in the environment. The operational behaviour level simulates behaviour such as road crossing, obstacle avoidance and the interaction with other pedestrians, and provides the tactical behavioural level with feedback about the environment and changes in the pedestrians' situation.

The "integrated approach" by Papadimitriou et al. [13] therefore addresses the need for incorporating a sophisticated framework into pedestrian behaviour models. This framework should be capable to address the pedestrian decision making and action performance throughout the entire environment usage phase.

"The ICE Concept" and "Six Modes of Egress Simulation" by Gwynne and Kuligowski, Gwynne and Boswell

In 2007, Gwynne and Boswell [34] presented thoughts about the management of people movement in complex environments such as high-rise office buildings and long-distance traffic terminals such as airports. In general, the authors classified people movement into three phases of movement in two types of scenarios:

> "There are three basic phases of population movement during the lifetime of a structure: ingress (people entering the structure); circulation (people moving about and making use of the structure); and egress (people leaving the structure). All occupants will find themselves in one of these three phases at any one time when using the structure [...]. In addition to these phases, the building can be utilised under two different types of scenario: non-emergency (e.g. standard, daily usage, etc.), or in some type of emergency scenario (e.g. a breach of security, a fire, a natural hazard, etc.)."
>
> *Gwynne and Boswell [34]*

The authors argue, that the design of complex environments and especially the design and implementation of the required procedures do focus too narrowly on specific scenarios and situations. Instead, Gwynne and Boswell postulate:

> "... the procedural responses need to be flexible enough to address the potential for several types of movement co-existing and also their transition from one type of movement to another."
>
> *Gwynne and Boswell [34]*

The analysis of Gwynne and Boswell of different types of people movement within complex structures and their implications for the implemented procedures within complex environments have been formalised by Gwynne and Kuligowski [9] as suggestions for future development for evacuation simulation models. For this purpose, Gwynne and Kuligowski [9] have introduced the ICE Concept.

> "A building can be seen as a people movement system that operates in different states. This system is formed from three phases termed ICE: ingress (people enter the building); circulation (people use the building); and egress (people leave the building). [...] it is beneficial to treat people movement as a single system that can exist in a number of states, rather than as a number of disparate entities."
>
> *Gwynne and Kuligowski [9]*

The authors argue, that for pedestrian behaviour simulation models to be able to simulate the entire ICE process – i.e. a structure's complete usage cycle – under both emergency and non-emergency conditions would be very beneficial for building planners and the planning and implementation of safety and security procedures.

> "To assess performance it is important to simulate all forms of people movement and the underlying influences. Simulation tools provide a mechanism by which to do this. Normally, these tools are applied to or are able to address a single phase of movement; e.g., evacuation, circulation, security, etc. This misses the impact of the historical experience that the individual brings with them (e.g., familiarity, etc.) and the possibility of several procedures being performed simultaneously and then interacting."
>
> *Gwynne and Kuligowski [9]*

For these reasons, Gwynne and Kuligowski have proposed a set of six modes for people movement simulation, which are desirable to be included in future evacuation or people movement simulation models, see Table 2.2 for an overview.

Table 2.2.: The six modes of people movement simulation by Gwynne and Kuligowski [9].

Mode	Interpretation
Naïve	Estimates people movement patterns throughout the building
Operational	Assesses people movement patterns under routine condition
Predictive	Predicts egress behavior from fundamental principles
Engineered	Answers key engineering questions using constrained behavioral assumptions
Interactive	Allows the user to interact with the simulation as it is running in order to influence the results produced
Real-Time	Runs simulations during an event/incident to provide feedback during the application of a procedure

The Naïve simulation mode is aimed to simulate pedestrians which enter a structure without any prior experience and familiarity with the environment. These agents would therefore require to explore the environment during their sojourn. They need to perceive and process relevant information about the environment and adjust their behaviour based on this information. This simulation mode would therefore be suitable to simulate e.g. first-time visitors to a shopping mall which need to search for locations at which they can purchase the goods they desire.

The second simulation mode that is introduced by Gwynne and Kuligowski is the Operational mode. This simulation mode is intended by the authors to represent the influence of experience with the structure in question. In the Operational mode, the agents will be equipped with different degrees of prior knowledge about the simulated structure. Based on these different levels of knowledge, the agents will use the structure in different ways. The usage of the structure would thereby include the purpose-related visiting of facilities within the structure by behaving according to the simulated intrinsic procedures. This simulation mode would therefore be suitable to simulate the daily routine of workers in a multi-occupancy office building including the entry control procedures.

The Predictive simulation mode postulated by Gwynne and Kuligowski is aimed to produce emergent behaviour from the simulation of individual decision making and adaptive behaviours based on the surrounding influences. The agents therefore need to be aware of their current situation and the surrounding structure and conditions. They need to be able to evaluate this information and thereupon make decisions regarding their next activities and behaviour. This simulation mode would therefore be suitable to simulate the alarm response of pedestrians during an emergency incident.

In contrast to the Predictive simulation mode, Gwynne and Kuligowski have also proposed the Engineered simulation mode which is aimed to simulate previously defined behavioural responses. The model user should be able to either deterministically or probabilistically assign behaviours to the pedestrians given certain conditions. With this simulation mode, the user can assess past emergency incidents based on ascertained data. As the authors note, this simulation mode is the rule-based behaviour model currently used by most evacuation simulation models.

In the Interactive simulation mode, the model user should be able to alter scenario conditions or the behaviour of the agents during the course of a simulation. The agents would then require to react to potential changes to the surrounding conditions and adapt their behaviour accordingly. This simulation mode would be suitable to simulate e.g. the impact of falling debris during a fire incident and the ensuing potential blocking of exit routes.

The final simulation mode proposed by Gwynne and Kuligowski, the Real-Time mode, is aimed to be linked into the security coverage of live-events such as public gatherings or the people movement within airport terminals. In the case of an incident, the authors propose that a pedestrian behaviour simulation model in Real-Time mode should be able to run faster than real time and predict outcomes of the current conditions and procedures, thereby enabling the safety officials to adjust the procedural processes in order to improve the potential future situation. This mode would therefore require for the pedestrian behaviour simulation model to be able to simulate procedural processes and adaptive behaviours of the agents in response to changes in the surrounding conditions.

Gwynne and Kuligowski [9] argue, that some pedestrian behaviour simulation models already incorporate some of the before mentioned simulations modes, but that currently no pedestrian behaviour simulation model comprises all proposed six modes of simulation. The authors therefore conclude:

> "All of these modes have great value; however, currently no model can address all of them. This will inevitably require the engineer to make a greater number of assumptions. Incorporating all of these modes into a single model would produce a number of benefits. The user would be able to represent the impact of occupant experience, the different phases of people movement, and the interaction between the procedures employed given a situation. This user will be able to do this during various phases of the lifecycle of the building. This should be a future goal, given the need for this integrated approach and the increasing interrelatedness of incident scenarios."
>
> *Gwynne and Kuligowski [9]*

"Five Grand Challenges in Pedestrian and Evacuation Dynamics" by Averill

In 2010 on the occasion of the Pedestrian and Evacuation Dynamics Conference 2010, Averill [10] identified "five grand challenges in pedestrian and evacuation dynamics" from the perspective of a building evacuation researcher:

1. "Develop and validate a comprehensive theory which predicts human behavior during pedestrian or evacuation movement"
2. "Create a comprehensive database of actual emergency data"
3. "Embrace variance" [10]
4. "Integrate results of evacuation models with fire models to enable accurate and reliable performance-based design"
5. "Embrace technology"

In his outlook for the pedestrian and evacuation dynamics community, the author mentions a wide range of topics that the community's researchers and practitioners need to address in the future. Amongst these topics is the demand for a general theory on human behaviour, especially during evacuation situations. Averill mentions human behaviours, which aren't entirely understood today, such as occupants pre-evacuation actions and evacuation decisions, their situation awareness and cue interpretation, the influence of their prior experience and risk perception as well as their social context. Averill argues, that once sound theoretical explanations of this kind of human behaviour are available, then a general model of these behaviours should be introduced in pedestrian behaviour simulation and especially evacuation simulation models.

2.3. Suggestions for Advanced Human Behaviour Modelling in Pedestrian Behaviour Simulation Models

As depicted in Section 2.2, several issues regarding the modelling of human behaviour in pedestrian behaviour simulation models have recently been raised by a number of expert researchers. Although the summarised reviews had different focus areas such as evacuation, pedestrian and crowd behaviour, all reviews agree that future pedestrian behaviour simulation models should incorporate an advanced representation of human behaviour. The expert research opinions from Section 2.2 on what kinds of individual pedestrian behaviour should be addressed in the future development of pedestrian behaviour simulation models have been summarised in Table 2.3.

All of these have a common suggestion: to encourage the development of bottom-up modelling approaches rather than the top-down modelling approaches that have been widely used until today. This would result in individual emergent behaviour, i.e. intrinsic behavioural processes producing externally observable behaviours. However, to be able to simulate pedestrian behaviour by such a bottom-up approach, the underlying human behaviours need to be studied and understood.

By incorporating some or desirably all of the behaviours listed in Table 2.3, pedestrian behaviour simulation models would be able to model more realistic and advanced pedestrian behaviours, especially in complex multi-purpose environment such as long-distance public transport facilities, leisure facilities and high-rise multi-occupancy buildings.

2.4. Survey of currently available Pedestrian Behaviour Simulation Models

In this section, currently available pedestrian behaviour simulation models are reviewed under consideration of the compiled suggestions presented in Section 2.3. The review of pedestrian behaviour simulation models thereby focusses on tools which already simulate some kinds of the suggested behaviours in Table 2.3 and which are therefore relevant for this thesis. The reviewed models include models which specialise in either the modelling of pedestrian circulation behaviour or evacuation behaviour, or models which address both behaviour stages, see Table 2.4. Because of their relevance to this thesis' subject area, two models which concern pedestrian movement but which have their origin in virtual reality simulations have also been added to this review.

Kuligowski et al. [25] and Challenger et al. [12] mention other (mostly commercial or consultancy licensed) pedestrian behaviour simulation models, which would have been of great interest for this thesis' literature review, such as CRISP [25], EPT [25, 65], Legion [12,

Table 2.3.: Individual pedestrian behaviours desirable to include in future pedestrian behaviour simulation models according to Gwynne and Kuligowski [9], Averill [10], Santos and Aguirre [11], Challenger et al. [12], Papadimitriou et al. [13].

Modelling Area	Behaviours/Components suggested to be modelled	Source(s)				
		[10]	[12]	[9]	[13]	[11]
Scenario	integrated building usage-cycle simulation (ingress, circulation, egress/evacuation) under emergency and non-emergency conditions		✓	✓	✓	
	incident alarm response phase	✓		✓		✓
	• imposed emergency response			✓		
	• predicted emergency response					
	▷ pre-evacuation decisions	✓				
	▷ pre-evacuation activities	✓				
Environment	representation of building amenities/features and points of interest/relevance		✓	✓		
	representation of purpose of building amenities (in response to pedestrian "expectation") and building usage		✓	✓		
	representation of characteristics of route and points of interest				✓	
Pedestrian	situational awareness: perception and evaluation of					
	• building facilities			✓	✓	
	• procedural processes			✓		
	• events, stimuli and surrounding conditions	✓	✓	✓	✓	✓
	(different degrees of) memory of previous usage of building and of procedures	✓	✓	✓	✓	✓
	advanced psychological or cognitive features					
	• representation of purpose and (multiple) intentions		✓	✓		
	• representation of emotions		✓			✓
	• representation of plans and tasks			✓	✓	
	• decision making model	✓		✓		
	▷ adaptive behaviour: action selection			✓	✓	✓
	▷ pre-trip planning behaviour				✓	

Table 2.4.: Overview of the reviewed pedestrian behaviour simulation models categorised by their main application area.

Main Application Area	Model	Source(s)
Circulation	Amanda	[35–39]
	Kitazawa and Batty	[40]
	Pedsim	[41, 42]
	SimPed	[43, 44]
	STREETS	[26, 45]
Evacuation	MASSEgress	[46–49]
Circulation and Evacuation	buildingEXODUS	[14], see Chapter 4
	MassMotion	[50–52]
	STEPS	[53–58]
Virtual Reality	COHUE	[59, 60]
	MACES	[61–64]

25, 66] or Myriad II [12, 25, 67]. Unfortunately, not enough published detailed information about these pedestrian behaviour simulation models could be obtained in order to allow to include these pedestrian behaviour simulation models in a comprehensive review.

2.4.1. Pedestrian Circulation Simulation Models

Amanda

The Amanda model ("A Multi-Agent model for Network Decision Analyses", Dijkstra et al. [38]) is a probabilistic multi-agent pedestrian model with main application of simulating pedestrian behaviour in shopping malls or urban shopping environments under non-emergency conditions [35–39].

The shopping environment is represented as a network of walkways connecting the simulated structure amenities, i.e. shops. The simulated shops are characterised by their range of products and a set of "appealing characteristics" [37] which correspond to a set of individual agent preferences, the "agent ideals" [38].

Prior to the start of the simulation, the agents are equipped with a set of intentions or goals that they wish to accomplish during the course of the simulation, e.g. the purchase of certain products or the intention to do window shopping. These assigned goals vary in importance on the agents' behaviour, simulating different "states of motivation" for each goal [39].

In order to accomplish their assigned goals, the agents seek to complete activities at the simulated shops in the environment. They therefore need to choose a shop for each of their intentions. The Amanda model realises this choice process by employing a parameterised probabilistic perception model. In summary, the agent will perceive a certain amenity in the structure with a certain probability dependent on several influences, such as the match of the amenities characteristics to the agent's preferences, the amenity's architectural appeal, the distance to the amenity, the agent's awareness and their motivational state. The model's parameters are calibrated based on empirical data [37, 39].

Upon the completion of an activity and also upon passing key locations in the environment, the agent reconsiders their planned set of activities, potentially changing their agenda [38]. Dijkstra et al. note, that time constraints, time considerations and different priorities for each activity are incorporated in the agenda rescheduling activity. The order of activities on the agenda and the thereby planned route through the environment can be altered. However, it could not be established during the course of this literature survey which decision basis and decision algorithms are used for the agenda rescheduling activity.

The Amanda model simulates pedestrian behaviour by allowing pedestrians with no prior spatial knowledge about the structure to explore the simulated environment and adapt their behaviour based on the perceived information. Once an amenity has been perceived by an agent, this amenity is added to the agent's spatial memory, their "consideration set" [39]. When in the future the agent reasons about conducting an activity during the agent's rescheduling activity, the agent refers then to their attained spatial memory in order to choose a location where to perform that activity.

Kitazawa and Batty

In 2004, Kitazawa and Batty [40] proposed a microscopic agent-based pedestrian shopping behaviour model for urban shopping environments. The model simulates pedestrian circulation movement under non-emergency conditions in a simulated street network connecting different amenities [40]. Every amenity is associated with a set of attributes: the amenity's size and their targeted types of costumers.

Pedestrians are represented by agents, which are assigned a set of individual attributes based on Geo-Information System information. The agent's attributes include a walking speed, fatiguability and a set of "tastes" [40] or preferences related to the agent's assigned income, gender and age.

Each individual agent "chooses" an initial activity schedule prior to the start of the simulation. The activity scheduling process comprises the two steps of choosing targets in accordance with the agent's assigned preferences, and a route choice process which determines the detailed route connecting the previously chosen targets.

The target choice process "identifies the attractiveness of each shop to each pedestrian" [40] and is therefore a global process. The amenities' attractiveness is determined by how well the amenities' attributes matches the individual agent's attributes and preferences, based on marketing data and neural network algorithms. In addition, the amenity's availability and the distance of the agent to the amenity in question is also taken into consideration.

These determinations result in a level of attractiveness of a given amenity for the individual agent. Each agent chooses those amenities where the individual attractiveness exceeds a global attractiveness threshold.

Once a set of targets has been determined by the target choice process, the agent decides on the route connecting the chosen targets in the simulated street network. The route is chosen by solving a Travelling Salesman Problem by maximising the route's utility. In the model presented in [40], a route's utility is based on the route's total distance, and genetic algorithms are used to solve the Travelling Salesman Problem.

The agent's activity scheduling process is enacted once prior to the start of the simulation and also as the representation of adaptive behaviour to dynamic events such as congestion, route blockages or time events, e.g. shop closing times. It has to be noted however, that no individual and therefore localised perception behaviour of these events has been implemented in the model. Instead, all agents receive an update of the current situation of the entire modelled environment in regular time steps. Should the situation of the environment have changed compared to the last time step, this triggers the activity scheduling event for all modelled agents.

Pedsim

The Pedsim microscopic pedestrian circulation model by Gloor [41, 42] has been developed to model recreational tourist movement such as hiking in a network of appropriate routes, e.g. hiking routes. Pedsim has been designed as a multiple simulation tool, i.e. information gathered by the pedestrians and the model during one simulation run can be memorised in general to inform succeeding simulation runs.

In Pedsim, the pedestrians or tourists are represented by individual agents with individual activity goals and an individual plan of their trip. The plan thereby refers to a set of activities which need to be accomplished at certain activity locations (e.g. “stay at a hotel”) and a route which connects the activity locations. During one simulation run in the Pedsim model, each agent realises one initially chosen plan.

The agent chooses their plan based on individually assigned “expectations” [42]. The agent's expectations refer to their entire plan, and it is the aim of the agents to choose a plan, i.e. activity locations but also especially a route which best match their expectations.

It is not stated in detail as to how the agents choose the activity locations required for their plan. But Gloor et al. state, that the decision is informed by Geo-Information System.

Since the main source of motivation for Pedsim has been the simulation of tourist hiking movement [42], a route as a sequence of links in the simulated network is evaluated based on the properties of its comprised links. Criteria for route evaluation are thereby e.g. aesthetics, difficulty and travel time. Based on these route properties and the agent's assigned expectations, a route is chosen by utility maximisation (or equivalently cost minimisation) techniques, see Section 3.2.1.1.

During the course of a simulation, the agents are capable of perceiving the landscape alongside the route and thereby comparing the route with their expectations. After a simulation run and thereby once the agents have completed their plans, the agents reassess their plans and potentially alter their routes for the next simulation run. The individual agents' assessments of the route network are generalised and stored in a global weighted network graph, which is adjusted in every simulation run.

In addition to trip replanning at the end of each simulation run, the agents are able to adjust their trip spontaneously during one simulation run. This replanning is triggered by the pedestrians perception of events such as congestion or bad weather. The agents will then adjust their plan accordingly by referring to the global weighted network graph.

SimPed

SimPed has been developed for the modelling of pedestrian circulation behaviour under non-emergency conditions in transfer stations. The pedestrians are modelled as a macroscopic pedestrian flow along a network of links. The main aim of the model development has been the "estimation of mean and variability of walking times incurred by transferring passengers" [43]. For this reason, SimPed produces – amongst others – outputs indicating Fruin's levels of service [68].

Although SimPed is a macroscopic model, the pedestrians are represented as individual entities. The individual entities have assigned a pedestrian type and a set of activities. By specifying the individual entity's pedestrian type, a pedestrian is in theory assigned a specific set of preferences and familiarity with the structure.

Daamen [44] however points out, that the current prototype of SimPed is only concerned with the modelling of "commuter" pedestrian types: "We argue that commuters and peak conditions are most important when assessing a design, since capacities are generally reached during peak hours." [44]. Simulated pedestrians in SimPed therefore are all assigned an identical set of preferences, and SimPed "... assumes all pedestrians to have complete information on both static and dynamic conditions in the station (no uncertainties)." [44]. This implies, that agents within SimPed are assigned a perfect knowledge of the simulated structural layout.

In SimPed, a set of activities which the pedestrians can perform during their sojourn in the simulated environment can be defined by the model's user, e.g. "buying a newspaper" or "visiting a shop". The set of activities is given by the user in a fixed sequence. All agents therefore perform all assigned activities in this given order. To perform an activity, the agents will – if necessary – queue until a service counter at the given amenity is available, at which point the pedestrians seeks the free service counter and experiences a delay at the counter given by a service time probability distribution.

As noted by Daamen, a user-defined activity can be either compulsory or elective. The agent would in theory be capable of dropping activities if they experienced time pressure.

However, Daamen notes

> "While some of these activities are discretionary (buying a newspaper), others are mandatory (buying a ticket before accessing a train when a passenger does not yet possess one). Due to the fact that only few sources are available on activity choice set generation (Arentze & Timmermans 2004), (Helbing 1997), (Penn 2003), (Timmermans et al. 1992) and the fact that the strategic level is considered exogenous to the simulation model described in this thesis, the subject is not dealt with any further."
>
> *Daamen [44]*

Based in the fixed sequence of activities given by the user, agents within SimPed are assigned a set of activity locations and a connecting route on entering the simulated environment.

Each agent chooses their set of activity locations and the connecting route based on the network's current global situation at the time of them entering the structure. The agent uses a deterministic utility maximisation approach based on the single parameter of total travel time to choose the activity locations and the connecting route. Once both the activity locations and the connecting route have been chosen, they remain fixed for the individual agent during the course of the simulation, i.e. adaptive behaviours are not modelled.

STREETS

In 1999, Schelhorn et al. [26] have proposed the agent-based pedestrian circulation model STREETS for the modelling of pedestrian activities on an urban scale. The urban area is thereby represented by a street network grid.

Modelling pedestrian activity behaviour with STREETS is accomplished by a two-phase process: in the "pre-model" phase [26], the agent population is generated based on Geo-Information System data. In the following simulation phase, the actual pedestrian circulation movement of the pre-initialised agents is simulated using the SWARM simulation environment [69].

During the population generation process in the pre-model phase, the agents are assigned initial activity schedules based on the individual agent's "socio-economic characteristics" [26] that have been assigned by the Geo-Information System, such as gender and income. An activity schedule is thereby a "sequence of locations which the agent intends to visit" [26]. The order in which the activity locations are visited is determined by utility maximisation determinations based on the single parameter of total route distance.

In addition to their socio-economic characteristics, the agents in STREETS are also assigned a set of "behavioural characteristics": maximum walking speed, a visual range and a level of fixation [26].

The agent's fixation is intended to represent the agent's focusing on their assigned activity schedule, and is a function of time. The agent's level of fixation increases the lesser time they have remaining for their activities in the environment. Therefore, the STREETS's level of fixation simulates the effect of time pressure on the agent.

Depending on their level of fixation as well as their agent type, agent's can decide to alter their assigned activity schedule based on visual perception of suitable buildings:

> "Building attributes such as type and general attractiveness are compared to the agents profile, and if a match is found then the location may be pushed onto the route as a new next destination."
>
> *Haklay et al. [45]*

Agents within the STREETS model are also capable to be influenced by other agents, although no reactive or adaptive behaviour to this influence has been implemented. If the agent arrives at an assigned activity location which is very crowded, the time to perform this activity increases relative to the level of congestion.

2.4.2. Evacuation Simulation Models

MASSEgress

MASSEgress (Multi-Agent Simulation System for Egress analysis [48]) is a recently developed agent- and rule-based crowd evacuation simulation model which specialises on the modelling of emergent social behaviours.

The pedestrians are represented by individual agents with an individual degree of familiarity with the structure. Since MASSEgress is an evacuation simulation tool, the recognised structural features an agent can be familiar with are the available exits from the structure. In addition, the social role of leadership can be assigned to individual agents.

The modelled agent behaviours include a visual perception module of the structure (i.e. obstacles, goal points and exit signs) and other pedestrians. The visual perception algorithm uses a ray of vision approach and is used for obstacle avoidance and to inform the targeting movement system.

Furthermore, an agent in MASSEgress is capable of the execution of seven behavioural decisions [46]: On the individual level, the agent is capable to (randomly) explore the environment, go to a certain point of interest in the structure, competitively seek for a nearby exit or queue at an exit. Socially, the agent can decide to form a "herd" with other agents, to follow a leader agent or to follow any other agent. These behavioural decisions are results of a decision making on the individual agent level.

MASSEgress simulates individual decision making by employing a perception-action approach: upon the internal triggering of a decision, the agent assesses their current situation in terms of congestion, tension level and the information provided by their visual perception feature. The situation is then interpreted, incorporating the agent's psychological factors:

the agent's familiarity with the structure, their level of urgency to exit and the agent's decision making type [46]. Based on this situation assessment, a decision rule from a global decision tree database is chosen and the resulting decision is realised.

2.4.3. Pedestrian Behaviour Simulation Models

buildingEXODUS

buildingEXODUS [14] is an agent-based, fine-grid simulation software tool with main emphasis on the simulation of emergency evacuation behaviour, but also comprising means to model pedestrian circulation behaviour. Since buildingEXODUS serves as the basis for the pedestrian behaviour simulation prototype developed in this thesis, it's capabilities and components are reviewed in detail in Chapter 4.

MassMotion

MassMotion [51] is an agent-based software tool which has been initially designed for simulating pedestrian circulation behaviour in a station environment. Bailey et al. [50] mention that MassMotion can be used to model pedestrian behaviour during an emergency evacuation by employing the model's built-in features in an appropriate way. The model has however not been specifically designed to model sophisticated evacuation behaviour.

A geometry in MassMotion is simulated as a floor-link network. Walkable areas are represented by "Floor Actors", links between these different geometry parts by "Link Actors" and points or regions of interest simulating possible origins and destinations for the agents by "Portal Actors" [52]. Link Actors simulate structural entities such as barriers, escalators or gates. When passing through a Link Actor, the agents can experience an impact on their walking speed or a pre-specified probabilistic time delay. A Portal Actor can be specified to act as either an entrance for the agents, and exit, or to act as both. Agents are assigned an entrance and an exit Portal Actor which determine their route within the simulated environment.

A given geometry is populated by employing so-called "Agent Schedules" [52]. An Agent Schedule is specified by the number of agents that are generated with this schedule, the time schedule according to which the agents are generated and a list of entrances and exits where the agents for this agent schedule enter and leave the simulation. The time at which an agent is generated as well as the assignment of the agents to the entrance and exit portals is governed by user-specified probability distributions.

After an agent has been generated, they choose a route from their assigned entrance portal to their assigned exit portal via appropriate geometry links by employing a probabilistic cost minimisation algorithm. The cost of an available route $c = c_{det} + c_{prob}$ is thereby calculated as comprising a subjective deterministic part c_{det} and a probabilistic part c_{prob}. The deterministic route cost c_{det} is thereby governed by the current conditions on the route in question and the specific agent's individual assessment of the route cost components [52]:

$$c_{det} = w_d \cdot \frac{d}{v} + w_q \cdot q + w_l \cdot l$$

where d is the route's remaining total distance, v is the agent's walking speed, q is the expected time spent queuing before the current link and l is a cost associated with the current link's type. Finally w_d, w_q, w_l are randomised agent parameters symbolising the individual agent's corresponding preferences. The weight parameters have been calibrated based on empirical data, which was obtained at the Union Station in Toronto [51]. The agent will determine their cost minimal route at their entrance portal and at every geometry link that they are passing during the simulation.

An agent will follow their chosen route by incorporating an adjusted Social Force model (see e.g. Helbing and Molnar [28]) for their locomotion behaviour. The Social Force model implemented in MassMotion has been calibrated according to Fruin's levels of service [68].

In MassMotion, the user can specify for simulated gates which are realised as a specific type of the "Link Actor" events at which the simulated gate will be opened or closed. The agents take the information about the availability of a simulated gate into account during their route cost calculations and will therefore react to these emergent global gate events.

As mentioned by Bailey et al. [50], MassMotion can be employed by the user to model goal-driven and information seeking pedestrian behaviours by assigning an agent a certain Link Actor as an intermediate destination and assigning this Link Actor a time delay distribution. Therefore, each traversing agent will experience a time delay, simulating for example shopping behaviour or the querying for information. Obviously it is also possible to model the arriving and departing of transport vehicles with MassMotion.

In a similar way, the user can simulate emergency evacuation behaviour with MassMotion. The agents' response times to an emergency alarm can be simulated by an appropriate time distribution within an Agent Schedule and the agents' exit choice is then governed by the user-specified probabilistic assignment of the Agent Schedule's set of exit portals.

Bailey et al. [50] also mention the possibility of simulating the impact of signage and different degrees of familiarity with the structure on the agents' behaviour. However, no details on the actual realisation of these behaviour could be established during this literature review.

STEPS

STEPS (Simulations of Transient Evacuation and Pedestrian movementS [53]) is a simulation tool which is capable of modelling circulation as well as evacuation behaviour within built environments. The model's main application area it the modelling of pedestrian circulation within traffic facilities such as station environments [57].

The geometry in STEPS is defined by a fine-grid structure and directional links connecting different floors of the simulated environment. By connecting two floors with a link object, one exit location per floor is generated in the model at the point where the link is connected to the given floor.

In addition to exits, specific points of interests – so-called “checkpoints” [57] – can be generated in the environment. Checkpoints can be targeted by the agents, and they can be assigned a time delay which the agent will then experience. Checkpoints can thereby used to simulate for example ticket booths.

Furthermore, the user can assign the modelled exits and checkpoints a “tag number” [57]. By assigning several checkpoints or exits the same tag number, these targets are then grouped and instead of assigning an agent a specific target, the user can assign the pedestrian a tag number which they shall target. The agent is then able to choose any of the checkpoints with the specific tag number in order to accomplish their assigned task.

Pedestrians in STEPS are simulated as individual entities. The agents are assigned five pedestrian attributes [57]: an individual walk speed, a level of “awareness” or familiarity with specific checkpoints or exits, a potential association with a group of agents and a pre-movement time. The pre-movement time determines the agent’s entry time in the environment and is therefore used to model a pedestrian’s response time in an evacuation scenario. The agent’s awareness attribute with regard to a specific exit or checkpoints determines the probability that the agent will know about the target in question.

In STEPS, the user can specify “routes” within the environment [58] and can assign agents to follow these pre-defined routes. A route thereby consists of a sequence of checkpoints, exits, tag numbers or lifts. By employing a set of routes, the user can therefore simulate e.g. the pedestrian circulation behaviour in a train station, where the agents enter the environment, need to purchase a ticket and then need to go to a platform. The agents locomotion between two route targets is governed by a potential distance map.

Two situations can require an agent to choose a specific target: if the agent has been assigned a tag number to visit in a circulation scenario or the agent has to choose an exit in an evacuation scenario. In these situations, the agent chooses a target based on a cost minimisation approach.

The target’s cost is thereby a function of an estimated time to reach the target $t_{walking}$ and an estimated queuing time at the target $t_{queuing}$. The estimated queuing time is also weighted according to the individual agent’s level of patience $w_{patience}$. Furthermore, the user can specify the global weights for the walking time W_{walk} and subjective queuing time proportions W_{queue} on the final target cost [58]:

$$c_{target} = W_{walk} \cdot t_{walking} + W_{queue} \cdot w_{patience} \cdot t_{queuing}$$

The target’s cost function is updated every time step, thereby enabling the agent to adjust their choice based on increased congestion around the target or emergent events such as a targeted exit becoming obstructed and therefore no longer being available.

2.4.4. Virtual Reality Crowd Models

Virtual reality crowd models are mainly used to populate virtual environments in for example computer games, architectural design presentations or virtual training systems. Although virtual reality crowd models seek to realistically simulate pedestrian behaviour, their main focus of application lies elsewhere. Examples include the telling of a game story, or the pleasant presentation of building architecture, or the simulation of pre-engineered training scenarios.

COHUE, incorporating DirectIA®
COHUE is a microscopic agent-based human behaviour model of urban-scale environments. It is one of the building components of the crisis management training system CRIMSON [70].

The COHUE urban simulation model uses a designated agent model, the DirectIA® decision engine (Direct Intelligent Adaptation [59]). The DirectIA® agent model is a simulation framework which specialises in the representation of autonomous agents with methods from the situated artificial intelligence [59]. As such, it is comparable to a cognitive architecture, see Section 3.1.

The DirectIA® framework comprises the simulation of goals or intentions, the so-called "motivations":

> "... motivation is an internal variable that takes into account both the internal state of the agent and the stimuli it receives from the environment, thus triggering behaviours in order to satisfy the agent needs."
>
> *Chiva et al. [59]*

By satisfying the agent needs "... the entity tries to maintain the [motivation] variable in an 'acceptable' state, thus 'satisfying the motivation'." [60]

The agents modelled with the help of the DirectIA® model are capable of perceiving their environment in terms of spatial information, stimuli and emergent events. This information is than processed by a simple directed graph, the "behavioural graph", which is formed of a motivational, a behavioural and an action selection layer [60]. The behavioural graph thereby behaves similar to an influence diagram (cf. e.g. Howard and Matheson [71]).

In the DirectIA® motivational layer, the modelled spatial information or modelled events are perceived as stimuli by the DirectIA® agent, evaluated by the agent's emotion attributes, resulting in an update of the agent's internal state variable which affects the agent's corresponding motivational level. Depending on the resulting level of activation of the agent's modelled motivations or goals, strategic behaviours in the behavioural graph are triggered, which in turn activate actions in the action selection layer.

Since the motivations modelled within the DirectIA® agent's behavioural graph are updated simultaneously, several motivations can be triggered which in turn could trigger several competing behaviours and result in potentially competing action suggestions. From these suggestions, one action needs to be chosen for the next action to be executed. The action selection algorithm thereby follows Tyrrell's hierarchical action selection process [72, 73].

A DirectIA® agent is modelled as an individual entity by the assignment of "initial values of state variables, relative weight of motivations defining the agent goals, and emotional parameters defining the agent sensitivity to stimuli coming from the environment." [60].

For these reasons, the DirectIA® agent model has been chosen by Chiva et al. [59], Comptdaer et al. [60] as the underlying agent framework for COHUE. Chiva et al. [59], Comptdaer et al. [60] demonstrate the capabilities of COHUE and DirectIA® by discussing the simulation of pedestrian behaviour in a train station. During the simulation, an attack on the train station and the emergent pedestrian evacuation behaviour is simulated.

No detailed description of COHUE's environment model is given. However, for the train station case study, a train station including outside exits, ticket offices as well as train platforms and train objects is generated. These spatial features are perceivable by the agents via the perception model of DirectIA®, about which no details have been provided.

In addition to this spatial information, the DirectIA® agents have been designed to be able to perceive and react to the emergent events of arriving trains, the opening or closing of external exits or ticket offices, the level of local population density, and the modelling of an emergency event.

An example to illustrate the DirectIA® behavioural graph, would be the evaluation of congestion. The agent's perception of a high population density causes a stimuli of elevated density stress which triggers the agent's density stress emotion. The density stress emotion activates the agent's internal annoyance state which then influences the corresponding modelled agent motivations to change their position within the environment. This motivation then triggers the behaviour to change the agent's position. This behaviour is then taken into consideration for the action selection algorithm, depending on the strength of the motivation to change the position and on the outcome of the other modelled motivational states.

In COHUE, the modelled pedestrians are able to choose and target an outside exit, to queue up for and buy a ticket and to take a train. If the agent's next action is to choose and target an exit, the agent always chooses the closest available exit.

The response to an emergency event is modelled in COHUE by introducing the impact of danger stimuli. The danger stimuli corresponds to the agent's modelled motivation to "get out", which causes the activation of the exit choice behaviour.

MACES, incorporating PMFserv

The MACES model (Multi-Agent Communication for Evacuation Simulation [63]) is an agent-based crowd simulation model for computer graphics applications. MACES' main focus is on the simulation of explorative and collaborative pedestrian wayfinding, e.g. in the case of an emergency [63].

MACES represents the simulated environment (especially buildings) on two levels. The first level, used for locomotion, is a continuous space representation. The second level, used for wayfinding, is a coarse-grid structure, the model's "cell and portal graph" [63]. The building's rooms and corridors are modelled as cells or nodes of a graph connected by edges or portals representing the building's internal doors. For each cell or graph edge, MACES computes a shortest route to the closest external exit and embeds this information in the cell, such that it can be queried by the agents.

MACES models the agents' locomotion and steering behaviour by a parameterised Social Force Model.

Agents in MACES are assigned an individual memory of the simulated spatial environment, their individual "cognitive map" [63]. The agent's cognitive map is also organised as a cell and portal graph. By exploration and perception while traversing the environment, the agents expand their individual cognitive map with spatial information and also include information about the location of hazards or blockages.

The information available on the individual agent's spatial memory is not only used for the agent's wayfinding, but can also be shared via communication. Communication can occur between agents who currently occupy the same room. Agents are able to communicate two types of information relevant to the future wayfinding: Agents can prevent other agents to proceed trough a certain door from the current room because of a known hazard behind this door. In addition, agents can prevent other agents from pursuing wayfinding in a certain direction from the currently occupied room, if they have knowledge themselves that no available exit lies in that particular direction. By this communication model, MACES simulates collaborative and informed wayfinding.

MACES also accounts for the simulation of different social roles. The model distinguishes between the modelling of trained leaders (e.g. fire fighters), untrained leaders and untrained followers [63]. Trained leaders are simulated by agents which have a complete individual cognitive map of the environment and which will help other agents with their memory information. Untrained leader agents are characterised by having a higher stress level tolerance (see below), by the willingness to help other agents and the readiness to explore the environment. Finally, untrained follower agents have got the potential to "panic" [63] and thereby lose their ability to rational decision making.

The individual agent's wayfinding behaviour in MACES when assigned the task to exit a building (e.g. during an emergency) is thereby highly influenced by the individual agent's own social role and knowledge, but also on the social roles and knowledge of the surrounding agents.

In general, the wayfinding procedure in MACES can be described as follows [63, 64]: At first the leaders present in a room share their spatial knowledge with the other agents present in the same room. The agents than query the cell and portal graph for the shortest route from the current room to an available exit. If according to their (newly attained) spatial knowledge this shortest route is still available, the agents proceed to the next room or corridor along this route. If however the shortest route is blocked by for example a hazard, the agents exhibit an adaptive behaviour based on their individual social role. A trained leader agent will query their (complete) spatial memory for the next shortest unblocked route to an exit and will proceed along that route. An untrained leader agent will react by exploring the building and proceed to the next room by using a Depth-First-Search algorithm. On the other hand, an untrained follower agent will simply follow another leader agent.

Pelechano et al. [64] describe the incorporation of a "psychological" model into the crowd simulation model MACES, the PMFserv model [74, 75]. Pelechano et al. use PMFserv to model psychological, emotional and goal related agent attributes as well as an enhanced agent decision making process.

PMFserv [64] is an agent model similar to a cognitive architecture, see Section 3.1. PMFserv incorporates a long term agent memory and a working agent memory: In the long term agent memory, the agent's general attitudes, beliefs, preferences, goals and psychological attributes are stored. The information in the agent's long term memory thereby builds the agent's reasoning and evaluation framework. A PMFserv agent decides on their next actions by processing perceived information from the environment with their working memory. The information processing thereby include the determination of the agent's individual stress level based on their physiological attributes, which in turn determines the agent's current level of awareness and their capability for rational decision making. Also, the agent's current importance levels of their modelled goals and motivations are updated. The agent than determines their currently available actions, based on their awareness level and their current motivations. The agent's currently available actions are than analysed by the PMFserv's intrinsic OCC emotion model (see Section 3.2.3). The agent's emotional response is summarised by assigning each currently available action a utility value. Finally, the agent chooses the action with the highest subjective utility.

Although Pelechano et al. [64] believe the incorporation of concepts such as PMFserv into a crowd simulation model to be beneficial for modelling emergent crowd behaviour, the idea seems not to have been pursued any further [62, 63].

2.5. Review and Remaining Challenges

This section will review the pedestrian behaviour simulation models surveyed in Section 2.4 under consideration of the research suggestions summarised in Table 2.3 in Section 2.3. It will further analyse and compare in detail the means by which the expert suggestions have been realised in the different reviewed pedestrian behaviour simulation models.

Analogically to the listing of expert suggestions in Table 2.3, Table 2.5 summarises the survey of the pedestrian behaviour simulation models undertaken in Section 2.4. Table 2.5 thereby lists, which of the suggested individual pedestrian behaviours in Table 2.3 are addressed by the surveyed pedestrian behaviour simulation models.

Table 2.5 gives an overview as to the current state of pedestrian behaviour simulation modelling tools with regard to the compiled expert suggestions. As can be seen, some features are more often addressed in the surveyed pedestrian behaviour simulation models, for example the representation of building facilities and of the pedestrians' tasks. Other suggested behaviours are however only sparsely addressed, for example the pre-evacuation decision processes during the alarm response phase and the representation of purpose within the environment.

It has to be emphasised, that Table 2.5 only serves as an indicator to which pedestrian behaviour simulation model specialises in what aspect. In order to further review the surveyed pedestrian behaviour simulation models, the different approaches by which certain aspects are addressed need to be analysed. During the analysis, it has been found that the used approaches in the different pedestrian behaviour simulation models vary significantly, especially with regard to the implemented degree of pedestrian individuality and self-reliance.

The results of the analysis of the surveyed pedestrian behaviour simulation models in Section 2.4 have been summarised in four tables. Tables 2.6 and 2.7 compare the models surveyed in Section 2.4 in terms of the representation of advanced individual pedestrian behaviour. Tables 2.8 and 2.9 compare the selected models in terms of the realisation of the modelling of the building usage cycle.

Table 2.6 is concerned with the representation of advanced behaviours in the individual modelled pedestrians.

In order to be able to pursue advanced behaviours, the agents would require to have a representation of their intentions in visiting the simulated environment. These intentions can be simulated as being an abstract goal information, e.g. "get a ticket" without any detailed intentions regarding where to achieve this goal. In addition or alternatively, the agents intentions can be simulated by plans, i.e. the intention to visit a certain facility in the simulated environment in order to perform any kind of activity at that facility.

Pedestrian behaviour is to a high degree dependent on their knowledge base about their own intentions but also about the environment that they are in. This knowledge forms the information base for the pedestrians behaviour, e.g. the adaptation to events. In general, there are two knowledge simulation possibilities: either the agents are given access to a global knowledge base, e.g. the agents have a complete knowledge of the simulated structure. On the other hand, agents can be assigned an individual memory, thereby realistically simulating the individual's potential limited knowledge about their environment.

The agents' rational decision making can be simulated to various degrees and incorporating a wide variety of approaches. On the very basic level, it can be distinguished whether a pedestrian behaviour simulation model simulates pedestrian decision making in a deterministic or a probabilistic way.

In order to process newly gained information, the agents need to evaluate the raw inform-

Table 2.5.: Overview of which suggested individual pedestrian behaviours (see Table 2.3) are addressed by the surveyed pedestrian behaviour simulation (PBS) models.

Modelling Area	Suggestions	Models										
		Amanda	Kitaz.,Bat.	Pedsim	SimPed	STREETS	MASSEgress	bdEXODUS	MassMotion	STEPS	COHUE	MACES
Scenario	integrated building usage-cycle simulation (ingress, circulation, egress/evacuation) under emergency and non-emergency conditions	□	□	□	□	□	–	□	□	□	□	–
	incident alarm response phase											
	• imposed emergency response	–	–	–	–	–	–	■	□	■	–	–
	• predicted emergency response											
	▷ pre-evacuation decisions	–	–	–	–	–	□	–	–	–	–	–
	▷ pre-evacuation activities	–	–	–	–	–	–	■	–	–	■	–
Environment	representation of building amenities/features and points of interest/relevance	■	■	■	■	■	□	□	□	□	■	–
	representation of purpose of building amenities (in response to pedestrian "expectation") and building usage	■	–	–	■	–	–	–	–	–	■	–
	representation of characteristics of route and points of interest	□	■	□	■	□	–	□	□	□	□	–
Pedestrian	situational awareness: perception and evaluation of											
	• building facilities	■	■	■	■	■	□	□	□	□	■	–
	• procedural processes	–	■	–	■	–	–	■	–	–	■	–
	• events, stimuli and surrounding conditions	□	□	□	–	□	□	■	□	□	■	□
	(different degrees of) memory of previous usage of building and of procedures	■	–	■	□	□	□	□	–	□	□	■
	advanced psychological / cognitive features											
	• representation of purpose and (multiple) intentions	■	□	■	■	□	–	□	–	–	■	□
	• representation of emotions	■	–	■	–	□	■	■	–	–	■	■
	• representation of plans and tasks	■	■	■	■	■	–	■	–	–	■	–
	• decision making model											
	▷ adaptive behaviour: action selection	■	■	■	–	■	■	■	–	□	■	■
	▷ pre-trip planning behaviour	□	■	□	■	□	–	–	–	□	–	–

Legend: ■: addressed □: partly addressed –: not addressed

Table 2.6.: Overview of pedestrian behaviour simulation models which incorporate an individual pedestrian representation for simulating advanced individual behaviours.

Model	Individual Pedestrian Representation			
	Intentions	Individual Memory	Rational Model	Evaluation Model
Amanda	G,P	GM,SM	prob	Ref
Kitazawa, Batty	P	-	prob	Ref
Pedsim	G,P	GM,PM	det	Ref
SimPed	G,P	PM	det	-
STREETS	P	PM	det	Ref
MASSEgress	-	SM	det	-
buildingEXODUS	P	PM	prob	Cat
MassMotion	-	-	prob	-
STEPS	-	SM	det	-
COHUE	P; G (DirectIA®)	GM (DirectIA®)	det (DirectIA®)	-
MACES	G (PMFserv)	SM; GM (PMFserv)	det (PMFserv)	-

Legend:

Intentions goals (G), plans (P)

Individual Memory structural memory (SM), goal memory (GM), plan memory (PM)

Rational Model deterministic (det), probabilistic (prob), specific decision making model

Evaluation Model categorisation (Cat), relation to appropriate references (Ref) ation and put it into perspective regarding their intentions and their background. Examples for modelling the evaluation of information comprise the sorting of the information according to pre-defined categories or the comparison of the information to appropriate references, e.g. the agent's preferences or general standards.

Table 2.7 compares the modelled situational awareness features of the individual agent. If the agents shall be able to be aware of their current situation and their surrounding conditions, they need to be able to perceive information. This information can be concerned with the simulated structural environment, potentially simulated procedures within the environment or other stimuli.

Table 2.7.: Overview of pedestrian behaviour simulation models which incorporate situational awareness modelling for simulating advanced individual behaviours.

Model	Situational Awareness Modelling			
	Structure Representation	Structural Information	Procedural Processes	Stimuli Modelling
Amanda	Am	Feat, Purp	-	Str
Kitazawa, Batty	Am	Feat	TC	Cong,Ev
Pedsim	Am	Feat	-	Str,Cong,Ev
SimPed	Am	Purp	TC,BoP	-
STREETS	PoI	Feat	-	Str
MASSEgress	PoI	-	-	Str,Cong
buildingEXODUS	PoI,RoI	-	TC,BoP	Str,Cong,Ev,Haz
MassMotion	PoI	-	-	Cong,Ev
STEPS	PoI	-	-	Cong,Ev
COHUE	Am	Purp (DirectIA®)	TC	Str,Cong,Ev,Haz (DirectIA®)
MACES	-	-	-	Cong

Legend:

Structure Representation	points of interest (PoI), regions of interest (RoI), amenities (Am)
Structural Information	facility features (Feat), facility purpose (Purp)
Procedural Processes	time constraints (TC), bindingness of procedures (BoP)
Stimuli Modelling	structure (Str), congestion (Cong), events (Ev), hazard (Haz)

Pedestrian behaviour simulation models simulate the underlying structure in various ways, all of which have in common a definition of the possible areas an agent can occupy. Apart from this fundamental structure representation, additional information about the environment can be modelled. Such additional information can include the modelling of points of interests which the agent can visit for some modelled purpose. Similar, whole regions of interest can be included. If the modelled points or regions of interest are linked to specific purposes, these areas are referred to as amenities in Table 2.7. In addition to embedding information on its purpose in the simulated structural element, other features can also be incorporated such as the targeted type of costumers of a shop.

All the information about the agents surrounding environment and their current situation, that can be evaluated by the agents are referred to as stimuli in Table 2.7. The evaluation of stimuli may lead to the adaptation of the agent's behaviour. Stimuli can be the modelled structural facilities and their embedded information, the impact of the presence of other agents as well as emergent events or hazards.

Table 2.8 displays the model components and its realisation concerned with the ingress and circulation phase of a building usage cycle.

In general it is possible in pedestrian behaviour simulation models to externally assign information or plans to the agent, or to simulate the individual agents choice process. External assignment can be made by manual user input, deterministic or probabilistic methods or by employing systems like the Geo-Information System. If the individual agents make individual choices, they can do that based on individual preferences. Simple choice methods include the deterministic or probabilistic choice. More sophisticated choice methods include utility maximisation (with the special case of minimising the total route distance) multi-criteria optimisation methods or discrete choice models.

For the modelling of individual pedestrian behaviour and if an agent has an appropriate individual memory model, this individual memory model can be assigned information prior to the start of the simulation, the agent's so-called circulation experience. The circulation experience would e.g. encompass information about a certain part of the simulated environment that the agent had visited beforehand: the simulation of the spatial information that has been obtained during this previous visit. In Table 2.8, the circulation experience refers only to information used during a circulation scenario. Experience relevant to an evacuation scenario modelling, e.g. the exit familiarity assignment, is compared in Table 2.9.

Table 2.8 further compares the methods used for the agents' route choice. In Table 2.8, the simulated route choice process is split into the process of deciding on the route's target locations and on the choice of the path connecting the chosen targeted locations. In pedestrian behaviour simulation models, it is generally possible to either externally assign targeted locations to the agents or to simulate an individual choice process.

While in the simulated environment, the agents can be equipped with the ability to adapt their behaviour. The adaptations can include (on different abstraction levels) a change of their goals, plans or their route.

Table 2.8.: Overview of pedestrian behaviour simulation models which incorporate models for the ingress and circulation simulation stage.

Model	Ingress and Circulation Stage			
	Individual Circulation Experience Assignment	Target Choice / Target Assignment	Path Choice	Adaptive Behaviour
Amanda	-	Choice: Pref,prob	-	G
Kitazawa, Batty	-	Choice: Pref,det	Pref,DCM	P
Pedsim	-	Assignment: GIS	Pref,UT	P
SimPed	-	Choice: UT	UT	-
STREETS	-	Assignment: GIS	SR	P
MASSEgress	-	-	-	-
buildingEXODUS	-	-	Pref,SR	P,R
MassMotion	-	-	Pref,DCM	R
STEPS	UI,prob	Assignment: UI	UT	R
COHUE	-	?	SR	P,R (DirectIA®)
MACES	-	-	SR	G,R (PMFserv)

Legend:

General Assignment	user input (UI), deterministic (det), probabilistic (prob), Geographic Information System (GIS)
General Choice	individual preferences (Pref), deterministic (det), probabilistic (prob), Utility Theory (UT), Shortest Route (SR), multi-attribute optimisation (MAO), discrete choice model (DCM)
Adaptive Behaviour	goals (G), plans (P), route (R)

Table 2.9 shows those model components concerned with the modelling of the alarm response phase during a building usage cycle simulation. The alarm response phase is thereby seen to be the stage in which the pedestrians make decisions which form the basis for their evacuation behaviour.

Table 2.9.: Overview of pedestrian behaviour simulation models which incorporate models the alarm response phase simulation state.

Model	Alarm Response Phase				
	Evacuation Starting Location Assignment	Familiarity Assignment	Exit Choice / Exit Assignment	Response Time Assignment	Pre-Evacuation Activities Assignment
Amanda	-	-	-	-	-
Kitazawa, Batty	-	-	-	-	-
Pedsim	-	-	-	-	-
SimPed	-	-	-	-	-
STREETS	-	-	-	-	-
MASSEgress	UI	UI,prob	-	-	-
buildingEXODUS	UI,rand	UI,prob	Choice: SR	UI,prob	UI,prob
MassMotion	UI,prob	-	Assignment: UI,prob	-	-
STEPS	UI	UI,prob	Choice: UT	UI,prob	-
COHUE	precSim	-	Choice: SR	precSim	precSim
MACES	?	?	Choice: SR	-	-

Legend:

General Assignment: user input (UI), random (rand), deterministic (det), probabilistic (prob), resulting from preceding simulation (precSim)

Exit Choice: individual preferences (Pref), Utility Theory (UT), Shortest Route (SR), multi-attribute optimisation (MAO), discrete choice model (DCM)

Any evacuation simulation with a pedestrian behaviour simulation tool needs to be initialised with certain information on the agents' prerequisites and their situation at the start of the evacuation process. This information can either be externally assigned or it can be the consequence of the preceding building usage cycle simulation. If the information is assigned externally, this can be achieved by user input which is randomly, deterministically or probabilistically assigned to the agents.

The information that is required for each individual agent to initialise an evacuation simulation, comprises the following items:

- the agent's location within the simulated environment at the start of the evacuation,
- the agent's familiarity with the modelled environment,
- the exit that the agent will initially target,
- the time between the start of the evacuation and the individual agent's initiation of their evacuation behaviour (referred to as *response time*),
- the activities that the individual agent might undertake during their response time period (referred to as *pre-evacuation activities*).

2.5.1. Review Summary

The summary tables Table 2.6 to Table 2.9 as shown in Section 2.5 present an overview of the realisation of certain individual pedestrian features in the surveyed pedestrian behaviour simulation models. The individual pedestrian features depicted in the summary tables have been mentioned as desirable features to be included in future pedestrian behaviour simulation models by expert researchers as outlined in Section 2.3 and Table 2.3. The summary tables Table 2.6 to Table 2.9 illustrate to which extend the surveyed pedestrian behaviour simulation models account for each mentioned desirable feature. As can be seen, no surveyed pedestrian behaviour simulation model accounts for all behaviour and scenario simulation features that have been emphasised by the expert researchers.

Regarding the representation of individualistic behaviours, see Table 2.6, only four of the surveyed pedestrian behaviour simulation models incorporate both goals and plans in the intention simulation. These four models comprise Amanda [35–39], Pedsim [41, 42], SimPed [43, 44] and COHUE [59, 60]. As can also be seen in Table 2.6, no surveyed pedestrian behaviour simulation model simulates a comprehensive individual memory list of a goal memory, a plan memory and a spatial memory. In addition, only very few surveyed pedestrian behaviour simulation models specify an evaluation system. These few models comprise Amanda [35–39], Pedsim [41, 42], STREETS [26, 45] and buildingEXODUS [14]. Since the simulated individual intentions, knowledge and evaluation processes inform the agent's rational behaviour, no known pedestrian behaviour simulation model can currently account for the entire spectrum of possible individualistic behaviour modelling.

As can be seen from Table 2.7, most surveyed pedestrian behaviour simulation models incorporate an advanced structure representation. Not only the spatial representation of the environment is modelled but also special regions or points of interest within the environment are represented. The only surveyed pedestrian behaviour simulation model which represents the environment as by a simplistic walk-way system is MACES [61–64]. However, only five out of eleven surveyed pedestrian behaviour simulation models incorporate purpose-related or feature-related structural information of facilities by simulating so-called amenities. Out of these five, only three surveyed pedestrian behaviour simulation models explicitly model purpose-related information in their environment model, which corresponds to the agent's modelled intentions. These three pedestrian behaviour simulation models which simulate the purpose related interaction between the agents and the environment are Amanda [35–39], SimPed [43, 44] and COHUE [59, 60]. Similarly, only a third of the surveyed pedestrian behaviour simulation models simulate procedural processes. These models are Kitazawa, Batty [40], SimPed [43, 44], buildingEXODUS [14] and COHUE [59, 60]. On the other hand, almost every surveyed pedestrian behaviour simulation model simulates the impact of external information or stimuli on the agents, thereby informing the agents' situational awareness. The only surveyed pedestrian behaviour simulation model which doesn't model any stimuli is SimPed [43, 44].

As illustrated in Table 2.8, only one of the surveyed pedestrian behaviour simulation models, the STEPS [53–58] model, explicitly assigns the individual agent an individual familiarity with the structure for the simulation of circulation behaviour. About half of the surveyed pedestrian behaviour simulation models simulate both the choice of appropriate trip targets and the choice of the connecting route. However, only three out of eleven of the surveyed pedestrian behaviour simulation models allow for the simulation of individualistic target choice, whereas the other pedestrian behaviour simulation models externally impose targets on the agents. The three target choice pedestrian behaviour simulation models are Amanda [35–39], Kitazawa, Batty [40] and SimPed [43, 44]. Nevertheless, almost all surveyed pedestrian behaviour simulation models simulate reactive or adaptive behaviour.

Table 2.9 illustrates how the surveyed pedestrian behaviour simulation models represent the transition from a normal circulation structure usage simulation to a potential emergency evacuation simulation, the simulated *alarm response phase*. As can be seen, only one surveyed pedestrian behaviour simulation model, the COHUE [59, 60] model, simulates this transition from circulation to evacuation within a running simulation. By explicitly simulating the alarm response phase, COHUE is thereby able to refer to the agents' simulated gathered knowledge and experience with the structure in order to inform the subsequent evacuation scenario simulation. All other surveyed pedestrian behaviour simulation models separate the circulation and potential evacuation simulation of a given environment. This requires the models to externally assign the initial evacuation conditions and prerequisites on the individual agents. This assignment is then down to the level of expertise of the user or the availability of appropriate data, in order to simulated realistic pedestrian evacuation behaviour.

2.6. Summary

In this chapter, the available literature in the field of pedestrian behaviour simulation relevant to this thesis' research topic has been reviewed. This chapter thereby addresses Research Objective 1 by identifying the modelling techniques in current pedestrian behaviour simulation tools of individualistic cognitive pedestrian behaviour.

At first, the main purpose and the general functionality of pedestrian behaviour simulation models has been described, see Section 2.1. Subsequently, the expert analysis of the current state of the art in the field of pedestrian behaviour simulation modelling has been summarised in Section 2.2. A list of desirable features regarding the modelling of individual pedestrian behaviour in complex multi-purpose environments to be included in future pedestrian behaviour simulation models has been recapitulated in Section 2.3.

Based on these collated suggested features, a requirement analysis of the currently available pedestrian behaviour simulation software tools has been compiled. At first, relevant pedestrian behaviour simulation models have been briefly described in Section 2.4. Subsequently, a detailed analysis of the surveyed pedestrian behaviour simulation models under consideration of the expert suggestions has been carried out in Section 2.5.

As a result from the review of currently available pedestrian behaviour simulation models in Section 2.5, one main problem has been identified: None of the surveyed pedestrian behaviour simulation models incorporate a general framework for modelling goal-driven, informed, cognitive, adaptive, situationally aware, individualistic pedestrian behaviour in complex multi-purpose environments. Although the different reviewed pedestrian behaviour simulation models simulate various aspects of individualistic pedestrian behaviour, no model could be found in which the simulated pedestrian behaviour is based upon a general human behaviour framework. Rather, the simulated pedestrian behaviours have been independently modelled, disregarding the cohesive cognitive abilities of the individual pedestrian. As such, the currently available pedestrian behaviour simulation models cannot produce realistic pedestrian behaviours by the means of a bottom-up approach.

This thesis aims to address this situation by proposing a holistic framework for the modelling of individualistic pedestrian behaviour in the context of pedestrian behaviour simulation. In the next chapter, selected research and modelling techniques are introduced and reviewed which are relevant to this thesis research topic in that they provide inspiration and means for the desired framework to simulate individualistic pedestrian behaviour in complex multi-purpose environments.

Chapter 3:

Literature Review on Cognitive Architectures, Related Concepts and Human Behaviour Research

During the review of current pedestrian behaviour simulation models in Chapter 2, it has been found that no current pedestrian behaviour simulation tool incorporates a holistic framework to model goal-driven, cognitive, adaptive, individual pedestrian behaviour. The reviewed pedestrian behaviour simulation tools each simulate certain purpose-related, cognitive or adaptive pedestrian behaviours. However, an approach for modelling these features by a comprehensive and yet consistent framework in a pedestrian behaviour simulation model could not be found.

An interesting approach to realise such a holistic individual pedestrian behaviour framework has been found when reviewing two virtual reality simulation models (see Section 2.4.4). The surveyed virtual reality models use approaches similar to a cognitive architecture to achieve a representation of the desired pedestrian behaviour. Cognitive architectures are by definition designed to replicate the human cognitive process in its entirety. For this reason, cognitive architectures and related concepts are further reviewed in this chapter and their potential benefits for this thesis' research are discussed.

In this chapter, the concept of a cognitive architecture in cognitive science and artificial intelligence research is outlined in Section 3.1. A survey of selected cognitive architectures is presented and the potential benefits of the concept of cognitive architectures to this thesis' research are analysed and discussed. As a response to this analysis, further relevant research disciplines are reviewed in Section 3.2 including a thorough review of current theories on human decision making. To conclude this chapter, Section 3.3 summarises the relevant inspirations from this literature review for the modelling of advanced human cognitive behaviour in pedestrian behaviour simulation models.

Pedestrian behaviour simulation models are designed with the explicit focus on modelling real human behaviour. Conclusively, if a concept is to be used for modelling individual cognitive pedestrian behaviour in a pedestrian behaviour simulation model, it needs to be designed to replicate real human behaviours as closely as possible. Therefore, the main emphasis of this chapter's literature review lies on concepts which have either been validated in empirical studies of human behaviour, or have been introduced by human behaviour science disciplines such as psychology, neurophysiology or behavioural sciences.

3.1. Cognitive Architectures

As has been pointed out in the Summary Section 2.6 of the literature review on current pedestrian behaviour simulation models, a holistic approach for modelling individual pedestrian behaviour is missing in current pedestrian behaviour simulation modelling tools. For a similar purpose, agent models similar to cognitive architectures are already used in virtual reality pedestrian behaviour simulation modelling tools [59, 60].

As Chong et al. have stated in their review on selected cognitive architectures, a cognitive architecture aims to provide a framework for the modelling of various aspects of human cognition behaviour:

> "An integrated cognitive architecture can be defined as a single system that is capable of producing all aspects of behaviour, while remaining constant across various domains and knowledge bases (Newell 1990; Anderson et al. 2004). This system would consist of many modules (or components) working together to produce a behaviour. [...] Integrated cognitive architectures are often used to explain a wide range of human behaviour, and to mimic the broad capabilities of human intelligence (Anderson et al. 2004; Langley and Choi 2006)."
>
> *Chong et al. [76]*

As such, the concept of a cognitive architecture is appropriate for this thesis' research. In this thesis' research, a way to model cognitive pedestrian behaviour by reactive or even proactive behaving software agents is sought. Such a model would be required to cover a wide range of human behaviours such as purposeful behaviour, human cognition and adaptive behaviour, each in correspondence to the pedestrians' surrounding environment and conditions, see Chapter 1. From these requirements, cognitive architectures provide a well-studied way to cover all the desired features with a single holistic human behaviour simulation framework.

To date available cognitive architectures interpret this mission in an individual way. In this section, a survey of three well established cognitive architectures is presented. Based on this survey, the concept of cognitive architectures is further analysed and reviewed with regard to this thesis' research topic.

3.1.1. Survey of selected Cognitive Architectures

A cognitive architecture is inspired by insights from various different research disciplines concerned with human cognition, such as cognitive science, neuroscience, behavioural science and psychology. Since these research disciplines themselves propose many different interpretations of the human cognition process, many different cognitive architectures exist.

For this thesis' survey on cognitive architectures, the three cognitive architectures Soar, CLARION and ACT-R have been chosen. All these cognitive architectures incorporate features to replicate the human cognition process including goal-driven, deliberate and adaptive human behaviour. These are the features that are sought in this thesis' research in order to improve pedestrian behaviour simulation. The three chosen cognitive architectures are also well-known and have been widely applied [76–79]. Chong et al. [76] state in their review on cognitive architectures that Soar "is one of the earliest and most extensively developed AI architectures in the history." and both ACT-R and CLARION "are based on a combination of artificial intelligence, cognitive psychology and some favour of neurobiology.". All of these architectures base on the pioneer work on cognitive architectures by Newell [80].

The surveyed cognitive architectures have in common, that they are mature and well known in the cognitive architecture research community. In addition, all surveyed cognitive architectures have been applied both in psychological puzzle and cognitive tasks such as e.g. the classic Tower of Hanoi task, and in virtual reality simulations [76, 77].

3.1.1.1. Soar

Soar is a cognitive architecture that has been in use since 1986 [81]. In Soar, a cognitive architecture is defined "as a theory of the fixed mechanisms and structures that underlie human cognition." [1]:

> "Soar is a theory of what cognitive behaviors have in common. In particular, the Soar theory posits that cognitive behavior has at least the following characteristics (Newell, 1990): It is goal-orientated. [...] It takes place in a rich, complex and detailed environment. [...] It requires a large amount of knowledge. [...] It requires the use of symbols and abstractions. [...] It is flexible, and a function of the environment. [...] It requires learning from the environment and experience."
>
> *Lehman et al. [1]*

Soar represents human cognition as a movement through a "problem space" [1]. Problem spaces thereby contain states, operators connecting states and goals, see Figure 3.1: "A state is a representation of the current problem-solving situation; an operator transforms a state (makes changes to the representation); and a goal is a desired outcome of the problem-solving activity." [81]. Soar thereby defines human cognition as the continuous selection of an action ("operator") in a given decision situation ("current state") to attain a new situation ("state") which is closer to a desired "goal".

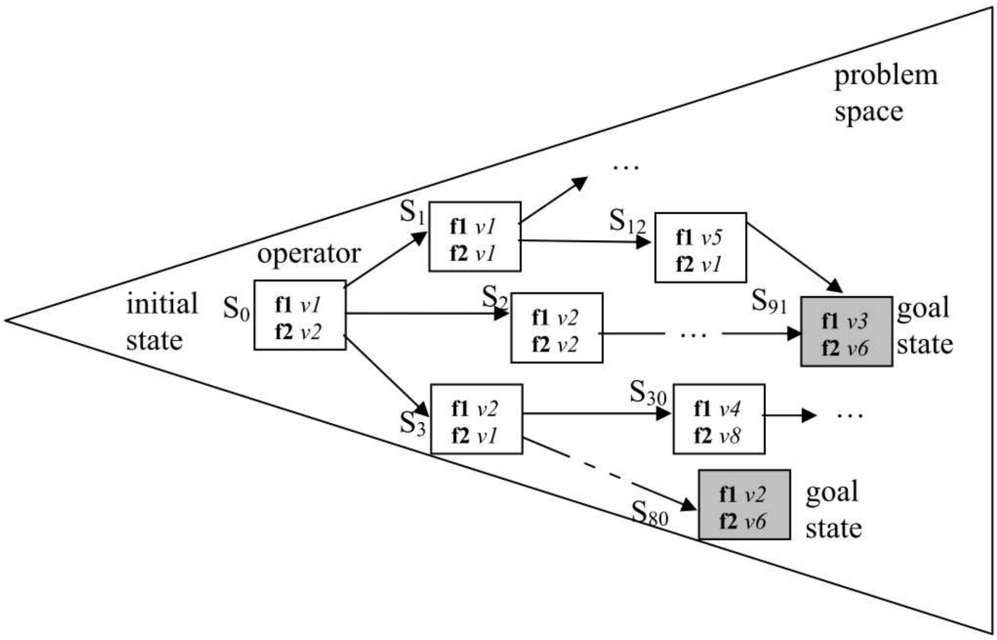


Figure 3.1.: A schema of a problem space in Soar, see Lehman et al. [1, Figure 4].

In Soar, an agent selects an action based on their knowledge. Knowledge is represented in terms of the modelled goals, states and operators. As such, knowledge can be expressed by *production rules* [1]. A production rule is a way to produce a decision for a certain action by matching the current situation in which the decision is to be made to other known situations. When the decision situation is matched, an appropriate action to be taken is chosen based on how beneficial similar actions the identified situation type have been.

In Soar, production rules are formulated as "if-then" rules [1]. A production rule's "if" part specifies the characteristics of situations when the production rule is applicable. The "then" part of a production rule specifies what changes to the situation, the available operators or the desired goals were entailed if the production rule was chosen. In other words, knowledge in Soar is information about what action might be appropriate in what type of situation. For example:

- *If* it is raining *and* you are taking a walk in the fields *and* you do not have an umbrella *then* you will become wet.
- *If* it is raining *and* you want to take a walk in the fields
  then taking an umbrella is better than not taking an umbrella.

Soar stores knowledge in both a long-term memory and a working memory system. In the working memory, knowledge regarding the current decision situation is accumulated, whereas the long-term memory contains knowledge that exists independently of the current decision situation [1]. Soar's long-term memory distinguishes between three types of knowledge, procedural, semantic and episodic: "Procedural knowledge is about how and when to do things [...] Semantic knowledge consists of facts about the world – things you believe to be true in general – things you 'know' [...] Episodic knowledge consists of things you 'remember' – specific situations you've experienced" [1].

If a Soar agent is in a specific decision situation, they choose an appropriate action to resolve the decision situation following Soar's "decision cycle" [1]: At first, information about the current state is accumulated in the agent's working memory. This is achieved through perceiving facts about the current situation using Soar's perception capability. In a second step, the Soar agent queries their long-term memory for all knowledge that is applicable to the perceived situation. Based on their recalled knowledge, the agent evaluates all actions that are available in the current situation for their desirability. Based on this desirability information, the agent then decides for the most appropriate action to be taken and executes this action.

In addition, Soar incorporates features to resolve ties during the decision cycle and to cope with decision situations in which the agent's knowledge base is insufficient. Soar further supports the learning of knowledge, i.e. production rules, from successfully resolved decision situations.

3.1.1.2. CLARION

CLARION (Connectionist Learning with Adaptive Rule Induction ON-line) has been first proposed in 1997 [82]. In CLARION, a cognitive architecture is understood as follows:

> "A cognitive architecture is a broadly-scoped, domain-generic computational cognitive model, capturing the essential structure and process of the mind, to be used for a broad, multiple-level, multiple-domain analysis of behavior (Newell 1990, Sun 2002). [...] In relation to building intelligent systems, a cognitive architecture specifies the underlying infrastructure for intelligent systems, which includes a variety of capabilities, modules, and subsystems. On that basis, application systems can be more easily developed."
>
> *Sun [83]*

The CLARION cognitive architecture consists of four "subsystems" [83]: the Action-Centered subsystem, the Non-Action Centered subsystem, the Motivational subsystem and the Meta-Cognitive subsystem. The Action-Centered subsystem controls all actions available to the agent. The Non-Action Centered subsystem maintains the agent's general knowledge. The Motivational subsystem provides the motivations for the agent's perception, action and cognition. And finally, the Meta-Cognitive subsystems monitors, directs and modifies the operations of the other subsystems [83]. Each of these four subsystems are further organised in a top-level and a bottom-level: The top-levels encode explicit knowledge whereas the bottom-level encodes implicit knowledge, see Figure 3.2.

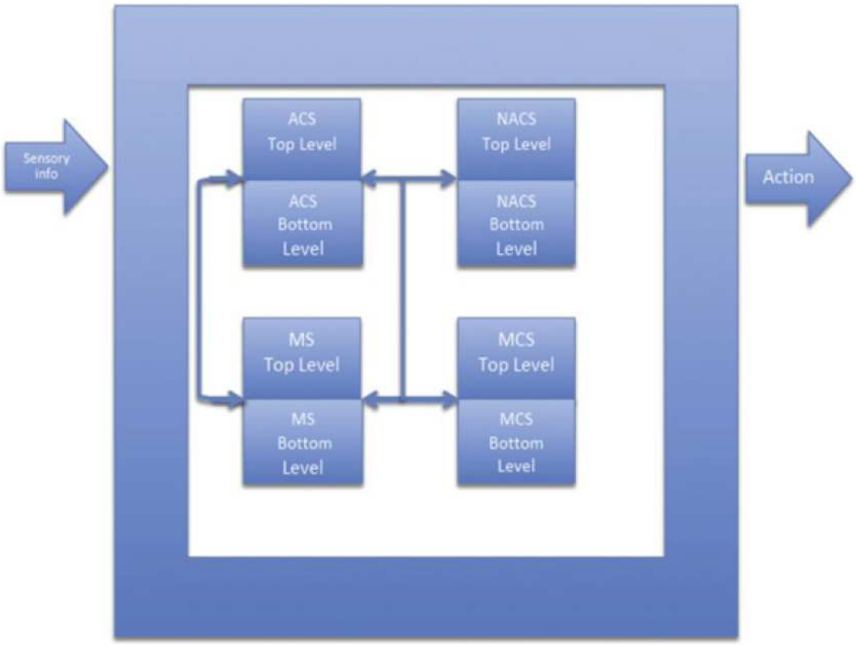


Figure 3.2.: The subsystems of the CLARION cognitive architecture, see Sun [2, Fig. 1].

The Action-Centered subsystem controls various aspects of the cognition cycle. With the bottom-level of the Action-Centered subsystem, the current situation is perceived and the available actions in this situation are evaluated. A possible action a is evaluated based on the "quality" $Q(x, a)$ with regard to the perceived state x: "$Q(x, a)$ indicates how desirable action a is in state x" [83]. One of the recommended algorithms by Sun [83] is reinforcement learning to compute the Q-values of the specific actions. The top-level of the Action-Centered subsystem contains production rules of the condition-action form. Thereby, an action is recommended by a production rule if the current situation matches the rule's condition. This production rule mechanism is similar to Soar's production rule mechanism, see Section 3.1.1.1. The information from the bottom-level and from the top-level can be aggregated by a weighted sum approach or other means, see Sun [82] for details. The best evaluated action is then chosen and the action is performed by the Action-Centered subsystem. Subsequently, the benefit of the chosen action is analysed which might result in updating the action's Q-value.

The Non-Action Centered subsystem "may be used for representing general knowledge about the world (i.e., constituting the 'semantic' memory [...]), for performing various kinds of memory retrievals and inferences." [83]. An agent's drives and their interactions are stored in the Motivational subsystem. As such, the Motivational subsystem "provides the context in which the goal and the reinforcement of the action-centered subsystem are set." [83]. The explicit goals such as "finding food" [83] are stored in the top-level of the Motivational subsystem. These goals may stem from implicit internal drives such as "being hungry" [83] which are controlled in the bottom-level of the Motivational subsystem. Sun [83] mentions

Maslow's hierarchy of needs as one approach to model goals and internal drives, see Section 3.2.4 for further details. The goals and drives stored in the Motivational subsystem may lead to actions or to preferring certain actions in certain decision situations. Finally, the Meta-Cognitive subsystem "monitors, controls, and regulates cognitive processes for the sake of improving cognitive performance" [83].

3.1.1.3. ACT-R

The Adaptive Control of Thought-Rational (ACT-R) cognitive architecture has been first introduced in the 1990s [84].

> "ACT-R is a cognitive architecture: a theory about how human cognition works. Its constructs reflect assumptions about human cognition which are based on numerous facts derived from psychology experiments."
>
> *Bothell [85]*

The ACT-R cognitive architecture consists of a set of subsystems or "modules" where each module processes a different kind of information. "The theory is not committed to exactly how many modules there are, but a number have been implemented as part of the core system." [3]. In the current version 6 of the ACT-R, the modules included in the core system are Procedural, Declarative, Goal, Vision, Auditory, Motor, Speech and Imaginal [85].

In the ACT-R the different modules interact via a central production system, the "Procedural system" [3, 85], see Figure 3.3. An important concept of the ACT-R is that the Procedural system doesn't interact with the other modules directly, but via "buffers". A buffer is a component of any module other than the Procedural system. Within the buffer, a limited amount of information is stored and only this limited amount of information can be processed by the Procedural system: "the content of any buffer is limited to a single declarative unit of knowledge, called a chunk in ACT-R." [3].

The Perceptual-Motor system of the ACT-R – including the Auditory, Motor and Speech module – largely reimplements the Perceptual-Motor system of EPIC, another cognitive architecture [3]. The ACT-R's Perceptual-Motor system differs from the EPIC system mainly in the way that visual perception is realised. Anderson et al. state, that "ACT-R historically was focused on higher level cognition and not perception or action. Perception and action involve systems every bit as complex as higher level cognition. Dealing with higher level cognition had seemed quite enough." [3].

The Goal module of the ACT-R enables the creation of persistent behaviour by "keeping track of what [the current] intentions are so that behavior will serve that goal" [3]. As for the other modules, multiple goals can be stored and managed in the Goal module of the ACT-R. However, since only a single goal can be stored in the Goal module's buffer, the ACT-R will choose actions always based on only the currently active goal within the buffer.

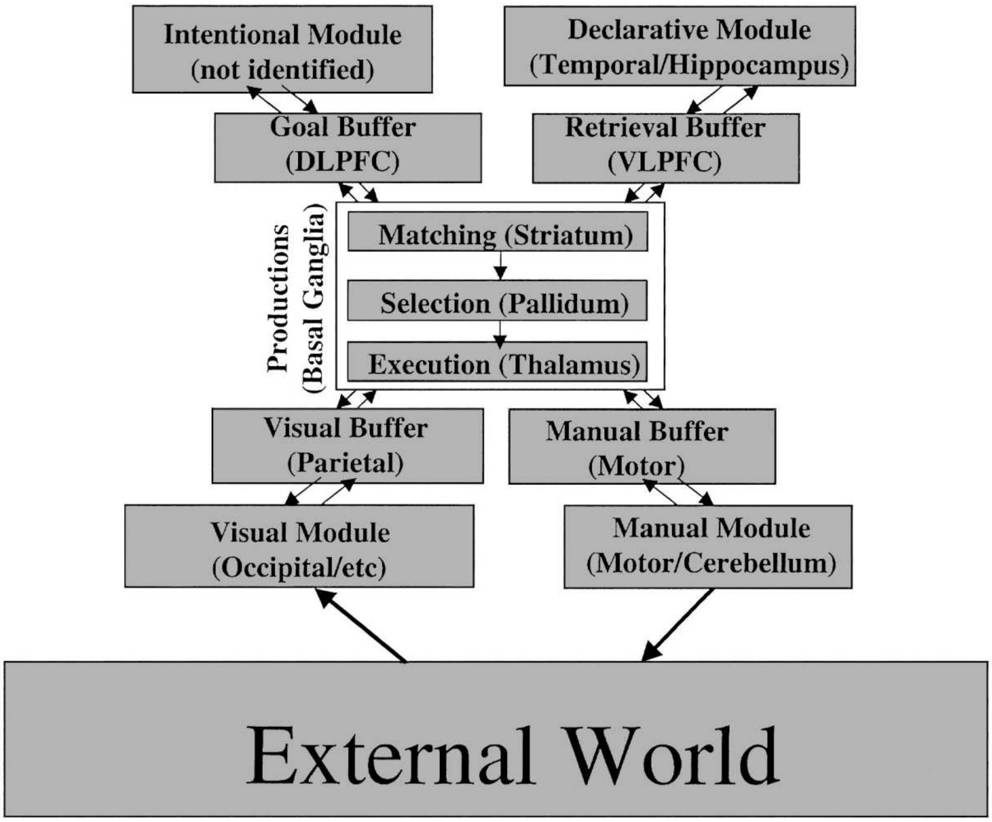


Figure 3.3.: The organisation of information in ACT-R 5.0, see Anderson et al. [3, Figure 1]

In the ACT-R, knowledge is represented as either declarative or procedural knowledge. Declarative knowledge in the ACT-R is understood to be facts about the world or episodic knowledge. Basically, declarative knowledge is knowledge that is required to resolve decision situations. By contrast, procedural knowledge in the ACT-R is understood to be knowledge about how in general decision situations can be resolved [86]. "The declarative memory system and the procedural system [...] constitute the cognitive core of ACT-R." [3].

The ACT-R's Declarative module represents the agent's knowledge memory. An important theory of the ACT-R is that such memorised knowledge is not readily available but need to be retrieved into the module's buffer by a memory recall mechanism [3]. The probability of a chunk of memory being recalled is dependent on its level of "activation". The level of activation thereby depends on the usefulness of the memory in the past and the relevance of the memory to the current situation. In addition, the level of activation of a memory chunk determines the time it takes to retrieve this memory.

The Procedural system manages the procedural memory of the ACT-R and as such implements and processes production rules [3]. The ACT-R's production rules consist of a condition and an action part. The rule's condition specifies a pattern in the buffers that the rule will match. Likewise, the rule's action specifies changes to be made to the modules' buffers. This is a similar production rule mechanism as the mechanisms used in Soar

(Section 3.1.1.1) or CLARION (Section 3.1.1.2).

Within the Procedural system, production rules are matched to the current content of the buffers, applicable rules are evaluated and a rule for execution is selected [3]. The production rules that match the current situation as depicted by the information contained in the buffers are compared and evaluated based on their utility. The utility of a production rule is estimated with regard to the agent's current goal and the cost of the production rule which is typically measured in time [3]. The utility calculation of a production rule comprises a random variation around the expected utility. The randomness is expressed as a probability that a certain production rule with a certain utility is chosen. This probability is based on the ratio of the utility of a certain production rule against the utilities of all other applicable production rules. With this mechanisms, a production rule with an expected utility value much higher than the expected utility values of the other production rules is most likely to be chosen. However, if several production rules with similar expected utilities are applicable, these production rules will be chosen with similar probabilities.

The Procedural system of the ACT-R is capable of adapting the parameters used for calculating a production rule's utility by learning from the rule's success/failure history. In addition, the ACT-R's Procedural system is capable of learning new production rules by aggregating existing production rules. Furthermore, Anderson et al. [3] have demonstrated that the components of the ACT-R could be matched to different regions of the human brain with the help of fMRI scans.

3.1.2. Discussion

The aim of this thesis is to identify a suitable way of modelling individual cognitive pedestrian behaviour for pedestrian behaviour simulation tools. As has been detailed in the research questions compiled in Section 1.2.4, this thesis research should identify suitable ways to model purposeful and goal-directed pedestrian environment usage; individual pedestrian decision making; individual pedestrian knowledge; and situational respectively contextual aware pedestrian behaviour. Furthermore, this thesis research should propose a comprehensive model for simulating individual cognitive pedestrian behaviour including the above mentioned behaviours in a pedestrian behaviour simulation model, see Research Objective 3. The resulting comprehensive model should be usable for the purpose of modelling pedestrian circulation and alarm response behaviour.

The survey of the concept of cognitive architectures in Section 3.1.1 shows that the cognitive architecture approach is suitable for developing such a comprehensive model of individual cognitive pedestrian behaviour. Cognitive architectures aim to represent human cognition in intelligent agents. As such, cognitive architectures intend to model the human cognition process in its entirety and as generically applicable as possible. All aspects of this thesis' research objectives such as the simulation of purposeful behaviour, human cognition and adaptive behaviour, each in correspondence to the pedestrians' surrounding environment and conditions, are included in the concepts of the surveyed cognitive architectures.

Within the concept of a cognitive architecture, the functionalities of the human mind can either be represented by one specifically designed component of the architecture designated for the specific task or by replicating the functionality through suitable interactions between different components of the architecture. The surveyed cognitive architectures [1, 3, 83] comprise several components in order to conceptualise the human behaviours relevant for this thesis' research. The organisation of these components differ from no explicit component structure in Soar via a fixed set of four subsystems in CLARION to a variable set of modules contained in ACT-R. Regardless of the actual architectural realisation, all surveyed cognitive architectures did however account for a set of basic components. Figure 3.4 illustrates the components common to all surveyed cognitive architectures and their respective interplay.

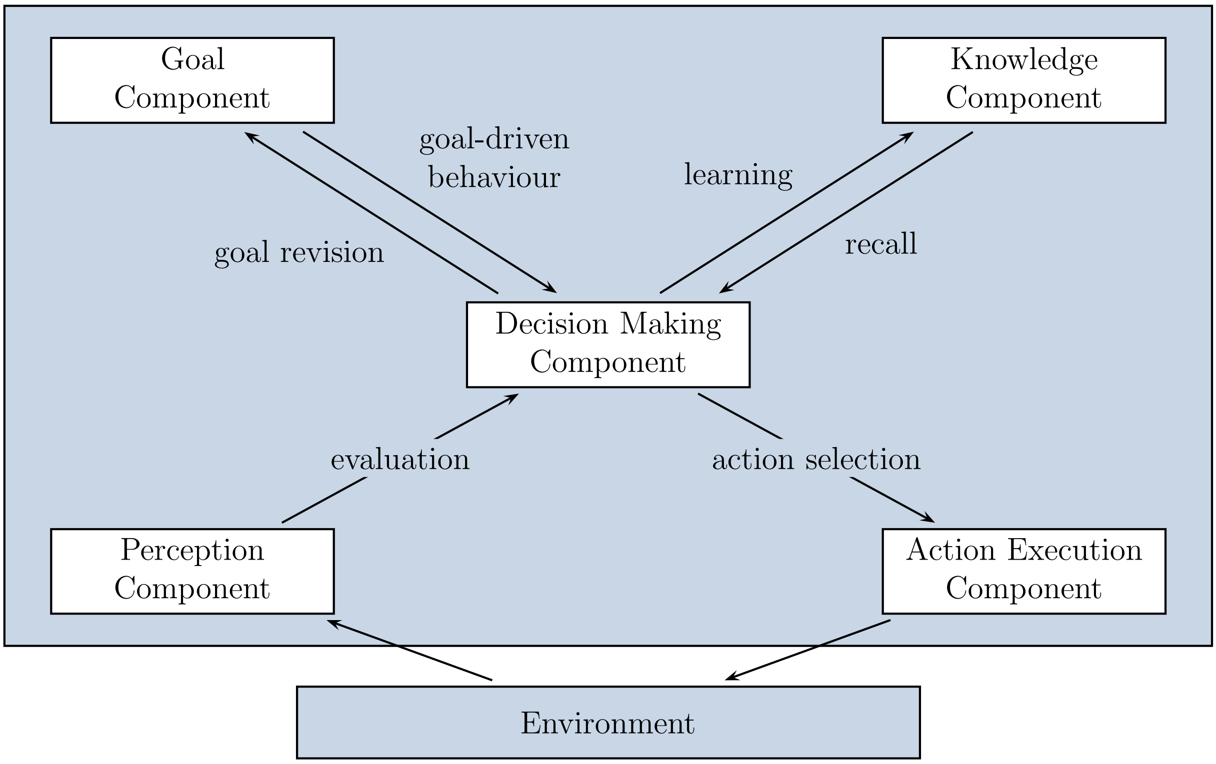


Figure 3.4.: The main components of a cognitive architecture.

Within a cognitive architecture agent model, the agent's perception component extracts and processes information. This information is extracted from the external environment and potentially internal agent processes. The agent perceives information that can be learned in their knowledge component, information that is linked to their goals, or information about the current state of the agent or the surrounding environment. This information is then evaluated by the agent, using intrinsic agent parameters such as simulated preferences or emotions. Through this evaluation process, the perceived information is put into perspective and made comparable regarding the agent's current situation.

The goal component stores and processes the agent's simulated goals or intentions. Goals are related to the model's field of application, but are abstract representations of purpose or preference in the modelled environment. The agent's goals govern their short and long term behaviour, since the agent tries to act in such a way as to meet or satisfy their goals. The agent's goals and their interdependency are reviewed and put into perspective based on the agent's current situation or external information.

The knowledge component stores and processes the agent's intrinsic knowledge about their environment. The type of knowledge that is modelled within the cognitive architecture is dependent on the agent model's field of application. Different cognitive architectures distinguish between different types of knowledge that is memorised such as semantic and episodic (Soar), semantic (CLARION) or declarative (ACT-R) memory. However, the cognitive architecture's knowledge component is characterised by storing information about the surrounding world in relation to the agent's characteristics. The agent can access this stored or learned knowledge memory in order to determine their next possible actions. The knowledge that is recalled is thereby dependent on the agent's current situation.

The decision making component plays the most vital part in a cognitive architecture. The decision making component connects the other architecture's components by processing the information provided by the goal, knowledge and perception component in order to instruct the agent's action execution component. The decision making component achieves this by temporarily storing the agent's currently processed information, including the agent's current motivational state (from the goal component), the agent's current information about the environment (from the perception component) and the agent's knowledge related to their motivational state and their current situation (extracted from the knowledge component). This temporal aggregated information is used to determine the agent's potential next actions. Subsequently, these potential next actions are evaluated and based on this evaluation one action is selected. This action is then referred to the action execution component.

Finally, the agent's action execution component implements the agent's selected actions in the environment.

Table 3.1 lists an overview in which subsystem of the surveyed cognitive architectures which component is realised.

3.1.2.1. What can be learned from Cognitive Architectures for this thesis' research?

All surveyed cognitive architectures share common assumptions about which components need to be modelled in order to reproduce purposeful, cognitive and adaptive human behaviour: perception of the environment, goal-driven behaviour, knowledge and memory, decision making and finally action execution in the environment (see Figure 3.4). It can therefore be concluded that the comprehensive pedestrian behaviour model to be developed in this thesis should contain realisations of these components and should implement suitable interactions between the realised components.

Table 3.1.: The parts of the cognitive architectures Soar, ACT-R and CLARION in which the general components of a cognitive architecture depicted in Figure 3.4 are represented.

Components	Soar	ACT-R	CLARION
Goal	goal states	Goal module	Motivational subsystem
Knowledge	long-term memory	Declarative module	Non-Action Centered subsystem
Decision Making	decision cycle	Procedural system	Action-Centered subsystem
Perception	perception of problem space	Visual and Auditory modules	Action-Centered subsystem
Action Execution	execution of operators	Motor and Speech modules	Action-Centered subsystem

From the survey of cognitive architectures, it can be learned that in order to realise goal-driven behaviour, *goals* should be represented. Goals should relate to a desirable state that the agent should be able to attain. As such, goals should be achievable by employing suitable actions. In the case of this thesis where pedestrian circulation and alarm response usage shall be modelled, *goals should relate to facilities within the environment* that can be visited by the agent. The actions that are available to the agent would correspondingly comprise actions to visit certain locations.

In a comprehensive cognitive pedestrian agent model, an agent's *knowledge* needs to reflect information about the environment or about the agent's state. The information that is contained in an agent's knowledge component is tailored to the specific task at hand. In the case of this thesis, the agent's knowledge should contain *information about locations within the environment* and how the locations relate to the agent's goals. The knowledge about a location within the environment should enable the agent to distinguish between the actions to visit the different locations.

A principle supported by all three surveyed cognitive architectures is, that an agent's knowledge is treated in two separate interacting systems: knowledge relevant for the current decision situation is retained in a *short-term working memory* whereas general knowledge is stored in a *long-term memory*. Knowledge from the long-term memory needs to be retrieved to the working memory in order to be used for deciding the agent's next actions. This distinction should also be replicated in this thesis' agent model.

Since knowledge in cognitive architectures is learned amongst other things by information directly perceived from the environment, this thesis' comprehensive agent model should contain a *perception* component which extracts *information from the environment* and translates the information such that it can be stored in the agent's knowledge component.

This thesis' comprehensive cognitive pedestrian agent model further needs to specify, in what kind of situations the agent's *decision making* is triggered. When the agent's decision making is triggered, the model further needs to determine by which means a suitable action is chosen.

3.1.2.2. Remaining Questions

A cognitive architecture "only" provides the framework with which e.g. an intelligent agent model can be realised. The content of the intelligent agent model, i.e. the actual behaviour model, is not provided by the architecture. Lehman et al. [1] explicitly state this principle in terms of the equation: "Behaviour = Architecture + Content". Consequently, methods on how to actually model the content of the agent behaviour need to be further identified. For this purpose, a further literature survey needs to be conducted to provide inspirations for the actual modelling of this thesis' cognitive pedestrian agent model. The literature survey shall thereby identify how similar modelling tasks have been realised in other agent models. Alternatively, suitable theories on human behaviour should be identified on which this thesis' comprehensive agent model can be based.

In summary, the following questions remain:

- On what basis is an action chosen compared to other competing action options?
- How to model the recall of knowledge and the learning of knowledge?
- How can the perception of information from the environment be modelled? How is the perceived information evaluated?
- Which goals are relevant? How do different goals relate to each other? How can motivations which lead to goals be modelled?

3.2. Survey of further related Research

As has been discussed in Section 3.1, the concept of cognitive architectures provides a useful inspiration of which components should be included in this thesis' comprehensive agent model. As has been pointed out in Section 3.1.2.2 however, cognitive architectures don't give answers on how the components necessary for the sought comprehensive agent model are to be realised in the given application domain. In order to answer the remaining questions listed in Section 3.1.2.2, this section comprises a survey of relevant models from other research disciplines. The models and research disciplines chosen for this survey provide insights into how the components of this thesis' comprehensive agent model (see Figure 3.4) can be modelled and implemented in the application domain of modelling realistic cognitive human behaviour in a pedestrian behaviour simulation tool.

3.2.1. Human Decision Making

In the current behavioural science and psychology research fields, three main approaches are considered as viable concepts for the modelling of parts of or the entire human decision making process: the mathematical optimisation based theory of *unbounded rationality*, the behavioural science based theory of *bounded rationality* and *probabilistic models* used in artificial intelligence or other related areas.

In general, a human decision making problem that needs to be solved by either of the three approaches mentioned above consists of the following components:

- a set of decision or choice alternatives from which the final decision needs to be drawn, the *choice set*
- a rule or method on how to evaluate and compare the different choice alternatives
- a criterion to determine whether one evaluated choice alternative is better than another evaluated choice alternative

Although these three decision making components are the same for all three approaches to model human decision making, the methods and underlying theory of the unbounded rationality, the bounded rationality and the probabilistic decision making approach differ considerably. On the other hand, the decision situations that humans in general face also differ to a high degree, dependent on the decision problem itself and also on the expertise and type of the decision maker. It is therefore necessary to determine an appropriate decision making modelling approach for each type of decision situation to be modelled.

3.2.1.1. Unbounded Rationality

In the current research literature, all decision making models that are entirely based on deterministic mathematical optimisation techniques are referred to as *unbounded rationality* models. Unbounded rationality models represent a human decision making task via an appropriate optimisation problem as defined in Definition 3.1.

Definition 3.1: Multi-Criteria Optimisation Problem

A **Multi-Criteria Optimisation Problem** is a pair $(\mathfrak{X}, f)$ where $\mathfrak{X}$ is a non-empty set and f a function $f : \mathfrak{X} \to \mathbb{R}^m$ for $m \in \mathbb{N}$. The objective of the mathematical optimisation problem is then to find all elements $x^* \in \mathfrak{X}$ that are optimal with regard to f [87].

The optimisation problem is characterised by the dimension of the image set $f(\mathfrak{X}) \subset \mathbb{R}^m$. m is than referred to as the *number of criteria* of the optimisation problem. In the special case that $m = 1$, the optimisation problem is called a Single-Criteria Optimisation Problem:

Definition 3.2: Single-Criteria Optimisation Problem

A **Single-Criteria Optimisation Problem** is a pair $(\mathfrak{X}, f)$ where $\mathfrak{X}$ is a non-empty set and f a function $f : \mathfrak{X} \to \mathbb{R}$. The objective of the mathematical optimisation problem is then to find all elements $x^* \in \mathfrak{X}$ that are optimal with regard to f.

For a Single-Criteria Optimisation Problem, the rule or method with which different alternatives are compared is the order relation "$x < y$" given in $\mathbb{R}$ for $x, y \in \mathbb{R}$. To solve a Single-Criteria Optimisation Problem, it only remains to define on what grounds one alternative is better than the other. With the order relation on $\mathbb{R}$ there are in general two possibilities:

$$x_1 \text{ is better than } x_2 \iff \begin{cases} f(x_1) < f(x_2) \\ f(x_1) > f(x_2) \end{cases}$$

However, it is in general irrelevant whether "optimal with regard to f" means minimal or maximal with regard to f:

Remark 3.1: Optimisation is Minimisation

Given the task to find $x \in \mathfrak{X}$ where x is optimal with regard to $f : \mathfrak{X} \to \mathbb{R}$. Since for each real-valued function f applies

$$\max f(x) = \min -f(x)$$

it is assumed without loss of generality that the objective of any mathematical Single-Criteria Optimisation Problem throughout this thesis is to minimise f.

Determining an optimal solution of a Single-Criteria Optimisation Problem or a solution within a certain distance to the optimal solutions is a well-studied problem [87, 88]. Exact solution algorithms and solution heuristics include the Branch-And-Bound Search Tree Algorithm as an example for a graph traversal algorithm or heuristics such as Local Search, Simulated Annealing or Genetic Algorithms.

It is possible, that for a given Single-Criteria Optimisation Problem more than one element $x^* \in \mathfrak{X}$ exists, which is optimal with regard to f. The set of all optimal elements of a given Single-Criteria Optimisation Problem $(\mathfrak{X}, f)$ is then denoted by

$$\mathfrak{P}_{(\mathfrak{X},f)} := \{x \in \mathfrak{X} \mid x \text{ is optimal with regard to } f\} \tag{3.1}$$

By contrast to Single-Criteria Optimisation Problems, Multi-Criteria Optimisation Problems for $m > 1$ can't be solved in a straight forward manner, since no order on the image space $\mathbb{R}^m$ of the function f exists. Instead, Multi-Criteria Optimisation Problems are solved by reducing the optimisation problem to an *Auxiliary Single-Criteria Optimisation Problem.*

An element $x \in \mathfrak{X}$ of a Multi-Criteria Optimisation Problem is then said to be optimal with regard to f, if x is an optimal element of the corresponding Auxiliary Single-Criteria Optimisation Problem. Equivalently to a Single-Criteria Optimisation Problem, the set of all optimal elements with regard to f of a Multi-Criteria Optimisation Problem $(\mathfrak{X}, f)$ is denoted by $\mathfrak{P}_{(\mathfrak{X},f)}$.

Two main approaches exist to model an Auxiliary Single-Criteria Optimisation Problem: Goal Programming or Utility Theory.

Goal Programming Method

Let $(\mathfrak{X}, f)$ be a Multi-Criteria Optimisation Problem as defined in Definition 3.1 with number of criteria $m > 1$. When using the Goal Programming Method to define an Auxiliary Single-Criteria Optimisation Problem, a vector $g \in \mathbb{R}^m$ needs to be given. Then g is regarded as the "goal" of the Multi-Criteria Optimisation Problem.

A comparison of different alternatives $x_1, x_2 \in \mathfrak{X}$ with regard to f is defined by how close any alternative matches the given goal g:

$$x_1 \text{ is better than } x_2 :\Longleftrightarrow d(f(x_1), g) < d(f(x_2), g) \tag{3.2}$$

where $d : \mathbb{R}^m \times \mathbb{R}^m \to \mathbb{R}$ is a norm on $\mathbb{R}^m$. Since a fixed g is used, one can define the scalarisation function d_g as

$$d_g : \mathbb{R}^m \to \mathbb{R} \qquad d_g(f(x)) := d(f(x), g) \tag{3.3}$$

The choice of the goal g is thereby highly dependent on the decision situation that is modelled by the original Multi-Criteria Optimisation Problem.

Utility Theory Method

Let $(\mathfrak{X}, f)$ be a Multi-Criteria Optimisation Problem as defined in Definition 3.1 with number of criteria $m > 1$. When using the Utility Theory method to define an Auxiliary Single-Criteria Optimisation Problem, a function u needs to be given:

$$u : \mathbb{R}^m \to \mathbb{R} \tag{3.4}$$

u is than regarded as stating the "utility" of an alternative.

A comparison of different alternatives $x_1, x_2 \in \mathfrak{X}$ with regard to f is defined by the extent of their "utilities":

$$x_1 \text{ is better than } x_2 :\Longleftrightarrow u(f(x_1)) < u(f(x_2)) \tag{3.5}$$

A common example for a utility function u is the weighted sum

$$u(f(x)) = \sum_{i=1}^{m} w_i f_i(x)$$

where a weight vector $w = (w_1, \ldots, w_m) \in \mathbb{R}^m$ needs to be given.

3.2.1.2. Probabilistic Models

Probabilistic models also use the Utility Theory Approach discussed in Section 3.2.1.1 where the decision alternative with the highest "utility" for the decision maker is chosen. However, in probabilistic decision making models – unlike in the unbounded rationality approach – the utility of an alternative is modelled by a random variable.

Two main approaches exist for the modelling of human decision making based on a probabilistic utility approach: Decision Networks and Discrete Choice Models.

Decision Networks

Decision Networks are a special case of Influence Diagrams which in turn are a special case of Bayesian Networks [89]:

$$\text{Decision Network} \quad \Longrightarrow \quad \text{Influence Diagram} \quad \Longrightarrow \quad \text{Bayesian Network}$$

In a Bayesian Network, the relations and dependencies between a finite set of random variables $\mathfrak{X}$ is encoded by a (simple) directed graph or digraph $D = (\mathfrak{V}, \mathfrak{E})$. Each random variable $X \in \mathfrak{X}$ is thereby represented by a vertex $v \in \mathfrak{V}$ of the digraph and a (directed) edge $e \in \mathfrak{E}$ of the digraph represents the conditional dependencies of the related random variables.

Let for each vertex $v \in \mathfrak{V}$ denote $pa(v)$ the set of "parents" of the vertex v:

$$pa(v) := \{w \in \mathfrak{V} \mid (w, v) \in \mathfrak{E}\}$$

For simplicity, let $\mathfrak{X}_{pa(v)}$ denote the set of random variables associated with all the parent vertices of the vertex v.

The probability distribution of the random variable $X_v \in \mathfrak{X}$ associated with the vertex v is then dependent on the conditional probabilities of the random variables associated with its parent vertices:

$$P(X_v) = P(X_v|\mathfrak{X}_{pa(v)})$$

An Influence Diagram is a special Bayesian Network which is designed to encode a decision making process. The set of random variables $\mathfrak{X}$ associated with an Influence diagram thereby comprises three types of random variables: conditional or situational random variables $\mathfrak{X}_S$, decision random variables $\mathfrak{X}_D$ and utility random variables $\mathfrak{X}_U$:

$$\mathfrak{X} = \mathfrak{X}_S \cup \mathfrak{X}_D \cup \mathfrak{X}_U$$

In addition to specifying the random variables and their conditional interdependencies, a set of utility function $\mathfrak{U}$ needs to be specified. $\mathfrak{U}$ then contains for each utility random variable in $\mathfrak{X}_U$ a utility function which is dependent on the state of the "parent random variables":

$$X = u(\mathfrak{X}_{pa(v)}) \text{ for } X \in \mathfrak{X}_U$$

When an Influence Diagram has been designed under consideration of certain regulations, it is called a Decision Network [71]: a Decision Network is an Influence Diagram which obeys the "single-decision maker rule" and the "no-forgetting rule" [71].

The "single-decision maker rule" implies, that in a decision situation modelled by a Decision Network a unique order of decisions to be taken is established. Mathematically speaking, a directional path connecting all vertices $\mathfrak{V}_D$ that represent the decision random variables $\mathfrak{X}_D$ must exist. Furthermore, the "no-forgetting rule" implies, that a "perfect recall is assumed of all observations and decisions made in the past." [89].

A Decision Network determines the expected utilities of all utility random variables in $\mathfrak{X}_U$ given the probabilistic information provided in the environment by the random variables in $\mathfrak{X}_S$ and given the probabilities of possible decisions for the decision random variables in $\mathfrak{X}_D$.

A Decision Network can therefore be used to model a complete chain of decisions under uncertain conditions. The model's uncertainty thereby lies within the uncertainty in the surrounding conditions represented by the situation random variables $\mathfrak{X}_S$, but also the uncertainty in the outcome of previous decisions, represented by the decision random variables $\mathfrak{X}_D$.

Discrete Choice Models

Discrete Choice Models replicate the entire decision making process, i.e. the characteristics of the decision maker, the choice set together with attributes of the different choice alternatives and finally the process by which the decision maker chooses one alternative [90].

The Discrete Choice Models thereby use a "Random Utility Approach" [90] to determine the utility U of a choice alternative:

$$U = U_{det} + \epsilon$$

At first, the deterministic utility of a choice alternative U_{det} is determined by a certain algorithm. A probabilistic error in form of the random variable ϵ is then added to the deterministic utility part U_{det}, resulting in the utility random variable U.

The deterministic utility U_{det} is calculated under consideration of both the decision maker's characteristics or preferences and the attributes associated with the choice alternative in question. Any method presented in the discussion of the Utility Theory in Section 3.2.1.1 would be valid.

The chosen probability distribution of the error random variable ϵ is dependent on the field of application of the Discrete Choice Model. The two main approaches according to Ben Akiva and Bierlaire [90] are Logit and Probit models. For Logit Discrete Choice Models, the random error ϵ is distributed according to a Gumbel distribution, whereas for Probit Discrete Choice Models, ϵ is distributed according to a Normal distribution.

3.2.1.3. Bounded Rationality

In the late 1950s, Simon [91, 92, 93] presented a theory opposing the up to then typical approach of employing unbounded rationality models of human decision making, especially in economics.

Mathematical optimisation models of human decision making – as proposed by the unbounded rationality approach – require the decision maker to have a perfect information base and enough time to compute the optimal solution for a decision situation. By contrast, Simon argued, that human beings are capable of drawing their decisions in complex environments, sometimes in a short time frame and based on possibly confusing or incomplete information. Simon therefore postulated [92], that because of these time and information limitations, mathematical optimisation is not an appropriate model to represent human decision making in general.

In 1990, Simon [94] summarised his research by describing his view on the human cognitive system:

> "Because of the limits on their computing speeds and power, intelligent systems must use approximate methods. Optimality is beyond their capabilities; their rationality is bounded."
>
> *Simon [94]*

Simon argues, that human cognitive behaviour is observed to depend on a limited short-term memory [95], the time consuming task of recognition [86] and the readiness of instinctive reactions. Any human decision making model should therefore be able to explain the influence of these limitations and observations.

Nevertheless, Simon [94] acknowledges, that under certain circumstances human beings are capable of drawing decisions which are close to the optimal solution in certain decision situations. These decision situations are referred to as "expert" decisions, where the decision maker can draw on a huge and readily available experience in that specific decision making task. In other, unfamiliar decision situations, Simon postulates that humans rely on heuristic decision making approaches:

> "When a great space of possibilities is to be explored [...] search becomes very selective. It is then guided by various rules of thumb, or heuristics, some of which are specific to familiar tasks, but some of which are more general."
>
> *Simon [94]*

Simon proposes cognitive architectures such as Soar or ACT-R (see Section 3.1) as a general framework for the human cognition process. However, the actual human decision making algorithms need to be chosen dependent on the actual decision situation.

In the remainder of this section, two approaches which try to explain (some aspects of) human decision making under Simon's "Bounded Rationality" theme are surveyed. First, the Naturalistic Decision Making approach is described which studies the capability of human expert decision making. Furthermore, the Adaptive Toolbox as a collection of methods for explaining human heuristical decision making is discussed [96, 97].

Naturalistic Decision Making

Originated in 1989, the Naturalistic Decision Making framework "is an attempt to understand how people make decisions in real-world contexts that are meaningful and familiar to them", Lipshitz et al. [98]. The main focus of the Naturalistic Decision Making theory is therefore the decision making of experienced experts in decision situations regarding their field of expertise.

The Naturalistic Decision Making approach is characterised by "proficient decision makers, situation-action matching decision rules, context-bound informal modelling, process orientation, and empirical-based prescription" [98].

One of the most prominent models of human decision making under the Naturalistic Decision Making scheme is the Recognition-Primed Decision Model by Klein [99]. Klein argues, that when experts are faced with decision situations in their field of expertise, these experts are capable of finding (almost) optimal solutions to the given decision problem. This near-optimal performance can be observed even in stressful and highly pressing situations, as Klein [100] has shown in his field observations of fire fighters.

Klein [99] explains the observed performance of experts in the Recognition-Primed Decision Model. The Recognition-Primed Decision Model is applied in decision situations, where the decision maker has access to a profound knowledge base which they have acquired by experience or training. Also, the decision maker seems to employ the Recognition-Primed Decision Model mainly in cases of high stress and time pressure [98].

The Recognition-Primed Decision Model postulates, that the experts (subconsciously) identify patterns in a given decision problem. Based on these patterns as a set of cues, the expert searches their (substantial) knowledge base for decision situations which closely match the observed cues. For any relevant found decision situation, the expert can then recall their former actions in resolving the former decision problems. Given this contextual information, the expert is capable of comparing different scenarios and promptly estimate possible outcomes of their available decisions. By this pattern-matching recognition process, the expert decision maker can rapidly make informed decisions.

Klein [100] also observed during his field observations, that expert decision makers are very efficient in this pattern-matching recognition task. In most of the cases, the first subconsciously recognised experience produced a satisfyingly good match to the given decision situation.

The Adaptive Toolbox

The Adaptive Toolbox proposed by Gigerenzer and Todd [96], Gigerenzer and Selten [97] is a collection of simple heuristic decision making algorithms:

> "First, it refers to a collection of rules or heuristics rather than to a general-purpose decision-making algorithm [...]. Second, these heuristics are fast, frugal, and computationally cheap rather than consistent, coherent, and general. Third, these heuristics are adapted to particular environments, past or present, physical or social. [...] Fourth, the bundle of heuristics in the adaptive toolbox is orchestrated by some mechanism reflecting the importance of conflicting motivations and goals."
>
> *Gigerenzer and Selten [101]*

The decision heuristics in the Adaptive Toolbox follow a common process [101]: At first, either choice alternatives themselves or cues regarding a given set of choice alternatives are searched to inform the decision making process. This search is undertaken until either the available information is exhausted or a "stopping rule" is evoked. This stopping rule encodes the decision criterion for the modelled decision situation. Once the search process has been stopped, a decision is drawn by using a simple "decision rule".

The heuristics provided in the Adaptive Toolbox have been studied and analysed in a large number of empirical studies, cf. Marewski et al. [102]. Also, the methodologies and application areas of the different heuristics in the Adaptive Toolbox have been intensively reviewed and discussed in the peer research literature [103–107].

In the following, a well-known example from the Adaptive Toolbox and its application area are discussed, the Take-the-Best Heuristic. The Take-the-Best Heuristic is applied in decision situations, where the decision maker has to retrieve information from their long-term memory in a short amount of time [102].

In the decision situations where the Take-the-Best should be applied, the decision maker has to decide between two competing choice alternatives [108]: In the Take-the-Best Heuristic, the decision maker compares these two choice alternatives based on a set of "cues" [108]. These cues are related to certain attributes of the given choice alternatives. A cue basically states whether a choice alternative meets the preferences of the decision maker (which results in a positive cue value), or whether the alternative does not meet the decision maker's preferences (results in a cue value of 0), or whether the choice alternative cannot be assessed given this cue. The set of cues upon which the decision maker draws his decision thereby needs to be tailored to the situation in which the decision problem takes place.

The most crucial feature of the Take-the-Best Heuristic is however, that the decision maker doesn't randomly assess the two given choice alternatives based on their set of cues. Instead, the cues are ordered in a hierarchy, reflecting the importance of the information provided by the cues to the decision maker. The two choice alternatives are hence assessed in order of this cue hierarchy, beginning with the most important cue to the decision maker and so on. The Take-the-Best Heuristic then postulates, that the decision maker will stop the choice alternative assessment as soon as one of the two choice alternatives returned a positive cue value and the other choice alternative didn't. The latter choice alternative is then dismissed and the decision maker decides for the choice alternative with the positive cue return.

The Take-the-Best Heuristic is summarised as follows by the Adaptive Toolbox's process of search, stopping rule and decision rule (see above):

1. "Search by validity: Search through cues in order of their validity. Look up the cue values of the cue with the highest validity first." [108]

2. "One-reason stopping rule: If one object has a positive cue value (1) and the other does not (0 or unknown), then stop search and proceed to Step 3. Otherwise exclude this cue and return to Step 1. If no more cues are found, then guess." [108]

3. "One-reason decision making: Predict that the object with the positive cue value (1) has the higher value on the criterion." [108]

3.2.2. Memory Modelling

Human memory has been proven to have a great impact on human behaviour in wayfinding or space recognition tasks [7, 109–111]. In contrast to the storage and retrieval of information in computational physical or digital memory, human beings aren't capable of perfect information storage and information recollection. Humans "learn" information and "recall" certain types of information when triggered by their cognitive process. The human learning and recalling procedures thereby depend to a high degree on the extent of relevance of the perceived information to their general and current situation and intentions.

All cognitive architectures surveyed in Section 3.1.1 comprise a sophisticated model for memorising knowledge and for recalling knowledge from memory. Out of these three memory models, the memory model of the ACT-R is explicitly based on an extensive analysis of empirical research on human memory performance by Anderson and Schooler [112]. Anderson et al. [86] have further tested and calibrated their theory based on empirical studies on human memory performance and on human performance data in the literature. Since the memory model of the ACT-R has also been successfully matched to human brain functions [3], this memory model has been chosen to be adopted for this thesis' research.

In the ACT-R cognitive architecture, the memory model “constitute(s) the cognitive core” of the architecture [3]. Anderson and Schooler focussed on how available human memories are dependent on their pattern of past use. During the analysis, Anderson and Schooler found – in compliance with Ebbinghaus [113] – that the probability of humans recalling specific memories follows a power function related to the time since the information to be memorised was last presented to the individual. Similarly, the human learning performance of specific memories also follows a power function of the number of times that the memory information has been “practiced” [112] or encountered.

Regarding the structure of the human memory, Anderson and Schooler postulate that “human memory mirrors, with a remarkable degree of fidelity, the structure that exists in the environment” [112]. Anderson and Schooler postulate, that human memory is thereby not only based on information from the environment, but the way the information is provided within the environment is replicated in the human memory. It also determines the readiness or recall probability of the memory item. The authors argue, that “memory has the structure it has because the environment has the structure it has.” [112].

In 1998 and in 2004, Anderson et al. [3] extended and formalised their findings by introducing a parameterised list memory model of free recall, the ACT-R’s “declarative memory model”. In the ACT-R’s declarative memory model, memorised information is organised as so-called memory “chunks”. Chunks are “schema-like structures” [86], which represent units of memories. Anderson et al. postulate, that the memory chunks replicate information available in the environment, including cause and coherency associations. A memory chunk thereby consists of several “cues” and their interdependencies.

The declarative memory model [3] postulates that a memory chunk can be assigned a level of activation. Dependent on the chunk’s level of activation, it is more or less probable that the memory chunk is recollected during memory recall. The level of activation A_i of a memory chunk i is dependent on several influences:

$$A_i = B_i + \sum_j W_j \cdot S_{ji}$$

B_i is the chunk’s “base-level activation” [86] or “base-level learning” [3], and is logarithmically dependent on a power function of the time delays since the memory chunk i has been accessed. The W_j are weights inversely related to the number of times that the chunk i has been accessed. The S_{ji} are measures of the association of a given cue j to the memory chunk i. For a detailed description of the memory chunk’s activation see Appendix Section A.3.1.

3.2.3. Emotion Modelling

Emotions and feelings have a great impact on human cognitive behaviour as has been pointed out by neuroscientists, psychologists and behavioural scientists [114–116]. Emotions can be seen as facilitators for human cognitive decision making [114, 115, 117].

According to Wehrle [118], these insights have lead to the usage of (computational) emotion modelling in a variety of different fields such as psychology, neuroscience and cognitive science; engineering; and human-computer interaction science. The main aim of employing emotion modelling techniques is thereby to simulate emotions and their behaviour implications in a human-like manner [119].

Although – according to Wehrle [118] – the purposes and methods of emotion modelling vary throughout the different research domains, it is possible to express an emotion model as a sub-model of a cognitive architecture, see Figure 3.5.

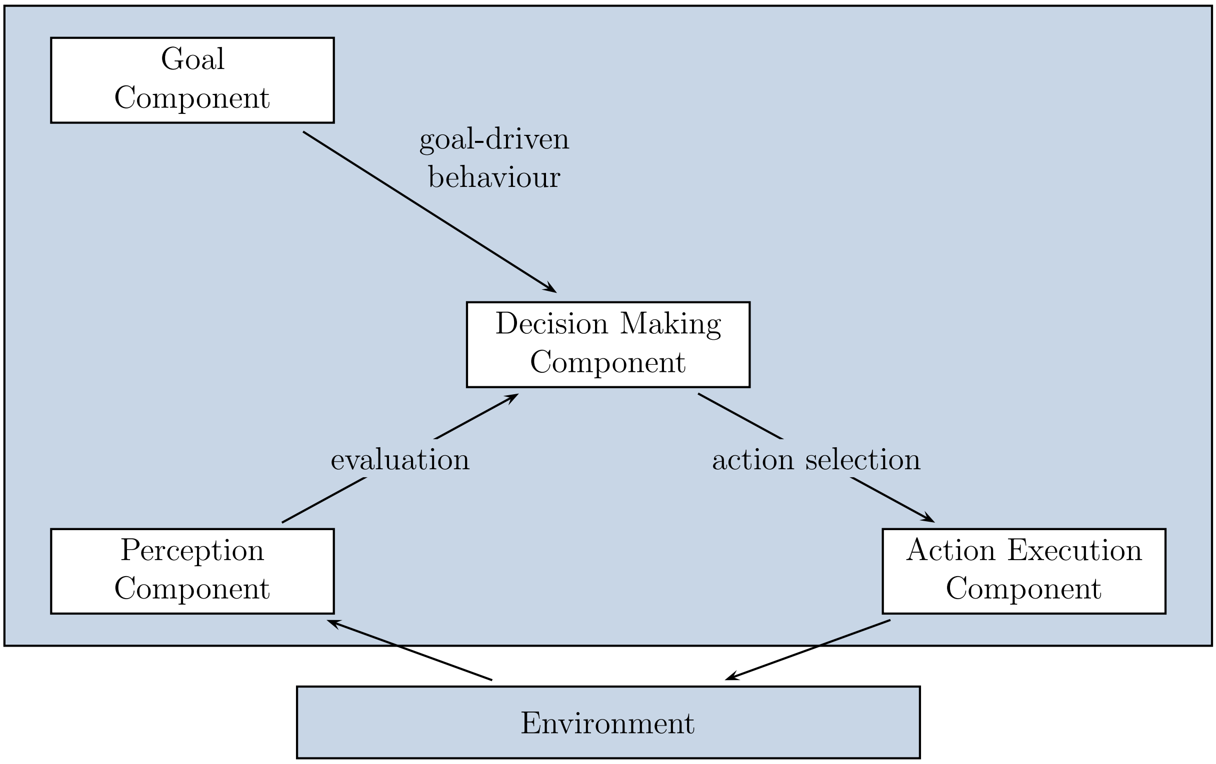


Figure 3.5.: The cognitive architecture components that are realised by an emotion model.

The main focus of an emotion model is to evaluate perceived information from the external environment and relate this information to intrinsic goals and preferences, which finally results in the decision for a specific action. This action can be a certain facial expression for communicating agents, or a certain adaptive behaviour.

The OCC emotion model for agents [119, 120] has emerged as a standard for emotion modelling over the recent years. It has been employed in many different fields of application, including the simulation of gambling behaviour [121], the PMFserv cognitive architecture [74] and even a conceptual framework for crowd modelling [122].

The OCC model [120] is mostly concerned with the evaluation of perceived information. Ortony et al. [120] argue, that humans are capable of perceiving “three major aspects of the world, upon which one can focus, namely, events, agents or objects”.

> "When one focusses on events one does so because one is interested in their consequences, when one focuses on agents, one does so because of their actions, and when one focuses on objects, one is interested in certain aspects or imputed properties of them qua objects."
>
> *Ortony et al. [120]*

In the OCC model, each of these three types of perceived information (consequences of events, actions of agents, aspects of objects) are associated with a fixed set of "emotion types" [120]. In total, the OCC model comprises 22 emotion types, examples being "satisfaction" and "disappointment", "joy" and "distress", "pride" and "reproach", "love" and hate", etc.

In correspondence to the three possible types of perceived information, an agent in the OCC model is able to quantify this information by relating it to a set of goals, a set of standards and a set of attitudes: The emotional reactions to consequences of events are quantified based on their level of desirability, which is determined by consulting the agent's goals. Those emotional reactions caused by the actions of other agents are quantified based on their level of praiseworthiness. This is is determined by comparing the actions to the agent's standards. Finally, the aspects of perceived objects are emotionally quantified based on their level of appealingness, which is determined based on the agent's attitudes.

In summary, the agent can only determine their emotional reaction to the perceived information by comparing and evaluating the information with regard to an appropriate reference background. This reference background is thereby in-built in the agent's emotion model.

In the OCC model, each emotional type is associated with a reactive behaviour [119]. The strength or markedness of this reactive behaviour is thereby dependent on the strength of the emotional reaction.

In 2002, Bartneck [119] reviewed the OCC model for simulating "embodied characters". Bartneck found that the OCC emotion model is an excellent basis for the purpose of simulating communicative agents, but Bartneck also identified shortcomings of the OCC model. Bartneck mainly criticised the lack of an in-built history functionality which would ensure the modelling of consistent and non-repetitive behaviour. Furthermore, Bartneck argues, that no interaction between the different emotion types is integrated in the model.

3.2.4. Motivational Action Selection

De Sevin's action selection architecture is closely linked to emotion models: In emotion models, the emotional response to perceived environmental information drives the decision making and action selection process. In de Sevin's model, the agent's intrinsic goals and motivations are the causal trigger for the action selection process, see Figure 3.6.

In 2006, de Sevin has proposed an action selection model for the simulation of autonomous agents in persistent worlds [4, 123–126]. The proposed action selection model is based on Tyrrell's hierarchical action selection algorithm [72].

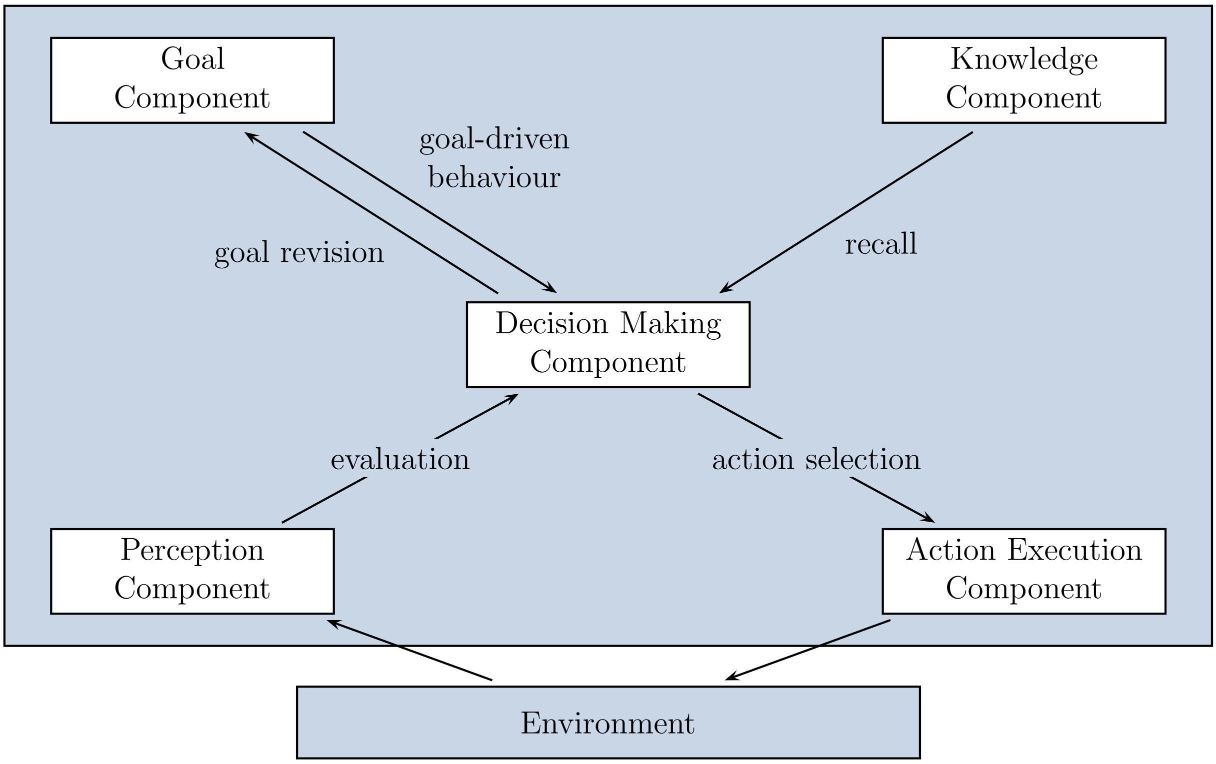


Figure 3.6.: The cognitive architecture components that are realised by de Sevin's motivational action selection model.

In de Sevin's agent action selection model, an agent acts based on an intrinsic set of simulated motivations. The agent has got a fixed set of actions at their disposal in order to satisfy their motivations. Motivations are simulated by an intrinsic set of motivational functions. These motivational functions are monotonically increasing over time. A threshold system for the motivational functions is introduced, thereby assigning a motivation's comfort zone, tolerance zone and viability zone. The agent's aim is to keep every motivational function in the comfort zone.

In regular time intervals, the agent's next action is chosen from the set of possible actions based on the state of all the agent's motivations: The agent's motivational states are translated via a hierarchical classifier system [72] into preference values for specific actions in the action choice set.

If an action from the action choice set has received a preference value much higher than all alternative actions, this action is chosen to be the agent's next action. If however several actions have received comparable preference values, the next action is chosen based on a hierarchy system for the agent's motivations.

This hierarchy system is based on the strength of the motivations and the motivation's category. In a natural manner, the current importance of an action related to a motivational function in the viability zone is higher than the importance of a motivational function in the tolerance zone. Based on the "hierarchy of needs" proposed by Maslow [127], the simulated motivations in de Sevin's action selection model are categorised into a hierarchy of basic, essential and secondary motivations. Basic motivations include for example “hunger”, “thirst” and “rest”; essential motivations include for example “clean”, “sleep” and “wash”; and secondary motivations include for example “read”, “watch TV” and “water plants”. The simulated agent’s highest priority is to satisfy their basic motivations, followed by their essential motivations and last by their secondary motivations.

It has to be noted, that the action selection algorithm by Tyrrell [72, 73] (and therefore de Sevin’s action selection algorithm) is based on empirical data of animal behaviour observations and not on empirical data of human action selection. Also, the motivational functions used in de Sevin’s action selection model have been inspired by Maslow’s “hierarchy of needs” theory [127, 128], which is also mainly based on animal observations. Nevertheless, Maslow’s theory has been widely adopted and discussed in modern day psychological science [128, 129].

3.3. Summary

In this chapter, relevant research areas and suggested techniques for the modelling of human cognitive behaviour have been introduced and discussed. With the presented techniques, it is possible to simulate advanced pedestrian behaviours in a pedestrian behaviour simulation model. This chapter therefore addresses Research Objective 2. From the surveyed research, methods and theories have been chosen to be used for this thesis’ comprehensive agent model, see Chapter 5.

In Section 3.1, the concept of a cognitive architecture has been introduced. From a survey of three cognitive architectures in Section 3.1.1, it has been identified in Section 3.1.2 that a cognitive architecture is a suitable approach to develop a comprehensive agent model for advanced human cognitive behaviour in complex multi-purpose environments. For the purpose of this thesis’ research, it has been identified that the comprehensive cognitive agent model to be developed in this thesis should comprise the following components: a component to store and manage goals, a component to store and retrieve knowledge about where to satisfy the goals, a component to retrieve relevant information from the environment, a component to decide on the agent’s actions based on their goals and knowledge, and finally a component to execute the chosen actions. Thereby, a suitable approach to address Research Objective 3 has been identified.

During the review of the cognitive architecture approach, issues that are not covered by cognitive architectures but are on the other hand required for the comprehensive cognitive pedestrian agent model sought in this thesis have been identified, see Section 3.1.2.2. Based on these remaining questions, a further literature survey has been conducted to find suitable inspirations for addressing this thesis’ research questions.

In Section 3.2.1, a detailed survey of the current state of the art of theories and models for the replication of human decision making has been undertaken, thereby addressing Research

Question 2. It was found that a great number of profoundly different approaches for the understanding and modelling of the human decision making process are proposed in the disciplines of psychology and behavioural research. None of the presented approaches claims to be a universal human decision making model. Rather, the different models approximate human cognitive behaviour. Depending on the actual decision situation, certain models approximate the actual human decision making processes better than others. Therefore, the decision situations which are to be modelled in this thesis need to be analysed and categorised. An appropriate human decision making model then needs to be chosen for each type of decision situation to be modelled. The decision making component of this thesis' comprehensive agent model hence combines different theories of human decision making in one comprehensive decision making model, see Section 5.4.

All surveyed cognitive architectures comprise sophisticated models for human knowledge and memory. From the surveyed cognitive architectures, the ACT-R comprises a memory model which is based entirely on human behaviour research. It has therefore been decided to use the ACT-R's memory model in order to model pedestrian knowledge and experience, see Research Question 3. The knowledge component of this thesis' comprehensive agent model is hence based upon the ACT-R's memory model, see Section 5.3.

Cognitive architectures provide the framework to model advanced cognitive behaviours such as situational and contextual awareness (see Research Question 4) or motivational behaviour (see Research Question 1). However, the actual content of the behaviour models is not specified by a cognitive architecture. For this reason, concepts for the actual modelling of such advanced cognitive behaviours have been surveyed. During this literature survey, emotion models such as the OCC model (see Section 3.2.3) have been identified as suitable inspirations on how to implement situational and contextual awareness. These concepts have therefore been included in this thesis' comprehensive agent model, see Section 5.6.2. For the modelling of goals and motivational behaviour, Maslow's "Hierarchy of Needs" has been identified as a suitable inspiration for this thesis' comprehensive agent model, see Section 5.2.5. The motivational action selection model by de Sevin [4] also utilises Maslow's "Hierarchy of Needs", see Section 3.2.4. The motivational functions found in de Sevin's work have also contributed to modelling goal-driven behaviour in this thesis' comprehensive agent model, see Section 5.6.1.

To summarise, a comprehensive agent model for advanced cognitive pedestrian behaviour has been devised in Chapter 5: the Cognitive Pedestrian Agent Framework (CPAF). The architecture and components of the CPAF are based on insights found in various research disciplines which have been introduced and discussed in this chapter.

Chapter 4:

The buildingEXODUS Software Tool

This chapter will give an overview of the buildingEXODUS software tool and its currently available model features for simulating advanced pedestrian behaviours in buildingEXODUS. buildingEXODUS is a well established simulation tool in the pedestrian behaviour simulation community [11, 12, 25, 67] which has been developed for over 25 years. buildingEXODUS has advanced its features continuously with the last version (v5) being released in April 2012 [14].

In the latest buildingEXODUS version, a plug-in interface has been introduced which allows for an easy extension of the features already available in buildingEXODUS. This plug-in interface facilitates the development and integration of new pedestrian behaviour simulation methods. This interface been used in this thesis to integrate the Cognitive Pedestrian Agent Framework developed in this thesis (see Chapter 5) into buildingEXODUS. For the remainder of this thesis, this integration is hence referred to as the *buildingEXODUS Cognitive Pedestrian Agent Framework (CPAF) Plug-in*. The buildingEXODUS CPAF Plug-in extends and uses the relevant components of buildingEXODUS which are embedded in a global agent scheme. Several components of buildingEXODUS are improved and further artificial intelligence elements are added on top of the buildingEXODUS architecture. These added elements include an abstract decision making entity based on an advanced knowledge representation.

4.1. buildingEXODUS

The EXODUS suite of software tools developed by the Fire Safety Engineering Group at the University of Greenwich have been designed to primarily simulate pedestrian evacuation behaviour from various enclosures. The EXODUS software suite comprises several evacuation models: buildingEXODUS, airEXODUS, maritimeEXODUS and railEXODUS. While all these evacuation models are build on the same core evacuation model, each of these models is capable of accounting for specific modelling requirements in its field of application. For example maritimeEXODUS is capable of simulating pedestrian movement on inclined planes.

buildingEXODUS represents pedestrians as individual software agents. The agents behave probabilistically according to a set of pre-defined global rules and a set of individual attributes (see Section 4.1.2). Both time and space representation are discrete in building-EXODUS: an agent can occupy only discrete points on a spatial grid (see Section 4.1.1) at discrete points in time.

The time during a simulation in buildingEXODUS is determined by the *simulation time* τ. Due the discrete time representation, the simulation time τ can only attain specific values τ_i:

$$\tau \in \{\tau_i \in \mathbb{R}^+ \mid i \in \mathbb{N}\}$$

The time between two admissible points in time is called the simulation *time step* and is denoted by $\mathbf{T}^{\text{TimeStep}} \in \mathbb{R}^+$. In buildingEXODUS, $\mathbf{T}^{\text{TimeStep}}$ is a constant. The time τ_i then denotes the simulation time after the i-th time step:

$$\tau_i := i \cdot \mathbf{T}^{\text{TimeStep}} \qquad \text{for } i \in \mathbb{N}$$

4.1.1. Environment Model

buildingEXODUS represents the environment by a fine-grid structure built of nodes and arcs. The nodes in buildingEXODUS represent points in space that can be occupied by at most one agent at any simulation time τ. An arc between two nodes indicates that the agents can move between these two points. Each arc is assigned a length, which determines the distance between the nodes that are linked by the arc. From the specification of the arcs' length and by setting a random origin point, each node can be assigned a pair of coordinates $(x_1, x_2) \in \mathbb{R}^2$ in the plane.

Usually, the nodes in buildingEXODUS are arranged on a regular grid of grid size 0.5 m, see Figure 4.1.

When specifying the length of the arcs as in Figure 4.1, it follows that the smallest amount of space that can be occupied by a simulated pedestrian is 0.25 sqm, since not more than one agent can occupy one node at any point in time.

A three dimensional environment can be modelled with the 2D spatial grid model of buildingEXODUS by simulating each floor of a multi-level building by a single floor plane. The floor planes are then linked by special nodes called *transit nodes* in buildingEXODUS [14]. Each node in the buildingEXODUS's environment representation can hence be identified by their pair of plane coordinates $(x_1, x_2) \in \mathbb{R}^2$ and the floor number x_3 of the encompassing floor plane.

Pedestrian movement in buildingEXODUS is governed by a so-called *Potential Map* [14], which is encoded in the environment. A potential map assigns each node a "potential" value, thereby determining a node's distance from a targeted location, see Figure 4.2.

In Figure 4.2, a simple integer potential map is shown in which the nodes are connected

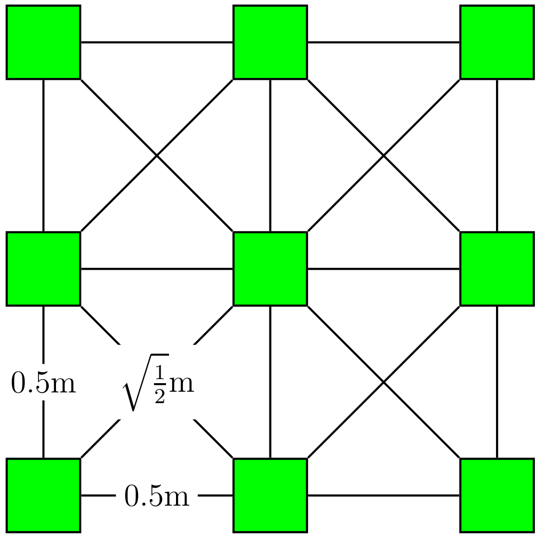


Figure 4.1.: The default spatial grid specification in buildingEXODUS.

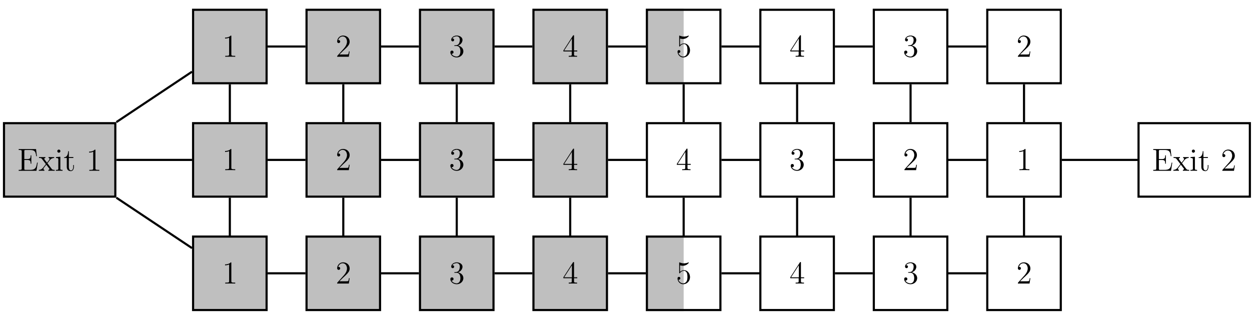


Figure 4.2.: Example potential map for a simple geometry with two exits, Galea et al. [5, Figure 2.5].

only via horizontal and vertical arcs. The potential map system implemented in buildingEXODUS also respects diagonal node connections and their implications on the distance to be travelled between two nodes. The potential map in buildingEXODUS is therefore a floating point potential distance map, see Figure 4.3.

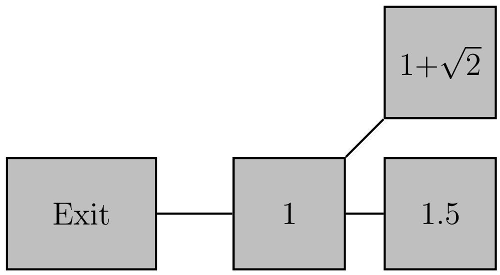


Figure 4.3.: Distance potential map for three nodes and one exit.

Agent movement based on a potential map follows a rule-based system. When the agent determines which node to occupy in their next step, they choose a node that has a lower potential value than their currently occupied node. If several nodes with a lower potential value exist, the agent randomly chooses a node with minimal potential value. "If more than one node is available that reduces the potential, the node reducing it by the largest amount will be selected." [14].

In buildingEXODUS, nodes can be specified by the model user to be set as so-called *target nodes*. For each of these target nodes, buildingEXODUS determines an individual distance potential map. When an agent is assigned to walk to a certain target node, they will follow this node's individual distance potential map. Any node in buildingEXODUS can be set to be a target node. Some nodes are automatically set to be target nodes, for example nodes representing external doors.

In addition to the potential map system, buildingEXODUS can internally determine the walking distance for an agent between two arbitrary nodes in the environment. This defines a walking distance metric in the buildingEXODUS's environment representation.

Nodes in buildingEXODUS can not only represent walkable areas but also a variety of other objects such as seats, doors, stairs, escalators, etc. Moreover, arcs can also be attributed with specific features, such as a route that is cluttered with debris during a fire incident and which therefore takes longer to traverse for the agents. For more detailed features of the environment model in buildingEXODUS the interested reader is referred to Galea et al. [14].

In addition to simulating individual nodes that are connected to represent the walkable area of a given environment, buildingEXODUS is capable of abstractly representing rooms and compartments in a building. This is achieved by *compartment zones*. A compartment zone is a set of nodes which the model user can specify within the modelled environment. buildingEXODUS is than capable of producing zone usage statistics. Furthermore, it is possible for the model user to direct agents to these compartment zones.

4.1.2. Pedestrian Model

The software agents that simulate pedestrians in buildingEXODUS are characterised and individualised by various agent parameters. Since buildingEXODUS is primarily designed as an evacuation simulation tool, these parameters mainly determine the agent's physical locomotion, their psychological state and their alarm response behaviour (see Section 4.4).

The attributes which characterise an individual agent in buildingEXODUS can be grouped into four categories. The first attribute category comprises all physical attributes such as age, gender, mobility and walking speed. Further, buildingEXODUS simulates psychological attributes such as patience and the agent's alarm response time. Their individual sojourn time in the environment, the total travelled distance or the cumulative time that the agent has spent waiting in a queue or congestion are categorised as the agent's experiential parameters. Finally, the physical impact of a fire hazard and the accompanying toxic gases are determined with the agent's hazard parameters.

Since this thesis is concerned with cognitive behaviour during pedestrian circulation and the alarm response phase, only a limited set of agent parameters are of direct relevance for this thesis and the therein developed agent framework. Table 4.1 lists a brief overview of the agent parameters that are further discussed in detail in this chapter.

Table 4.1.: The subset of agent parameters available in buildingEXODUS that are relevant to this thesis.

Parameter	Symbol	Category	Description	Section
Fast Walking Speed	v_f	physical	Fast Walking Speed	4.1.2
Drive	D	psychological	Self-assertion ability in locomotion	4.1.2
Patience	P	psychological	Maximum time spent standing still in congestion or a queue	4.1.2
Occupant Itinerary List	OIL	experiential	A list of tasks that the agent needs to accomplish prior to exiting the environment	4.1.2.1
Urgency	U	psychological	Reaction to perceived time pressure	4.3.1
Response Time	T_{resp}	psychological	Time delay between an occurred alarm event and the initiation of travel to an exit	4.4
Occupant Exit Knowledge	OEK	experiential	A list of exits that the agent is familiar with	4.4

The agent's walking speed governs the number of time steps that it takes the agent to traverse an arc of a given length. In buildingEXODUS, three walk speeds for the simulation of pedestrian walking behaviour exists: a fast walk speed constant v_f, a normal walk speed constant v_n and the agent's current walk speed $v(\tau)$ at the simulation time τ. The fast and normal walk speeds are constant agent parameters, whereas the agent's current walk speed $v(\tau)$ is dependent on the state of the walkable area, the level of congestion that the agent experiences and the agent's physical and psychological state. The normal walk speed v_n is fixed to be 90% of the fast walk speed v_f. It is therefore sufficient to specify only the agent's fast walk speed constant.

The agents' fast walk speed can be assigned by the user in buildingEXODUS. However, the default value of the fast walk speed agent parameter amounts to $v_f = 1.5\frac{m}{s}$, resulting in a normal walk speed of $v_n = 1.35\frac{m}{s}$. On a normal walkable area, the agents within buildingEXODUS will always aim to travel with their fast walk speed ($v(\tau) = v_f$) and aim to fall back on their normal walk speed only on difficult terrain ($v(\tau) = v_n$). Naturally, the agent's current walk speed is further reduced if they experience congestion, need to wait in a queue or are hindered by their physical capabilities [130, 131].

The drive attribute of an agent is a measure of how assertive the agent is during a potential competition for occupiable space. If the situation occurs that two agents desire to move to the same node as their next step, the agent with the significantly higher drive attribute will win this conflict situation and therefore can proceed to the desired node. If the drive attributes of two pedestrians in a situation as described above are comparable, it is randomly determined which of the two agents will get to proceed to the desired node.

The patience attribute of an agent is a measure of how long the agent is willing to be halted by congestion or an unordered queue in front of a desired target. The patience attribute thereby states the maximum amount of time that an agent will be willing to remain continuously stationary before seeking alternative options.

Agents in buildingEXODUS don't possess an individual decision making entity. Instead, their behaviour is governed by global probabilistic rules and the values of their individual agent parameters. Also, agents in buildingEXODUS have only got a rudimentary individual knowledge representation, their Occupant Exit Knowledge (see Section 4.4). This is partly indebted to the fact, that agents in buildingEXODUS have a limited structural perception capability. Regarding structural information, the agents are capable of indirectly perceiving exit signs (see Section 4.5.1) and of building a "cognitive map" of their surroundings with regard to the connectivity of rooms, corridors and exits [132, 133].

Nevertheless, agents in buildingEXODUS are able to individually perceive the impact of time pressure, congestion and fire hazards and adjust their behaviour accordingly, see Sections 4.3.1 and 4.5.2.

4.1.2.1. Occupant Itinerary List

In the buildingEXODUS simulation tool, an agent feature has been developed which allows for the simulation of activities in the modelled environment, the so-called *Occupant Itinerary List*. Since buildingEXODUS focusses on evacuation simulation, the itinerary feature has been primarily developed to simulate pre-evacuation activities (see Section 4.4). However, the same feature can also be used to simulate pedestrian circulation behaviour.

The individual agents can be assigned their individual Occupant Itinerary List. This Occupant Itinerary List is an ordered list of *tasks*. The agent's tasks are intended to represent their plans in the modelled environment. These tasks therefore realise plans of what to do, where and in what order. An agent is required to work through their Occupant Itinerary List before leaving the modelled environment.

A task on the individual agent's Occupant Itinerary List is characterised by a set of parameters, see Table 4.2 for an overview.

Table 4.2.: The general parameters of a task t in buildingEXODUS.

Parameter	Symbol
Nodal Task Location	-
Type	-
Index on the OIL	$\pi(t)$
Start Time	$\tau_{start}(t)$
End Time	$\tau_{end}(t)$
Remaining Distance	$d(t)$
Status	-
Importance	$I(t)$

Since tasks realise plans, a task is associated with a nodal task location in the building-EXODUS's environment model, indicating where the task needs to be performed. A task's type attribute indicates what activity shall be performed, and the order of the planned tasks is given by their position π on the (ordered) Occupant Itinerary List.

buildingEXODUS can simulate a various range of different activities indicated by a task's type attribute. These actions comprise e.g. to open a closed door, to enter a queue in front of a target, to join a group or to wait until a specific point in simulation time. In the buildingEXODUS CPAF Plug-in, three basic task types have been used to simulate the pedestrians' behaviour: "delay" tasks, "wait" tasks and "way point" tasks.

"Delay" type tasks are general tasks for modelling the time an agent spends at a given location. In order to accomplish their "delay" task, the agent is required to occupy the specified location for a given time range. "Wait" type tasks are general tasks for modelling time limitations or time instructions. "Wait" type tasks are accomplished when the agent has to be present at the specified task's location at a given point in time. If the agent reaches the given location before the specified point in time, the agent will stay and wait at the given location. "Way point" tasks are general tasks for informing the agent to visit a specific location in the environment. The "way point" task is accomplished as soon as the pedestrian has passed by the given location within a given range. The activities encoded by “delay”, “wait” or “way point” type tasks are specified in detail by a set of activity parameters dependent on the task type, see Table 4.3.

Table 4.3.: Activity task parameters in buildingEXODUS for different task types.

Task Type	Parameter(s)	Description
“delay”	T_{min}, T_{max}	T_{min} and T_{max} denote the minimal respectively maximal time delay that the agent will experience when performing the corresponding task.
“wait”	R, τ_{wait}	R indicates the range around the task’s nodal location within which the agent needs to remain until the simulation time τ has exceeded the time τ_{wait}.
“way point”	R	R indicates the radius around the task’s nodal location within which the agent needs to pass by.

For each task in buildingEXODUS, the points in the simulation time when the task has been started τ_{start} and when it has been accomplished τ_{end} are stored. This implies for the “delay” and “wait” type tasks:

$$\begin{aligned} \text{the “delay” task } t \text{ is accomplished} &\implies \tau_{start}(t) + T_{min}(t) \leq \tau_{end}(t) \leq \tau_{start}(t) + T_{max}(t) \\ \text{the “wait” task } t \text{ is accomplished} &\implies \tau_{end}(t) \geq \tau_{wait}(t) \end{aligned}$$

By assigning each task on their Occupant Itinerary List a status attribute, the agent keeps track of which tasks have been accomplished and which have not. The status of a task in buildingEXODUS can be either ongoing, active, completed or dismissed. A task t is referred to as “ongoing”, if this is the agent’s current task, i.e. the agent is currently travelling to or undertaking the task. If a task’s status is “ongoing” then the task’s end time has not yet been reached. The index of the currently ongoing task on the agent’s Occupant Itinerary List is denoted by π_0 in this thesis. A task t is marked as “completed”, if the task has been successfully accomplished. On the other hand, a task t is marked as “dismissed” if the agent has decided to no longer try to achieve this task. A task t is referred to as “active” if it is neither ongoing, nor completed, nor dismissed. Table 4.4 lists the implications of a task’s status attribute for the task’s start and end time and its position on the Occupant Itinerary List relative to the position of the currently ongoing task π_0.

buildingEXODUS allows for the distinction between plans based on how important the activity is to the agent. For this reason, the tasks on the agent’s Occupant Itinerary List are assigned an importance value. The importance value $I(t)$ of a task t is thereby confined to a finite interval:

$$0 \leq I(t) \leq 100 \qquad \forall t \in \text{OIL}$$

A task of importance value 100 is regarded as being of the highest importance to the agent whereas a task of importance 0 is regarded as being of low importance.

Table 4.4.: The implications of the status attribute of a task t in buildingEXODUS at simulation time τ.

Status	Position on OIL	Task Start Time	Task End Time
ongoing	$\pi(t) \equiv \pi_0$	undefined	undefined
		$\tau_{start}(t) \leq \tau$	$\tau_{end}(t) > \tau$
completed	$\pi(t) < \pi_0$	$\tau_{start}(t) < \tau$	$\tau_{end}(t) < \tau$
dismissed	$\pi(t) \neq \pi_0$	undefined	undefined
active	$\pi(t) > \pi_0$	undefined	undefined

The tasks' importance attribute allows for the categorisation of tasks in buildingEXODUS and for constructing a relative hierarchical system of the individual tasks on the agent's Occupant Itinerary List. This is an important pre-requisite for any cognitive processes to be introduced for the agent in buildingEXODUS and the buildingEXODUS CPAF Plug-in.

Based in its importance value, a task can be categorised as either being compulsory or as being elective. *Compulsory Tasks* are tasks that must be completed e.g. "purchase a train ticket prior to boarding the train". *Elective Tasks* are tasks which are completely voluntary and – while desirable to complete – are not essential, e.g. "purchase a newspaper". In buildingEXODUS, compulsory tasks are represented by having the highest importance value, whereas elective tasks have a lower importance value:

$$\begin{aligned} \text{the task } t \text{ is compulsory} \quad &:\Longleftrightarrow \quad I(t) = 100 \\ \text{the task } t \text{ is elective} \quad &:\Longleftrightarrow \quad I(t) < 100 \end{aligned}$$

Although elective tasks are not essential to be completed, the agent might prefer to achieve some elective tasks over other elective tasks on their Occupant Itinerary List. To simulate this task preference, the elective tasks in buildingEXODUS can be placed into a hierarchy by assigning them any importance value from the open interval $[0, 100)$.

If a task t is of the "wait" type and also being set as compulsory, t is referred to as a critical time task: *Critical Time Tasks* are tasks which must be completed by a particular point in simulation time, e.g. "board the train before 17.45". In the remainder of this thesis, the index of the next to be tried critical time task on the agent's Occupant Itinerary List is denoted by π_{cr}:

$$\pi_{cr} := \min\{\pi(t) \in \{\pi_0, \ldots, |\mathrm{OIL}|\} \mid t \text{ is a critical time task and } t \text{ is either active or ongoing}\}$$

The agent's behaviour is therefore mostly governed by those tasks which are compulsory or time critical.

4.2. Ingress Modelling

In buildingEXODUS, agents can be automatically generated during the run of a simulation. Each individual agent can be assigned a simulation time, at which they enter the modelled environment. When generating an agent, buildingEXODUS uses pre-specified agent populations. These agent populations can be set by the user prior to the run of a simulation in buildingEXODUS.

A pedestrian population is characterised by a range of parameter values for each buildingEXODUS agent parameter. Any individual agent that is generated using a certain agent population scheme will therefore be assigned their agent parameters as random values within the population's parameter ranges. Similarly to the agent parameters, the buildingEXODUS model user can also specify a set of itineraries and associate this set with an agent population. On generation, each individual agent will hence be assigned one of the pre-specified itineraries as their individual Occupant Itinerary List, based on a specified probability distribution.

The actual generation of agents during the run of a simulation can be achieved in buildingEXODUS by two means: source nodes and Scenario Specification Files.

Source nodes [14] are specialised nodes on which agents are generated based on a time schedule that has been embedded in the node. Each source node is initialised with an agent population and a set of possible itineraries within the environment. The agents are then generated according to the time schedule specified in the source node and randomly assigned their parameters.

A more sophisticated way of generating agents during the course of a simulation are Scenario Specification Files. Scenario Specification Files are script files that can be imported by buildingEXODUS. In these Scenario Specification Files, the user can specify an agent population from which the agents to be generated shall be drawn. The user can then specify a number of agents and their individual entry times in the environment. buildingEXODUS will then generate an agent from the given agent population at the user-specified times during the course of the simulation.

Contrarily to source nodes however, the user can also choose to manually adjust some of the agent parameters for some individual agents, thereby potentially deviating from the parameter ranges given by the chosen agent population scheme. In particular, the user can choose to assign each individual agent an individual itinerary, and thereby potentially link the agent's entry time and their assigned Occupant Itinerary List. In addition, the user can specify in the Scenario Specification File for each individual agent their entry point in the environment. This can be used to simulate pedestrians entering a modelled environment by several different entrance points. Instead of having to initialise a source node for every entrance point, the information can be gathered in one Scenario Specification File.

Furthermore to the generation of the agents during a simulation, Scenario Specification

Files can also be used to specify emergent events which should occur during the simulation run. An example for events that can be modelled with the buildingEXODUS's Scenario Specification Files would be the closure of an external exit. The time during the simulation that this event should occur can be specified by the user. Moreover, the user can then specify adaptive behaviours of the pedestrians agents at the time of the event by altering the individual agents' itineraries at the event time. However, this adaptive behaviour would be externally imposed.

The capability of Scenario Specification Files to simulate emergent events can be used to simulate an alarm event and therefore to switch from a pedestrian circulation simulation to an evacuation simulation. However, as has been noted above, the agents' alarm response behaviour would have to be pre-specified by the model user in the Scenario Specification File. Consequently, the individual agent's alarm response behaviour would not be dependent on their individual situation and their attributes.

In summary, Scenario Specification Files do pose a flexible and sophisticated way of generating an agent population and simulating emergent events in buildingEXODUS. However, the Scenario Specification Files need to be set by the user, which is a time consuming task for large environments and a large agent population. Also, the itinerary and reactive behaviour to emergent events of the agents are entirely scripted by the model user and therefore not a result of any individual cognitive agent processes or the emerging situation.

4.3. Circulation Modelling

As has been mentioned in Section 4.1.2.1, pedestrian circulation behaviour is simulated in buildingEXODUS by assigning itineraries to the individual agents. The agents will then follow their assigned Occupant Itinerary List and accomplish the given tasks in the given order, thereby replicating pedestrians' building usage behaviour.

Whereas in previous versions of the buildingEXODUS software tool, the agent's Occupant Itinerary List has been a fixed agent parameter, the current release version of buildingEXODUS allows for the simulation of emergent and reactive pedestrian behaviour to perceived time pressure.

4.3.1. Situational Awareness Modelling: Urgency

In the current developmental version of buildingEXODUS, a basic model for representing the impact of time pressure on the agent's itinerary planning has been introduced, the *Urgency Model*.

The Urgency Model [14] can be used to realistically simulate pedestrian behaviour in e.g. long-distance traffic facilities, see Hollmann et al. [134]. In long-distance traffic facilities, the pedestrians' behaviour is governed by the transport time schedule: Pedestrians enter the facility and desire to board a mode of transport at a given point in time. Depending on the time that the pedestrians have arrived at the facility, they engage in activities in the environment, either in order to “kill time” or because of necessity. However, the pedestrians are aware of the time constraints posed by the departure time of their desired mode of transport and will, if necessary, adjust their behaviour accordingly.

This adaptive behaviour to time constraints is simulated by the buildingEXODUS's Urgency Model. The Urgency Model simulates the impact of time pressure on the agent by introducing a new agent parameter, the agent's *urgency*. During a pedestrian circulation simulation with buildingEXODUS, the agents monitor their time situation and relate this information to their planned activities, their Occupant Itinerary List. The agent will adjust their behaviour and their Occupant Itinerary List should their planned list of activities be no longer compatible with their current time planning.

The Urgency Parameter

In buildingEXODUS's Urgency Model, the urgency agent parameter has been introduced which reflects the agent's perceived time pressure. The urgency parameter U is a psychological agent parameter (see Table 4.1), that is dependent on the agent's time situation at simulation time τ and which can attain a value of either 0 or 1:

$$U \equiv U(\tau), \qquad U(\tau) \in \{0, 1\} \quad \forall \tau \in \mathbb{R}^+$$

An urgency value of 1 thereby represents that the agent is experiencing a significant amount of time pressure, whereas an urgency value of 0 represents no experienced time pressure.

In the Urgency model, the urgency parameter is linked to the agent's walk speed, drive and patience attributes. Consequently, since the urgency parameter is variable, this implies that the drive and patience attributes are also no longer constants for the agent, but can change during the course of the simulation. For this reason, a base drive D_0 and base patience P_0 attribute have been introduced in the buildingEXODUS's Urgency model. The agent's current patience $P(\tau)$, drive $D(\tau)$ and walk speed $v(\tau)$ at simulation time τ are then determined from the agent's current level of urgency $U(\tau)$ by the following relationships:

$$P(\tau) = P_0 \cdot (2 - U(\tau)) \tag{4.1a}$$

$$D(\tau) = D_0 \cdot (0.5 + 0.5 \cdot U(\tau)) \tag{4.1b}$$

$$v(\tau) = (v_f - v_n) \cdot U(\tau) + v_n \tag{4.1c}$$

As can be seen from the above relationships, an agent that experiences no time pressure is less assertive in spatial conflict situations with other agents. They are also more patient when waiting in queues or congestion and they travel with a relaxed walk speed. Under time pressure, the agent will fall back on their normal assertiveness and patience level as well as their default fast walk speed.

Time Evaluation

The agent's urgency parameter is assessed and updated at specific points in time during a circulation simulation. To assess their current time situation, an agent determines their *available time* T_a and a set of *estimated required times*.

The agent's available time is simply given by the time that is left until the agent's next critical time task $t_{\pi_{cr}}$:

$$T_a := \tau_{wait}\left(t_{\pi_{cr}}\right) - \tau \tag{4.2}$$

Hence, T_a determines the agent's time constraint.

The agent further needs to evaluate their current time planning. They therefore assess their current Occupant Itinerary List and estimate the time that is required to accomplish all ongoing and active tasks until their next critical time task. When estimating their time requirements, the agent needs to account for potential delays caused by congestion and queues. Furthermore, the agent takes into account variations that they themselves can influence by e.g. walking faster.

To simulate this estimation process of the time that the agent requires to complete their tasks until their next critical time task, four estimated required time parameters are determined by the buildingEXODUS's Urgency model, see Table 4.5.

Table 4.5.: The estimated required time parameters of the buildingEXODUS's Urgency Model.

Parameter	Equation	Description
T_0^{ERT}	$T_0^{\text{ERT}} = t_1 + t_2 + t_3 + t_4$	Urgency Escalation Time
T_1^{ERT}	$T_1^{\text{ERT}} = t_1 + t_2 + t_3$	Normal Walk Time
T_2^{ERT}	$T_2^{\text{ERT}} = t'_1 + t'_2 + t'_3 + t'_4$	Drop Task Zone
T_3^{ERT}	$T_3^{\text{ERT}} = t'_1 + t'_2 + t'_3$	Fast Walk Time

As can be seen in Table 4.5, the Urgency Model's estimated required time parameters are sums of time parameters which relate to the agent's Occupant Itinerary List and walk speed, see Table 4.6.

In Table 4.6, l denotes the length of the agent's remaining path from their current location via any ongoing and active task to their next critical time task. Further, T_{md} denotes the sum of the tasks' maximum delay times:

$$T_{md} := \sum_{\substack{\pi_0 \leq \pi(t) \leq \pi_{cr} \\ t_{\pi(t)} \text{ of "delay" type}}} T_{max}(t_{\pi(t)})$$

Finally, ρ denotes an estimate of the population density around the agent. ρ can attain any

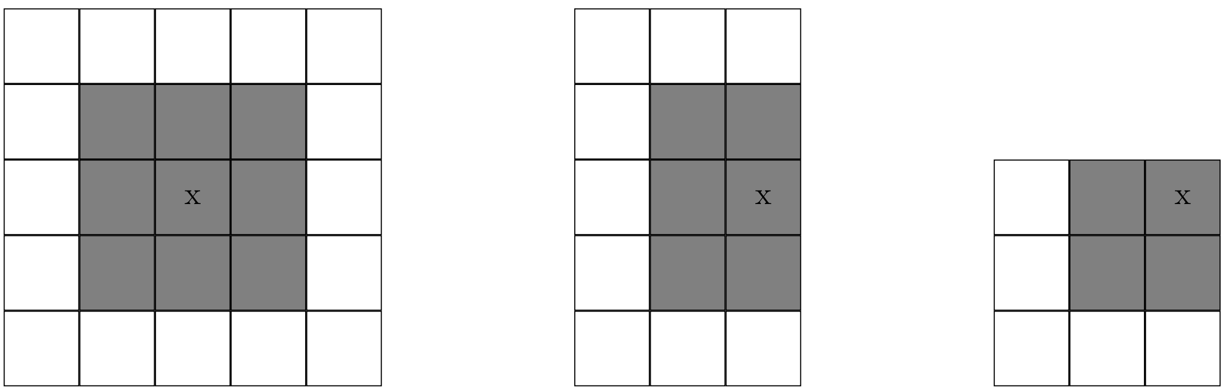
Table 4.6.: The components of the estimated required time parameters in buildingEXODUS's Urgency Model.

Parameter	Description	Equation
t_1	Unobstructed *normal walk* travel time plus the sum of the maximal delay times of the tasks on the Occupant Itinerary List until the next critical time task	$t_1 = l \cdot v_n^{-1} + T_{md}$
t_2	Estimate of congestion	$t_2 = \rho \cdot t_1$
t_3	Normal walk comfort zone	$t_3 = 0.5 \cdot (t_1 + t_2)$
t_4	Normal walk urgency escalation time	$t_4 = t_3$
t'_1	Unobstructed *fast walk* travel time plus the sum of the maximal delay times of the tasks on the Occupant Itinerary List until the next critical time task	$t'_1 = l \cdot v_f^{-1} + T_{md}$
t'_2	Estimate of congestion	$t'_2 = t_2$
t'_3	Fast Walk comfort zone	$t'_3 = 0.2 \cdot t_3 = 0.1 \cdot (t_1 + t'_2)$
t'_4	Fast Walk urgency escalation time	$t'_4 = t'_3$

value between between 0 and 1 and is defined as:

$$\rho := \frac{n_p - 1}{n_n}$$

n_n is thereby the number of nodes in the Moore Neighbourhood (cf. e.g Kretz [135]) of the node currently occupied by the agent, see Figure 4.4. Consequently, n_p denotes the number of agents in this Moore Neighbourhood.



(a) $n_n = 9$ **(b)** $n_n = 6$ **(c)** $n_n = 4$

Figure 4.4.: The Moore Neighbourhoods of the node x for different connectivities.

Time Assessment

When the agent enters the simulation, the time that the agent has initially at their disposal T_a is evaluated, see Equation (4.2). Also, the estimated required times to complete the tasks on agent's individual Occupant Itinerary List up to their next critical time task are evaluated, see Table 4.5. The amount of time that the agent has available is then compared to their individual time estimates. This time assessment is repeated in dynamic time intervals.

Every time the agent assesses their time situation, they follow a decision tree algorithm, see Figure 4.5.

In the decision tree algorithm illustrated in Figure 4.5, the agent's available time T_a is compared to the most conservative required time estimate T_0^{ERT}: if $T_a \geq T_0^{\text{ERT}}$ 2, then the agent's urgency parameter is set to zero 8, simulating that the agent continues pursuing their agenda unhurriedly. If however $T_a < T_0^{\text{ERT}}$ but still $T_a \geq T_1^{\text{ERT}}$ 3, the agent switches to an urgent behavioural state 9.

If the agent's available time is less than their normal walk time estimate T_1^{ERT}, they first check whether they have any elective tasks left on their Occupant Itinerary List before their next critical time task. If this is not the case, i.e. if $\pi_0 = \pi_{cr}$ 4, then the agent has no possibility of reducing their time pressure by adjusting their agenda. Instead, they turn to an urgent behaviour 9. If however the agent still has some elective tasks planned prior to their next critical time task, i.e. if $\pi_0 < \pi_{cr}$, then the agent considers adjusting their plans. The extent of the adjustments thereby depend on the perceived severity of the agent's time pressure situation.

In the case that the agent is in a moderate time pressure situation, i.e. $T_a < T_1^{\text{ERT}}$ but still $T_a \geq T_3^{\text{ERT}}$ 5, the agent tries to relieve their time pressure by dismissing the least important active task that they had planned prior to their critical time task. If the agent is however experiencing extreme time pressure, i.e. if $T_a < T_3^{\text{ERT}}$, the agent first checks whether their planned critical time task is still attainable, i.e. whether $T_a > 0$ 6. If this is not the case, then the agent will simply dismiss this unattainable critical time task and proceed with their remaining plans 11. If their planned next critical time task is still in theory achievable, the agent checks whether they have any means of adjusting their plans until their next critical time task left.

If the agent has still got some elective tasks planned prior to their critical time task, i.e. if $\pi_0 < \pi_{cr}$, then the agent will dismiss all these elective tasks in an attempt to at least be able to accomplish their critical time task 10. On the other hand, if the agent can't adjust their Occupant Itinerary List because their next critical time task is their currently ongoing task (i.e. $\pi_0 = \pi_{cr}$), the agent will resort to become hurried by setting their urgency parameter to 1 9.

If the agent has made any adjustments of their Occupant Itinerary List during their time assessment process, the agent will immediately evaluate their new time situation and restart the time assessment process with their newly perceived information. This process is repeated until the time assessment has resulted in an adjustment of the agent's urgency parameter.

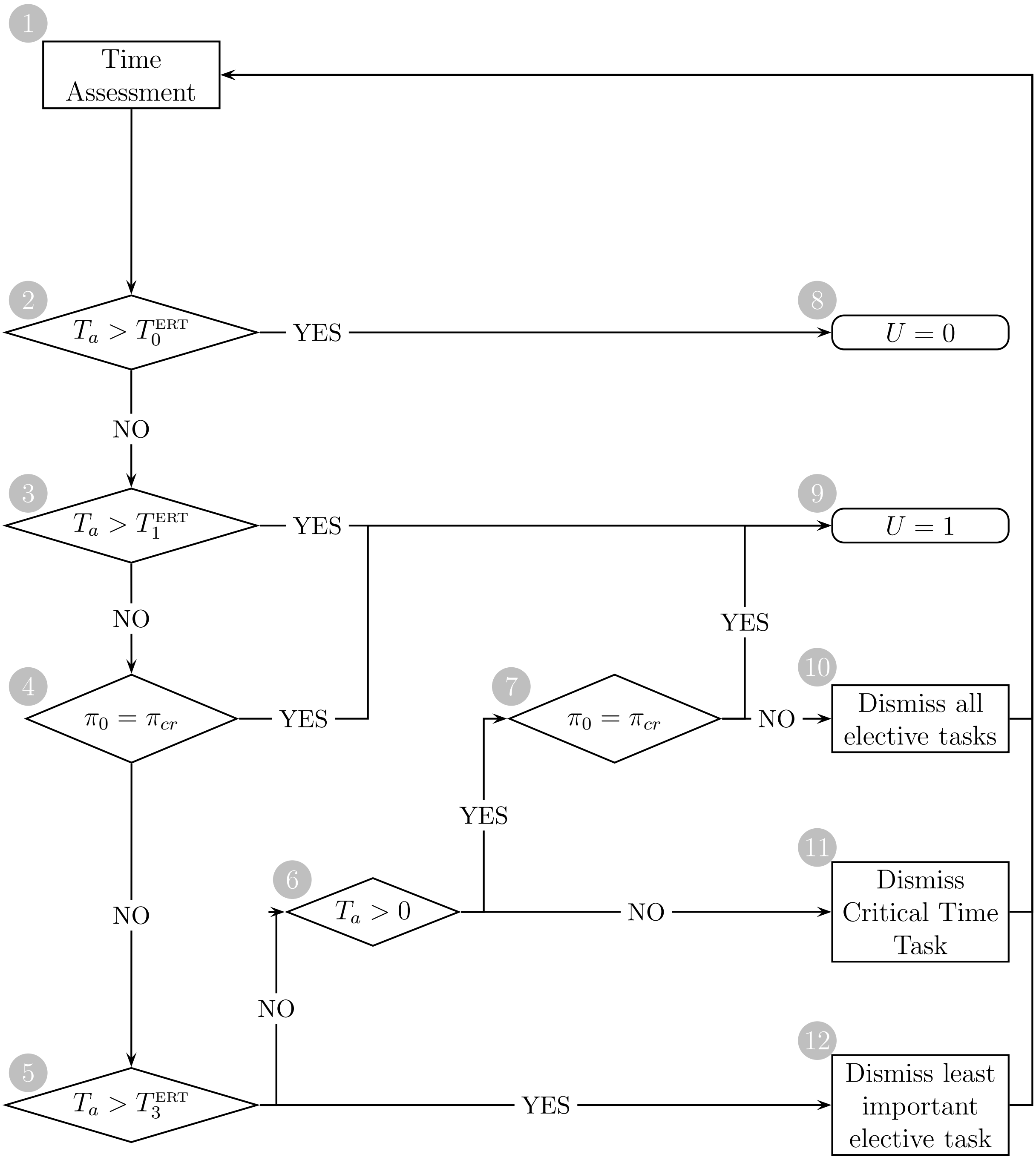


Figure 4.5.: The Urgency Model's Decision Tree

Regular Time Monitoring
The agent's time situation is evaluated and assessed in dynamic time intervals during the course of the simulation. The agent assesses their time situation for the first time once they have entered the environment. After each successful time assessment, the agent then determines when to best re-assess their plans. The amount of time T_{ass} after which the agent next assesses their time pressure situation is thereby dependent on the severity of the currently perceived time pressure.

$$T_{ass} := \begin{cases} T_1^{er} - T_3^{\text{ERT}} & \text{if } T_a \leq T_0^{\text{ERT}} \\ 10 & \text{if } T_0^{\text{ERT}} < T_a \leq T_0^{\text{ERT}} + 10 \\ T_a - T_0^{\text{ERT}} & \text{if } T_0^{\text{ERT}} + 10 < T_a \end{cases}$$

4.4. Alarm Response Phase Modelling

The response of pedestrians to an alarm event is simulated in buildingEXODUS by imposing several parameters on the agents. The model user can thereby decide whether to manually assign these response attributes and behaviours, or whether the model itself should make the assignment based on user-specified probability distributions.

The attributes and the behaviours with which buildingEXODUS simulates the individual alarm response behaviour of the agents include the assignment of:

- a targeted exit,
- a time delay between the alarm event and the initiation of the travel towards the assigned exit, the agent's *response time*,
- a set of activities that the agent should perform before initiating their travel towards their targeted exit, the agent's *pre-evacuation activities*

In buildingEXODUS, three means exist to assign a targeted exit to the individual agent. The first method simply assigns each agent their closest available exit as their target exit. This assignment thereby represents the most ideal exit choice. The second method allows the model user to assign each individual agent a fixed exit that they will target in the case of an alarm events. Finally in the third method, the agents can be assigned an individual knowledge or familiarity with certain exits in the environment. This is achieved by assigning each agent during the simulation initialisation stage a set of exits. This set is referred to as the agent's *Occupant Exit Knowledge* [14]. The agent is then assumed to be familiar with these exits and therefore, in reaction to an alarm event, to choose one of these known exits as their targeted exit. When responding to an alarm event, agents which have been assigned some familiar exits will therefore choose the closest exit from their Occupant Exit Knowledge as their targeted exit.

After the alarm event has occurred, the agents will travel towards their targeted exit, once their individual response time has elapsed. The agents' response time is one of their psychological agent parameters, see Table 4.1. The individual agent's response time T_{resp} is assigned during the agent population initialisation stage, based on a user-specified probability distribution.

As has been described in Section 4.1.2.1, buildingEXODUS enables the user to simulate activities that pedestrians perform after an alarm has been sounded, but before actually evacuating. The so-called pre-evacuation activities are specified by tasks on the agents' Occupant Itinerary Lists.

Smoke and gases that are produced by a fire incident have an irritable and toxic effect on pedestrians in the incident's proximity. The pedestrians are therefore alarmed and stressed by these emissions. The irritating and alarming effect of smoke and gases of a fire incident is simulated in buildingEXODUS. If an agent perceives a certain level of smoke and gases or if the surrounding temperature exceeds a certain level, the agent will immediately initiate their evacuation, even if their response time hasn't yet elapsed [14]. Thus, this reactive behaviour results in overwriting the agent's alarm response behaviour, including their pre-evacuation activities.

4.5. Evacuation Modelling

After their response time has elapsed, the individual agents in buildingEXODUS begin their evacuation stage by walking towards their previously assigned exit. During this evacuation stage, agents in buildingEXODUS are capable of perceiving and reacting to information regarding the structural environment (see Section 4.5.1) and of reacting and adapting to external stimuli (see Section 4.5.2).

4.5.1. Structural Awareness Modelling: Exit Signage

Agents in buildingEXODUS are capable of indirectly perceiving exit signs. An agent in buildingEXODUS can perceive a sign by passing through the sign's Visibility Catchment Area [14]. The Visibility Catchment Area thereby is the collection of all nodal locations in the geometry, from which the simulated sign can be seen by the agents, see e.g. Galea et al. [14], Xie [136], Xie et al. [137, 138] for further details.

Exit signs are simulated as sign objects in buildingEXODUS that can point either to an external exit door or to another sign object. When an agent passes by an exit sign object on their travel towards their targeted exit, they will perceive and interpret the information provided by the sign object with a certain probability. The probabilities for both the perception and correct interpretation of an exit sign object is dependent – amongst others – on the distance and angle of the agent with respect to the exit sign object, see Xie [136], Filippidis et al. [139].

If the agent has perceived and correctly interpreted an exit sign object, the agent then "chooses" between two options. The first option is to follow the exit sign and therefore adjust their currently targeted exit to the one which the exit sign object points to. The second option is to ignore the exit sign and continue travelling towards their previously chosen targeted exit. The agents in buildingEXODUS use a rule-based approach to decide between these two competing options: If the exit that is pointed to by the perceived exit sign object is closer than their currently targeted exit, the agent will adjust their targeted exit and hence follow the exit sign. If their currently targeted exit is the closest exit, the agent will continue to travel towards this exit. However, the agent will add the exit which has been perceived via the exit sign object to their list of known exits, their Occupant Exit Knowledge.

4.5.2. Adaptive Behaviour to Stimuli

buildingEXODUS incorporates various adaptive behaviours to external stimuli. Agents can decide to redirect because of congestion in front of external exits. Also, agents in building-EXODUS are able to perceive the smoke produced by a fire incident and to adapt their plans based on low visibility.

In addition to these cognitive behaviour adaptations, toxic gases and smoke produced by a fire hazard also influences the agents' walking behaviour: Agents aren't following a direct line of travel when walking through smoke, they are slowed down by the impact of toxic gases and they may decide to no longer walk but crawl to their targeted exit. These behaviours are described in detail by Galea et al. [14].

Adaptive Exit Selection

The adaptive behaviour to congestion is a reaction to the local level of congestion. This behaviour is triggered when the agent approaches their targeted exit during an evacuation scenario. Upon entering the proximity of their targeted exit, the agent evaluates the congestion level in front of the targeted exit by determining a time estimate on how long it will take to reach this exit. This time estimate takes into account the time required to cover the distance to the targeted exit and an estimate of the amount of time that is required for the congestion in front of the exit to dissolve.

Once the agent has assessed the congestion situation in front of their targeted exit, they also assess all other exits that are known to them for a comparison. For those of their known exits which are visible from the agent's current position, the agent will assess the congestion situation in front of these exits in the same manner as described above. On the other hand, for those exits known to the agent but invisible from their current position, the agent only estimates the time that it would take to walk to these exits.

After the agent has assessed all their known exits, the time estimates for reaching each of these exits are compared. If the time estimate for the currently targeted exit is not the minimal time estimate, the agent will decide to change their targeted exit to the one with the minimal estimated time to reach this exit. The agent therefore will redirect because of the level of congestion in front of the originally targeted exit.

Redirection caused by Smoke Barriers
Agents in buildingEXODUS are able to perceive whether they are encountering a smoke barrier on their way to their targeted exit [14]. If the agent has detected a barrier of smoke that blocks their currently selected way to their targeted exit, the agent can elect to adjust their targeted exit.

When detecting a smoke barrier, the agent determines the visibility afforded by the smoke filled area in order to estimate the severity of the smoke. If the determined visibility is greater than the distance to their targeted exit, i.e. if they can "still see" their targeted exit, the agent will continue to pursue their route and walk through the smoke barrier. If however the visibility in the smoke barrier is smaller than the distance to their targeted exit, the agent will redirect to the closest known exit in a direction of travel that is not blocked by the encountered smoke barrier.

4.6. Summary

This chapter addresses Research Objective 1 by surveying the pedestrian behaviour simulation buildingEXODUS. In addition to the general survey of pedestrian behaviour simulation tools in Chapter 2, buildingEXODUS has been analysed in greater detail, since it serves as the base technology for this thesis' buildingEXODUS Cognitive Pedestrian Agent Framework (CPAF) Plug-in. As can be seen from this survey, the pedestrian behaviour simulation tool buildingEXODUS is a complex model for the replication of human behaviour, especially in the event of a fire.

With buildingEXODUS it is possible to simulate a wide range of pedestrian behaviours, from which only a few have been described in this chapter. Nevertheless, buildingEXODUS is – like many other pedestrian behaviour simulation models – dependent to a high degree on informed user input, and therefore on the expertise and knowledge of the model user. Most simulation parameters have to be specified either directly or via appropriate probability distributions. The specified inputs therefore often pre-determine the produced results, and only little emergent behaviour can be observed. buildingEXODUS focus application area lies in the simulation of pedestrian evacuation behaviour due to incidents involving fire hazards. Even so buildingEXODUS is capable of also simulating pedestrian circulation behaviour, it is currently not possible to model a building's entire usage cycle.

In conclusion, buildingEXODUS is a sophisticated pedestrian behaviour simulation model which has been tested and validated against data obtained by empirical trials and reported data in the literature. As an agent- and rule-based pedestrian behaviour simulation model, it enables the simulation of individual pedestrian behaviour. However, to simulate advanced cognitive behaviours in complex multi-purpose environments and other behaviours suggested by researchers (see Table 2.3), the buildingEXODUS tool needs to be enhanced.

Chapter 5:

The Cognitive Pedestrian Agent Framework

In response to the review of selected pedestrian behaviour simulation models (see Section 2.5.1) with regard to the model suggestions summarised in Table 2.3, a new framework for simulating advanced cognitive pedestrian building usage behaviours in a pedestrian behaviour simulation model is introduced, the *Cognitive Pedestrian Agent Framework (CPAF)*. This framework builds on the concept of cognitive architectures introduced in Section 3.1. For the actual agent behaviour modelling, the CPAF combines ideas from human decision making research, emotion models and motivational action selection models, see Section 3.2. In this chapter, the CPAF's core components are motivated and a detailed description is given.

While describing the CPAF's components in this chapter, examples on how these components can be realised are given. For demonstration purposes, an implementation of the CPAF for the pedestrian behaviour simulation tool buildingEXODUS has been realised, the buildingEXODUS CPAF Plug-in. Examples on the CPAF's generic components and possible realisations of the CPAF are hence frequently made by referring to the developed buildingEXODUS CPAF Plug-in.

5.1. Overview of the Cognitive Pedestrian Agent Framework

The main characteristics of the CPAF are the agents' ability to exhibit goal-directed and purposeful behaviour. The agents are capable of making plans prior to their actual sojourn in the studied environment, based on their individual biases and their individual experience. During their sojourn in the simulated environment, the agents then have the ability to perceive, assess, interpret and evaluate emergent events. The impact of these events is determined and adaptive actions – if necessary – are chosen by the agent's decision making entity, based on the agent's acquired knowledge. The structure of the CPAF can be illustrated as in Figure 5.1.

As depicted in Figure 5.1, the modelled environment in the CPAF is reflected by a spatial component (the goal locations) and a component related to the environment's purposes (the goals), see Section 5.2. The spatial information can be perceived via the agent's structural perception capability, see Section 5.5. The agent not only perceives their spatial environment, but is in addition capable of perceiving procedural processes and congestion. The impact of this perception is evaluated by external stimuli representations (the emotions, see Section 5.6.2). These various perception processes inform the agent's knowledge component (the agent's Spatial Memory Set) and influence their simulated goals which are maintained in their goal component, see Section 5.3.2. The agent plans or adapts their behaviour based on their knowledge and goals, under the influence of the representation of internal stimuli (the motivations, see Section 5.6.1) and their personal preferences (Section 5.3.1). This is achieved by the agent's decision making component, see Section 5.4. The invocation of decision making instances lead to the alteration of existing or the creation of new plans in the agent's working memory. The agent then executes their decided plans in their decided order via their action execution component.

5.2. Environment Representation in the Cognitive Pedestrian Agent Framework

In order to pursue a goal-directed behaviour, the agent needs to be aware of both, their individual needs or desires and – in correspondence to these needs – the purposes of their surrounding environment. Therefore, the CPAF adds the notion of needs both to the agent model and to the simulated environment within a pedestrian behaviour simulation model. This follows the ideas of goals or desires from motivational action selection and emotion modelling research. The representation of goals or desires enables the agent to pursue a goal-directed behaviour, to classify their behaviours and aims with relation to their environment and to handle emergent events.

5.2.1. Environment Space

The CPAF requires certain information about the modelled environment from the underlying pedestrian behaviour simulation model to be able to build their goal information layer upon this information. At first, the CPAF requires the definition of the modelled environment space as the set of all permissible spatial locations:

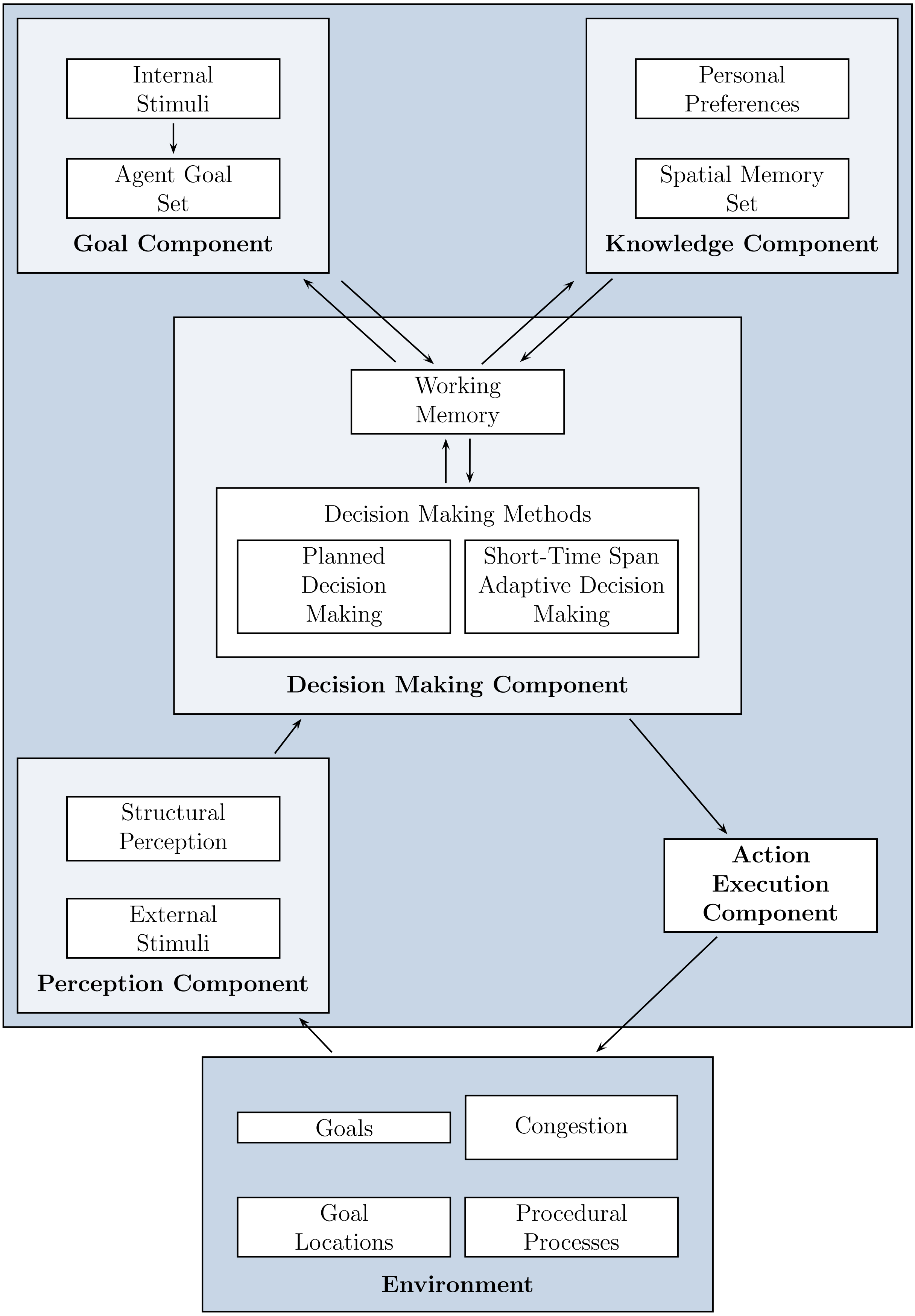


Figure 5.1.: The Cognitive Pedestrian Agent Framework (CPAF).

Definition 5.1: Environment Space

The CPAF's **environment space** $\mathbb{E}$ is a subset of the three-dimensional real space:

$$\mathbb{E} \subset \mathbb{R}^2 \times \mathbb{N}$$

$\mathbb{E}$ contains all spatial location coordinates which can be occupied by the agents.

For example, the environment space of the buildingEXODUS CPAF Plug-in is given by the multi-level 2D-nodal grid geometry in buildingEXODUS (see Section 4.1.1):

$$(x_1, x_2) \text{ represents a node in buildingEXODUS on floor } x_3 \implies (x_1, x_2, x_3)^T \in \mathbb{E}$$

Subsequently, the CPAF requires a notion of distance between two spatial locations in form of a walking distance metric ∂ on the modelled environment space:

$$\partial \colon \mathbb{E} \times \mathbb{E} \to \mathbb{R}_0^+, \quad \partial(x, x') := \text{walking distance between the spatial locations } x, x' \tag{5.1}$$

For example for the buildingEXODUS CPAF Plug-in, the CPAF's distance metric ∂ is realised by using the buildingEXODUS's walking distance functionality.

At any given point in time, the agents in the CPAF can be traced. Therefore, let $x_{current}(\tau) \in \mathbb{E}$ denote an agent's current environmental location at simulation time τ. For example in the buildingEXODUS CPAF Plug-in, $x_{current}(\tau)$ can either be represented by a node or by a location between two nodes if the agent is currently walking from one node to the next.

5.2.2. Goals

To be able to model goal-directed pedestrian behaviour in complex multi-purpose environments, an additional layer of information is introduced. This information represents the purpose of both an agent's action and a given facility in the environment, the so-called *goal*. Goals represent within the agent model the agent's individual desires and needs, and therefore within the environment model the purposes that can be satisfied by visiting a facility in question.

Goals are categorised by their assigned relative importance range: some goals might be of crucial importance, and are therefore treated as compulsory, whereas other goals are only treated as being voluntary or elective. The main goal of visiting an environment – if existent – and all potentially associated sub-goals will therefore be modelled as compulsory goals, whereas all additional goals that can be satisfied at facilities within the environment are treated as elective goals. The CPAF therefore attributes the importance of certain plans on the agent's itinerary, to the underlying goal of a task, rather than to the task itself. With the goal's attributed relative importance range, it is not only possible to distinguish between compulsory and elective goals, but also to establish a hierarchy amongst the elective goals, if appropriate. This hierarchy will be dependent on the goals that are to be modelled for the specific simulation purpose.

Each goal is assigned a goal action. The goal action determines whether the goals can be regarded as satisfied by a certain task, if the agent has either spent a certain amount of time at the task's location ("delay" goal action), or has waited at the given location until a specific time ("wait" goal action), or has passed by the task's location ("way point" goal action). The goal's goal action therefore follows the type attribute of a task in buildingEXODUS (see Section 4.1.2.1). Similarly, each goal is assigned certain activity parameters which detail the specific actions that need to be undertaken to accomplish the goal. These activity parameters are dependent on the goal's action type and follow the buildingEXODUS's task activity parameters as outlined in Table 4.3: A goal of action type "delay" comprises two completion time attributes, which simulate the minimal respectively maximal time period necessary to accomplish the goal itself, e.g. the amount of time needed to eat a meal. Goals of the action types "wait" and "way point" comprise a radius attribute to further detail the area where the agent has to wait respectively the distance within which the agent needs to pass by.

In the remainder of this thesis, the set of all modelled goals within a modelled environment will be referred to as the *Global Goal Set (GGS)*. For a goal $\widehat{g} \in$ GGS, the goal's attributes will be denoted as depicted in Table 5.1.

Table 5.1.: Notations for selected attributes of a goal $\widehat{g} \in$ GGS in the Cognitive Pedestrian Agent Framework.

Attribute(s)	Description
$[\mathbf{I}_{low}(\widehat{g}), \mathbf{I}_{up}(\widehat{g})]$	The relative importance range of $\widehat{g}$.
$[\mathbf{T}_{min}(\widehat{g}), \mathbf{T}_{max}(\widehat{g})]$	The completion time range of $\widehat{g}$, if $\widehat{g}$ is of the "delay" goal action.

5.2.3. Goal Locations

In the CPAF, the simulation of purpose or goals within the environment model is achieved by the concept of *goal locations*. A goal location represents the simulated spatial location or area within a modelled environment that can be targeted by an agent in order to fulfill certain goals. The set of all modelled goal locations in a modelled environment is referred to as the environment's *Goal Location Set (GLS)*.

For example, goal locations in the buildingEXODUS CPAF Plug-in are realised by either of the two environment representations available in buildingEXODUS: single nodes or compartment zones (see Section 4.1.1).

A goal location $l \in \text{GLS}$ occupies a certain spatial area $\Lambda(l) \subseteq \mathbb{E}$ of the environment. For example in the buildingEXODUS CPAF Plug-in, a goal location represented by a node in a regular grid of grid size $0.5m$ occupies a spatial area of $0.25m^2$. A compartment zone which comprises n nodes therefore occupies a spatial area of $n \cdot 0.25m^2$. However, when determining distances between goal locations, every goal location l is represented by a single spatial location $\lambda(l) \in \mathbb{E}$ using the CPAF's environmental location function:

Definition 5.2: Environmental Location Function

Let $\mathbb{E}$ be the environment space and let the set of all modelled goal locations be denoted by the Goal Location Set (GLS). The CPAF's **environmental location function** λ assigns each goal location $l \in \text{GLS}$ a representative spatial location in the environment space: $\lambda\colon \text{GLS} \to \mathbb{E}$. λ is bijective.

In the buildingEXODUS CPAF Plug-in, the user defines a representative node for each goal location by a keyword matching mechanism.

To reflect the notion of goals within the environment, each goal location is associated with one or multiple goals from the Global Goal Set that can be achieved at the specific goal location. The set of goals that is associated with a goal location l is denoted by $\mathfrak{G}(l)$. On the other hand, the set of all goal locations where a goal $\widehat{g} \in \text{GGS}$ can be accomplished will be denoted by $\mathfrak{L}(\widehat{g})$ in the remainder of this thesis.

It is in general possible, that for two goals $\widehat{g}, \widehat{g}' \in \text{GGS}$ one or multiple goal locations in the Goal Location Set exist, where both goals $\widehat{g}$ and $\widehat{g}'$ can be accomplished. In this case, the corresponding goals are called compromise-qualified:

Definition 5.3: Compromise-qualified Goals

Two goals $\widehat{g}, \widehat{g}' \in \text{GGS}$ are called **compromise-qualified**, if $\mathfrak{L}(\widehat{g}) \cap \mathfrak{L}(\widehat{g}') \neq \emptyset$.

In a simulated complex multi-purpose environment, it is very likely that within the modelled environment several goal locations exist, where one specific goal can be accomplished. As a result, the agents will face decision situations during the course of the building usage simulation of a complex multi-purpose environment, in which they have to decide between goal locations. For this reason, each goal location is attributed with feature-related parameters. These parameters allow the agent to distinguish between the different goal locations and thereby make an informed decision. A goal location's feature-related parameters are modelled as a set of feature attributes $F(l) \in \mathbb{R}^s$ for $l \in \text{GLS}$.

On the other hand, a CPAF agent is equipped with decision preference attributes which correspond to the modelled feature parameters, see Section 5.3.1. By comparing a goal location's feature parameters with their preferences, an agent can then define a preference for goal locations with certain features.

For example, the set of goal location feature parameters F depicted in Table 5.2 have been implemented in the buildingEXODUS CPAF Plug-in for demonstrating the CPAF's capabilities in a comprehensive verification case, see Chapter 9.

Table 5.2.: An example for a possible list of goal location feature parameters for use with the Cognitive Pedestrian Agent Framework. These feature parameters have been implemented in the buildingEXODUS CPAF Plug-in.

Parameter	Name	Domain	Interpretation
F_1	price	$\{0, 1, 2\}$	price category of goal location: inexpensive, moderate and luxury product price range
F_2	brand	$\{0, 1, 2\}$	brand category of goal location: local, nationally known and internationally known brand
F_3	size	$\{0, 1, 2\}$	size category of goal location: small, medium and large sized goal location

When modelling a specific complex multi-purpose environment, the user therefore needs to assign each goal location $l \in \text{GLS}$ its individual set of goal location feature attributes $F(l) \in \mathbb{R}^s$ (see Appendix Chapter B).

Example 5.1: Goal Location Feature Parameters

A goal location $l \in \text{GLS}$ with the feature parameter realisation $F(l) = (0, 2, 1)^T$ is categorised as being inexpensive, being of an internationally known brand and being medium sized.

5.2.4. Departments

A goal location $l \in \text{GLS}$ can consist of several parts or departments. Departments represent parts of the goal location's spatial area at which different activities can be undertaken:

$$\Lambda(l) = \Lambda(l_1^d) \cup \ldots \cup \Lambda(l_n^d)$$

for the sequence $\mathcal{D}(l) = (l_1^d, \ldots, l_n^d)$ of departments of the goal location l. The goal location's departments reflect the different activities the agents needs to do in order to satisfy the related goal. For example in a shop, the agent would need to browse through the range of products and then queue up in order to pay for the desired goods. Therefore, such a shop can be represented by a goal location with two departments, the first department for the product selection area and the second department for the checkout queues.

The activities that the agent can perform in the goal location's departments can either be needed to satisfy the desired goal, or not. In the case of the previously mentioned shop, both activities are obligatory in order to fulfill the desired goal of purchasing an item at the given shop. On the other hand, a coffee shop can be modelled as consisting of two departments, one for queuing at the counter to receive the desired food and the other department for sitting down to consume the food. In this case, the queuing department is obligatory in order to fulfill the goal of eating something, but the agent doesn't need to sit down to eat their food in all cases and therefore can decide to take the food away. For this reason, the departments of a goal location are assigned a type attribute, which determines what kind of activity can be performed in that particular department, e.g. browsing through the display, queuing or sitting down. This type then determines, whether the associated activity is necessary to complete the goal location's associated goal, or not.

Each department $d \in \mathcal{D}(l)$ in a goal location stores its spatial size and two service time attributes, $\mathbf{T}_{min}(d)$ and $\mathbf{T}_{max}(d)$. These service time attributes are dependent on the size of the department and thereby simulate the time that an agent would need to engage in service activities. For example, it may take more time to browse through a larger shop than through a smaller one.

In addition to its spatial size, each department within a goal location has an attributed capacity, i.e. the maximum number of agents that can occupy the department at the same time. With this information, the agent is able to assess the current level of population density in the goal location and decide to adapt their behaviour in response, see Section 5.6.2.1. If a goal location $l \in \text{GLS}$ is modelled to contain no departments, the goal location itself is assigned two service time attributes $\mathbf{T}_{min}(l)$ respectively $\mathbf{T}_{max}(l)$ and the standard capacity of $2\frac{\text{people}}{m^2}$.

For example, the set of departments depicted in Table 5.3 have been implemented in the buildingEXODUS CPAF Plug-in for demonstrating the CPAF's capabilities in a comprehensive verification case, see Chapter 9.

Table 5.3.: An example for a possible set of departments for use with the Cognitive Pedestrian Agent Framework. This set of departments has been implemented in the buildingEXODUS CPAF Plug-in.

Name / Type	Department Action	Capacity $\frac{\kappa}{\text{area}}$ $\left[\frac{\text{people}}{m^2}\right]$	obligatory
"selection"	delay	2	yes
"queue"	queue	–	yes
"seating"	delay	1	no

With the list of departments as depicted in Table 5.3, a shopping goal location can therefore be modelled as consisting of a selection department where the agent needs to select a product which they want to purchase and a queuing department where the agent needs to queue in order to pay for the selected product. In the same way, a goal location at which the goals to eat or to drink can be satisfied, can be modelled as comprising a department to queue for ordering food or drinks and a seating department where the agents can consume their purchase.

5.2.5. Goal Representation

The goals of a given environment model can be grouped in three categories: "activity goals", which represent the desires to perform a certain action; "navigational goals", which represent the desire to navigate to a certain spatial location; and "procedural goals", which reflect those needs and desires that are the result of the environment's intrinsic procedural processes.

Procedural goals are used to represent the purpose of the environment. The realisation of procedural goals is therefore strongly depends on the type of the modelled complex multi-purpose environment. Table 5.4 lists examples for possible procedural goals in an example of a complex multi-purpose environments.

Table 5.4.: Examples for procedural goals that can be used for the modelling of procedural processes in complex multi-purpose environments.

Example Environment	Goal Name
Airport	"check in"
Airport	"pass security check"
Airport	"wait at gate"
Airport	"board plane"
Train Station	"buy ticket"
Train Station	"wait at platform"
Train Station	"board train"
Football Stadium	"watch game"
Office Building	"attend meeting"
Office Building	"lunch time"

Examples for possible "activity" and "navigation" goal realisations are depicted in Table 5.5. This set of goal realisations has been implemented in the buildingEXODUS CPAF Plug-in for demonstrating the CPAF's capabilities in Chapters 8 and 9.

The goals to eat and drink represent the general action of purchasing and consuming food at the assigned goal location. Since it is in general quite common, that at a given outlet in a complex multi-purpose environment food as well as drinks can be purchased, these two goals have been set to be compromise-qualified (see Definition 5.3). The goal to rest represents the tiredness of an agent and can therefore be accomplished at e.g. seating areas. The desire to rest, as well as the desire to eat and the desire to drink, are postulated to be dynamic and dependent on the time the agent has spent in the environment. For this reason, these three goals are set to be related to the set of agent motivations "hunger", "thirst" and "fatigue"

Table 5.5.: Example goal realisations for use with the Cognitive Pedestrian Agent Framework. These goal realisations have been implemented in the buildingEXODUS CPAF Plug-in.

Name	Goal Category	Goal Action	Relative Importance Range	Completion Time Range [s]
"eat"	Activity	delay	$[40, 99]$	$[60s, 900s]$
"drink"	Activity	delay	$[40, 99]$	$[60s, 300s]$
"rest"	Activity	delay	$[10, 79]$	$[300s, 900s]$
"shop"	Activity	delay	$[10, 79]$	$[30s, 600s]$
"service"	Activity	delay	$[10, 79]$	$[30s, 300s]$
"information"	Navigation	delay	$[10, 10]$	$[10s, 120s]$
"way point"	Navigation	way point	$[20, 20]$	n/a

(see Table 5.11) used for demonstrating the CPAF's capabilities in this thesis.

The service goal represents the desire to demand a certain service at the goal location in question, e.g. to hire a car or to visit a hairdresser. The goal to shop represents the desire of an agent to purchase some goods at the given goal location. The shopping activity therefore implies to select a product from the goal location's variety of goods and to afterwards purchase it.

The information goal represents the desire to visit information points in order to enquire for further information about the modelled environment, see Section 6.4.2 for a detailed discussion of this modelled behaviour.

The way point goal can be accomplished at way point goal locations. Way point goal locations or short way points are special goal locations that the user can specify in the simulated complex multi-purpose environment. These way point goal locations serve as temporary targets in the spatial environment that the agent needs to pass by. Therefore, these way point goal locations are usually representing key locations in the complex multi-purpose environment's corridor space, such as corridor junctions or squares. The set of way points as a subset of the Goal Location Set is called the *Way Point Set (WPS)*:

$$\text{Way Point Set (WPS)} \subseteq \text{Goal Location Set (GLS)}$$

The relative importance range of the representation of global goals in Table 5.5 has been inspired by Maslow's "Hierarchy of Needs" [127]. In Maslow's hierarchy, the lowest and thereby most urgent need level are the physiological needs like hunger and thirst. Therefore, the goals "eat" and "drink" are assigned the highest importance range. However, the third physiological need, the need to rest, is assigned a lower importance range. This can be justified, since the need to rest in a complex multi-purpose environment is usually a comfort need that evolves during the sojourn in the environment while pursuing other goals. The other needs such as the need to shop or to go to a service facility are similarly regarded to be less important than the need to eat and the need to drink, and it is therefore postulated that they can also be represented by a low relative importance range.

It has to be noted, that the relative importance ranges aren't disjoint. It is therefore possible that from an individual agent's perspective e.g. the goal to shop receives a higher importance than the goal to drink, although the goal to drink has a higher relative importance range than the goal to shop.

5.3. Attitude and Knowledge Representation

When modelling pedestrian building usage behaviour in complex multi-purpose environments, the agent needs to be able to assess their current situation, their plans and their surroundings. For this reason, a reference background of attitudes and knowledge is needed for the agent to set their observations into perspective and thereby evaluate them. For this reason, the agents in the CPAF have been equipped with decision parameters, their personal preferences, and a sophisticated knowledge system.

5.3.1. Personal Preferences

Each pedestrian in a complex multi-purpose environment has got different attitudes towards different facilities in the environment. For example one pedestrian might in general prefer to visit inexpensive outlets whereas another pedestrian might always prefer certain shop brands. In the CPAF, these attitudes are simulated by a set of individual agent parameters, their personal preference attributes $P = (P_1, \ldots, P_s)^T \in \mathbb{R}^s$.

The agent's personal preferences determine how the agent is meant to compare and evaluate known goal locations based on their features (see Section 5.2). Therefore, the set of personal preferences that are assigned to the individual agents reflect the assignment of feature parameters to each goal location, $F(l) = (F_1(l), \ldots, F_s(l))^T \in \mathbb{R}^s \ \ \forall l \in \text{GLS}$: the i-th goal location feature conforms to the i-th personal preference attribute:

$$F_i(l) \rightleftarrows P_i \qquad \forall\ 1 \leq i \leq s$$

The agent refers to their personal preference attributes when they need to distinguish between multiple goal locations. The agent's personal preferences hereby serve as a reference or ideal goal that the goal location features should meet as closely as possible.

In general, the decision parameters or personal preferences are of different importance to any pedestrian. To reflect this preference hierarchy, the order of the agent's personal preference attributes (and correspondingly of the goal location feature parameters) has been chosen to be decreasing with importance for the individual pedestrian:

$$P_i \text{ is more important than } P_j \quad :\Longleftrightarrow \quad i < j$$

For example, the personal preference attributes depicted in Table 5.6 have been implemented in the buildingEXODUS CPAF Plug-in for demonstrating the CPAF's capabilities in a comprehensive verification case, see Chapter 9.

Table 5.6.: Example personal preference attributes for use with the Cognitive Pedestrian Agent Framework. These personal preference attributes have been implemented in the buildingEXODUS CPAF Plug-in.

Parameter	Name	Domain	Interpretation
P_1	price	$\{0, 1, 2\}$	preference for inexpensive, moderate or luxury product price range
P_2	brand	$\{0, 1, 2\}$	preference for local, nationally known and internationally known brand
P_3	size	$\{0, 1, 2\}$	preference for small, medium or large sized goal location

Since the order of the pedestrian preference attributes determines their relative importance, in the realisation of the personal preference attributes as depicted in Table 5.2, the price category of a goal location is more important to any agent than its brand category which in turn is more important than its size category.

5.3.2. Information Storage

To ensure consistency in the behaviour of the agent (see Bartneck [119]), the agent needs to be aware of both their individual needs and also of the information that they have individually obtained from the environment. These information components form the basis for the agent's decision making entity, which manifests itself in the agent's plans and emergent behaviour. This information storage is therefore modelled within the agent's goal, knowledge and decision making component, and consists of three interrelated parts: the *Spatial Memory Set (SMS)*; the *Agent Goal Set (AGS)*; and a working memory, the *Agent Task List*.

The Agent Goal Set stores for each agent their individual realisation of the global goals that the agent wishes to satisfy during the course of the circulation simulation, their *agent goals*. An agent goal builds on a global goal from the Global Goal Set of the environment in question and the individual agent's personal interpretation of this global goal for their given circumstances, see Figure 5.2.

If an agent goal $g \in \mathrm{AGS}$ has been derived from the (global) goal $\widehat{g} \in \mathrm{GGS}$, this is denoted by $g \lhd \widehat{g}$. The individual agent interprets the global goal $\widehat{g}$ by assigning their agent goal g a relative importance $I(g)$ based on the (global) goal's relative importance

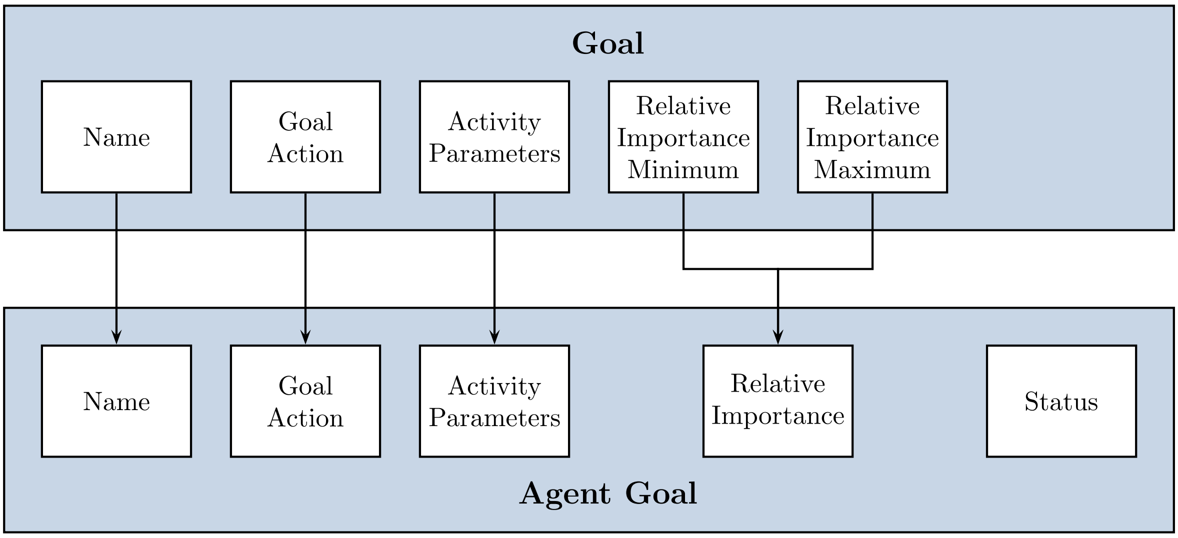


Figure 5.2.: Derivation of an agent goal from a (global) goal in the Cognitive Pedestrian Agent Framework.

range $I(g) \in [\mathbf{I}_{low}(\widehat{g}), \mathbf{I}_{up}(\widehat{g})]$. This simulates the fact that a specific goal can be of a different importance to different pedestrians. This is especially the case for goals related to the agent's internal stimuli, as described in Section 5.6.1.

Analogously as for the (global) goals, the set of all goal locations in the given modelled environment where the agent goal g can be accomplished is denoted by $\mathfrak{L}(g)$. The agent goal g can be accomplished at all goal locations where the (global) goal $\widehat{g}$ can be accomplished:

$$\mathfrak{L}(g) \equiv \mathfrak{L}(\widehat{g}) \qquad \text{for} \qquad g \lhd \widehat{g} \tag{5.2}$$

In their Spatial Memory Set, the agent stores information about the spatial environment by maintaining a list of the goal locations they have encountered. This information is generated by three means:

- the information belongs to the agent's previously acquired and general experience with the environment in question (see Section 6.2.1),
- the agent has gained the information during their sojourn in the environment by visual perception (see Section 5.5),
- the agent has enquired the information at special information goal locations (see Section 6.4.2).

The different sources for the agent's Spatial Memory Set also translate to different levels of quality of the stored spatial information: spatial information which is known from previous experience is regarded as being very reliable and readily available, whereas spatial information which has been learned during the current sojourn in the environment is regarded to be more volatile. Consequently, spatial information from previous experience is assumed to be stored permanently in the agent's Spatial Memory Set, whereas the information that the agent has assembled by means of perception or information enquiry is only stored temporarily as active, thereby simulating short-term memory.

For these reasons, an entry of the Spatial Memory Set comprises a goal location together with its associated goals and a recall probability. According to the ACT-R theory (see Section 3.2.2), the recall probability $P_{recall}(l, \tau, \mathfrak{G})$ of a goal location l at simulation time τ is dependent upon the agent's previous experience with the goal location, the time delay between these previous experiences and a measure of desirability, i.e. how useful this goal location is to the agent in terms of their assigned goals. By following the line of reasoning of the ACT-R theory (see Appendix A.3.1), the recall probability of a goal location l at simulation time τ can be expressed by:

$$P_{recall}(l, \tau, \mathfrak{G}) = \begin{cases} 1 & l \text{ is known from previous experience,} \\ \dfrac{1}{1 + e^{-\frac{5}{2}A(l,\tau,\mathfrak{G})}} & \text{else.} \end{cases} \tag{5.3}$$

The memory's activity $A(l, \tau, \mathfrak{G})$ at simulation time τ is dependent upon the agent's previous encounters with the goal location and the specific situational desirability of the goal location. This situational desirability is linked to the set of agent goals $\mathfrak{G} \subseteq$ AGS that is of interest to the agent at the time that the pedestrian tries to access their spatial memory. For example, in the situation that the pedestrian tries to remember a goal location which can satisfy their goals to "eat" and to "drink", the spatial memory's activity will be dependent on how many goal locations the agent knows which are related to these two goals, as well as the total number of goals that the goal location can satisfy, $|\mathfrak{G}(l)|$. Therefore, the memory's activity $A(l, \tau, \mathfrak{G})$ is given by (see Appendix A.3.1)

$$A(l, \tau, \mathfrak{G}) = \ln\left(\sum_{j=1}^{n} \frac{1}{\sqrt{T_j(l, \tau)}}\right) - \frac{\ln(|\mathfrak{G}(l)|)}{n} + \frac{1}{n}\left[2 \cdot (|\mathfrak{G}| + 1) - \sum_{g \in \mathfrak{G}} |\mathfrak{L}^{\mathrm{M}}(g)|\right] \tag{5.4}$$

In Equation (5.4), the set $\{T_j(l, \tau)\}$ denotes the time durations since the goal location l has been perceived by the agent for the j-th time, with n being the total number of perceptions of the goal location l. Further, the set $\mathfrak{L}^{\mathrm{M}}(g)$ denotes the set of goal locations that are stored in the agent's memory and which can satisfy the goal g.

The agent's working memory, their Agent Task List, contains the agent's concrete tasks: what the agent needs to do, where and in which order. In the CPAF, tasks on the agent's Agent Task List are created by employing decision making instances at various points during the simulation. The decision making instance thereby decides on a goal location for a given set of agent goals, linking together the information stored in the Spatial Memory Set and Agent Goal Set. Consequently, a task on the CPAF's Agent Task List stores references to those agent goals which are being associated with the task. If more than one agent goal is associated with a task, the task is called a *compromise task*. Furthermore, the task stores a reference to the goal location where the task is to be performed, a task type, task time parameters and a status of activeness. Let $t \in \text{ATL}$ denote a task on the agent's Agent Task List (ATL). Let further $l(t) \in \text{SMS}$ be the task's associated goal location and $\mathfrak{G}(t) \subseteq \text{AGS}$ the task's associated set of agent goals. The task's type attribute is given by the associated agent goals' goal action. Furthermore, the task's importance and task time attributes are given the corresponding parameters of the associated agent goals and goal location. In summary:

$$I(t) = \max_{g \in \mathfrak{G}(t)} I(g)$$

If t is a "delay" type task (and consequently all goals in $\mathfrak{G}(t)$ are of the "delay" goal action), then

$$T_{min}(t) = \mathbf{T}_{min}(l(t)) + \max_{g \in \mathfrak{G}(t)} \mathbf{T}_{min}(g)$$
$$T_{max}(t) = \mathbf{T}_{max}(l(t)) + \max_{g \in \mathfrak{G}(t)} \mathbf{T}_{max}(g)$$

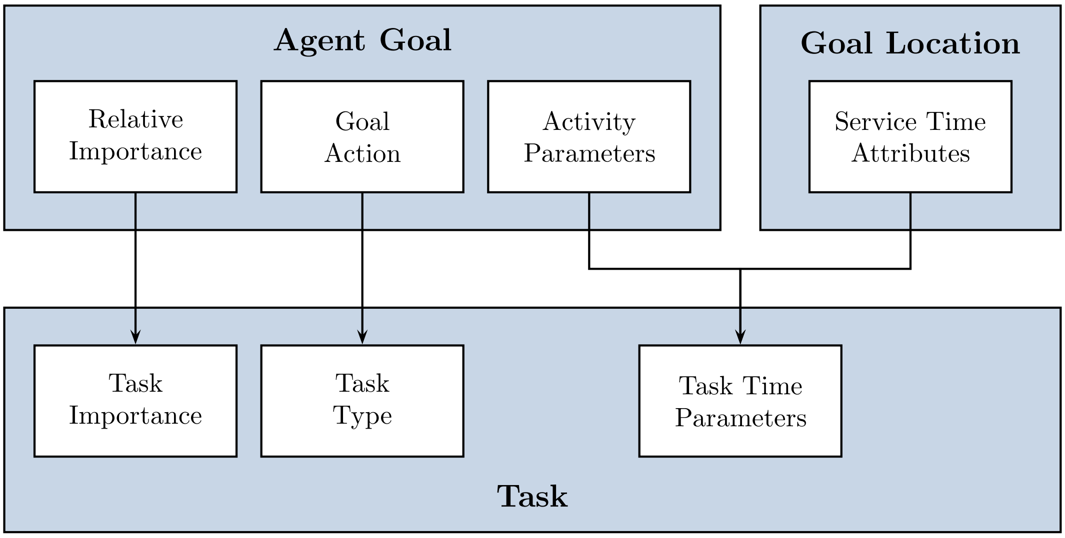


Figure 5.3.: Derivation of a CPAF task from the associated agent goal and goal location.

In the buildingEXODUS CPAF Plug-in, the CPAF's Agent Task List is realised as an enhanced form of the buildingEXODUS's built-in Occupant Itinerary List functionality, see Section 4.1.2.1.

A major challenge when modelling emergent goal-directed behaviours is to ensure, that the agents exhibit consistent behaviours. Inconsistent behaviours include the agent repeatedly exercising the same task, or infinite loops of adding and deleting the same plan. One possibility to prohibit those inconsistent behaviours is by employing a history functionality, as has been argued by Bartneck [119] (see Section 3.2.3). Hence, the CPAF information storage representation serves also as a history functionality for each of its elements, where items from the three different information storage parts are in general not deleted, but are rather kept in the information storage representation and marked as dismissed. For this purpose, each information storage entry has got an assigned status attribute.

The agent's spatial memory, the Spatial Memory Set, distinguishes only between active memory entries and inactive entries. The status of a memory on the Spatial Memory Set is thereby implicitly given, by its probability to be recalled in a given situation. The status attribute for agent goals on the Agent Goal Set stores whether an agent goal is still to be achieved and therefore the agent aims to take actions to satisfy this goal, whether the goal has already been achieved, or whether the agent has decided during the course of the simulation not to further pursue this goal and therefore suppress the goal in question. Similarly, tasks on the agent's working memory, their Agent Task List, are either marked as being active, ongoing, having been completed or having been dismissed, see Table 5.7 for an overview.

Table 5.7.: An overview of the possible status attributes for each information storage entity.

Information Storage Entity	Status	Status Implications
Agent Goal Set	satisfied	An associated task has been successfully completed.
	unsatisfied	An associated task exists on the Agent Task List but has not yet been completed or no associated task exists on the Agent Task List.
	suppressed	An existing associated task on the Agent Task List has been dismissed.
Spatial Memory Set	active	Implicitly given by recall probability.
	inactive	
Agent Task List	active	The task is neither dismissed nor completed nor ongoing.
	ongoing	The task is the agent's currently targeted task.
	completed	The task has successfully been completed.
	dismissed	The task has been dismissed and therefore will not be attempted anymore by the agent, even if the task is still to come.

5.4. Decision Making Model

The envisaged simulation of goal-directed behaviour in complex multi-purpose environments requires the agent to be able to make informed decisions while planning actions or when reacting to events. The CPAF therefore comprises a decision making entity which uses modelling approaches gained from human decision making research, see Section 3.2.1. The CPAF's decision making entity enables the agent to make informed decisions based on their individual information resources. The agent therefore draws their decisions based on the information provided via the CPAF's goal, knowledge and perception components to assess their situation, determine and compare their available options and come to a conclusion.

As has been discussed in Section 3.2.1, human decision making is highly dependent on the decision situation and the decision maker. The CPAF therefore comprises two different decision making models, a planned and an adaptive decision making model. The deployment of the two different models is dependent on the amount of time available for the decision to be made and the amount of information involved, see Table 5.8 for an overview.

Table 5.8.: Two instances of the Human Decision Making model.

Decision Situation	Planned Decision Making	Adaptive Decision Making
Time Constraints	no constraints	little time available
Information Base	complete	(potentially) incomplete
Mathematical Modelling	Multi-Criteria Optimisation	Lexicographic Heuristic

In the context of the CPAF, all decision situations which are faced by the agent are choice problems: the agent as the decision maker has to decide between a finite number of different options based on certain criteria. The problem statement of a choice problem needs to state the problem's choice set and the choice criterion:

Definition 5.4: Choice Problem Formulation

A **choice problem** is formulated by stating the problem's choice set and choice criterion. A **choice set** $\gimel$ of a choice problem is a non-empty discrete constraint set, and an element $\gamma \in \gimel$ of a choice set is called a **choice alternative**. The given choice alternatives are compared based on a **choice criterion** C which is a formulation of the choice problem's objective.

The choice criterion of a given choice problem is mathematically modelled by stating a function ζ that chooses one choice alternative γ^* from a suitable subset $\mathfrak{P} \subseteq \gimel$ of the problem's choice set:

Definition 5.5: Choice Rule

For a given choice problem as in Definition 5.4 with choice set $\gimel$, a **choice rule** of the choice problem is defined as a pair $(\zeta, \mathfrak{P})$ where $\mathfrak{P} \subseteq \gimel$ is a suitable subset of the problem's choice set and ζ is a function

$$\zeta : \{\mathfrak{P}\} \to \mathfrak{P} \qquad \zeta(\mathfrak{P}) = \gamma^* \in \mathfrak{P}$$

appropriate to represent the problem's choice criterion C. The subset $\mathfrak{P}$ is called a **choice candidate set** of the given choice problem and ζ its **choice function**.

Each choice alternative $\gamma \in \beth$ of the choice set $\beth$ is characterised by assigning it a set of attributes using an attribute function as defined in Definition 5.6:

Definition 5.6: Attribute Function

For a given choice problem as in Definition 5.4 with choice set $\beth$ let $\alpha : \beth \to \mathbb{R}^m$ be a function which assigns each choice alternative a set of m choice attributes appropriate to represent the problem's choice criterion C. The function α is then called an **attribute function** of the choice problem.

The choice problem's choice function ζ draws the final choice $\gamma^* \in \mathfrak{P}$ from the choice rule's choice candidate set $\mathfrak{P}$ based on the chosen attribute function α.

In the current version of the CPAF, ζ can be one of the functions displayed in Table 5.9.

Table 5.9.: Possible choice functions ζ for a given choice problem with choice set $\beth$, a chosen attribute function $\alpha : \beth \to \mathbb{R}^m$ and choice candidate set $\mathfrak{P} \subseteq \beth$ in the Cognitive Pedestrian Agent Framework.

Choice function ζ	ζ chooses a random element from the subset
ζ_{min}	$\left\{ \underline{\gamma} \in \mathfrak{P} \;\middle|\; \lVert\alpha(\underline{\gamma})\rVert_2 = \min_{\gamma \in \mathfrak{P}} \lVert\alpha(\gamma)\rVert_2 \right\} \subseteq \mathfrak{P}$
ζ_{max}	$\left\{ \overline{\gamma} \in \mathfrak{P} \;\middle|\; \lVert\alpha(\overline{\gamma})\rVert_2 = \max_{\gamma \in \mathfrak{P}} \lVert\alpha(\gamma)\rVert_2 \right\} \subseteq \mathfrak{P}$
ζ_{rand}	$\mathfrak{P}$

The choice problems in the CPAF are modelled and solved by either employing an unbounded rationality approach (Section 5.4.1) or a bounded rationality approach (Section 5.4.2), depending on the given decision situation. Therefore, to solve a given choice problem as in Definition 5.4, an appropriate choice model including an appropriate attribute function and an appropriate choice rule need to be stated.

5.4.1. Planned Decision Making

The Planned Decision Making model is used in situations, where the agent has got an ample amount of time at their disposal and therefore can unhurriedly evaluate the different choice alternatives. Additionally, the agent is assumed to have a lot of experience in taking the decision and a good information base to base their decisions upon. Consequently, the unbounded rationality approach (Section 3.2.1.1) is used as an approximation of expert decision making (see Section 3.2.1.3): the final choice is a choice alternative that is optimal with regard to the evaluated attributes.

Therefore, for a given choice problem formulation as in Definition 5.4 with choice set $\gimel$ and choice criterion C, an appropriate attribute function as in Definition 5.6 needs be chosen to represent the problem's choice criterion.

Since each choice alternative $\gamma \in \gimel$ is sufficiently characterised by their set of attributes $\alpha(\gamma) \in \mathbb{R}^m$, the optimality of an alternative is decided based on these attributes. Depending on the number m of attributes that each alternative is assigned, the optimality is determined by using either single-criteria optimisation techniques or multi-criteria optimisation techniques (see Section 3.2.1.1). Since Single-Criteria Optimisation Problems can be formulated as a special case of Multi-Criteria Optimisation Problems, all decision situations that are modelled with the CPAF's Planned Decision Making model are formulated as Multi-Criteria Optimisation Problems in the remainder of this thesis.

As a reminder, a Multi-Criteria Optimisation Problem has been defined in Definition 3.1 as a pair $(\mathfrak{X}, f)$ where $\mathfrak{X}$ is a non-empty set and $f : \mathfrak{X} \to \mathbb{R}^m$ a function with $m \in \mathbb{N}$ [87]. The objective of the mathematical optimisation problem is then to determine all optimal solutions $\gamma^* \in \gimel$ of the Multi-Criteria Optimisation Problem with regard to f:

$$\mathfrak{P}_{(\gimel, f)} = \{\gamma^* \in \gimel \mid \gamma^* \text{ optimal with regard to } f\}$$

As has been discussed in Section 3.2.1.1, the optimal solutions set of a Multi-Criteria Optimisation Problem is determined by solving an Auxiliary Single-Criteria Optimisation Problem. Since in general two possible Auxiliary Single-Criteria Optimisation Problem methods exists, this is encoded in the Planned Decision Making model by using a scalarisation function $z : \mathbb{R}^m \to \mathbb{R}$. The Auxiliary Single-Criteria Optimisation Problem $(\mathfrak{X}, z \circ f)$ needs than to be solved. In the special case that $m = 1$, no Auxiliary Single-Criteria Optimisation Problem is required and therefore $z = \mathbb{1}_{\mathbb{R}}$, $z(f(\gamma)) = f(\gamma)$.

In the CPAF's Planned Decision Making model of a choice problem with choice set $\gimel$, choice criterion C and chosen attribute function α, a Multi-Criteria Optimisation Problem $(\gimel, f)$ is used to decide the given choice problem. Hereby, the Multi-Criteria Optimisation Problem's objective function f is set as

$$f := h \circ \alpha$$

for a function $h : \mathbb{R}^m \to \mathbb{R}^m$ suitable for the given choice criterion C. By further choosing a suitable scalarisation function $z : \mathbb{R}^m \to \mathbb{R}$, the set of all optimal solutions with regard to $f = h \circ \alpha$ can be determined.

Since the choice criterion C of the given choice problem in the Planned Decision Making model is to choose an optimal choice alternative with regard to the relevant attribute function, the choice problem's choice candidate set $\mathfrak{P}^{\text{PDM}}$ is consequently the set of all optimal choice alternatives with regard to f:

$$\mathfrak{P}^{\text{PDM}} :\equiv \mathfrak{P}_{(\gimel,f)}$$

Since the choice alternatives contained in the choice problem's choice candidate set cannot be distinguished with regard to the chosen scalarisation function z, each choice alternative in the choice candidate set is equally well suited to be the final choice of the given choice problem. Therefore, the choice rule's choice function ζ^{PDM} of any Planned Decision Making model is set to draw a random element from the choice candidate set $\mathfrak{P}^{\text{PDM}}$:

$$\zeta^{\text{PDM}} :\equiv \zeta_{rand}$$

In summary, the CPAF's Planned Decision Making model of a given choice problem is defined as in Definition 5.7.

Definition 5.7: Planned Decision Making Model

A **Planned Decision Making (PDM) model** of a choice problem with chosen parameter set $(\gimel^{\text{PDM}}, \alpha^{\text{PDM}}, h^{\text{PDM}}, z^{\text{PDM}})$ solves the Multi-Criteria Optimisation Problem $(\gimel^{\text{PDM}}, f^{\text{PDM}})$ with $f^{\text{PDM}} := h^{\text{PDM}} \circ \alpha^{\text{PDM}}$ and scalarisation function z^{PDM}.
The function h^{PDM} is called the **objective function** of the Planned Decision Making model.
The Planned Decision Making's choice rule to choose a choice alternative from the choice problem's choice candidate set $\mathfrak{P}_{(\gimel,f)}$ is $(\zeta_{rand}, \mathfrak{P}_{(\gimel,f)})$.

In the context of modelling complex multi-purpose environments, the CPAF's Planned Decision Making model is used in the following situations:

- The agent chooses a goal location from a set of goal locations where they can satisfy a given set of goals (Section 6.1.1).
- The agent determines the route to take from a given location via a given set of targeted locations to a given destination (Section 6.1.3).

5.4.2. Short Time Span Adaptive Decision Making

The Short Time Span Adaptive Decision Making model is used in decision situations where the agent needs to make a decision in a short time span as in the case of emergent events or subconscious decision situations. In such situations, decision making research suggests, that human beings rely on brief and time-efficient heuristics, instead of time- and processing-cost expensive optimisation techniques [94] (see Section 3.2.1.3).

In a non-hurried decision situation, the decision maker would be able to find a suitable solution by comparing all given choice alternatives based on all their relevant information.

Conversely, in the short time span decision situations where the Short Time Span Adaptive Decision Making model is applied, the decision maker hasn't got enough time at their disposal to evaluate all relevant information for each given choice alternative. Therefore, the decision maker has to prioritise between the different relevant information options available. Under these conditions, an appropriate human decision making model for these requirements is the Take-the-Best Heuristic from the Adaptive Toolbox [108].

The Take-the-Best Heuristic uses an ordered set of "cues" [108] to distinguish between two given choice alternatives. In this context, Gigerenzer [108] defines a cue as the evaluation of a certain information attribute of the given choice alternatives. For example in the decision situation of deciding for a shop in a complex multi-purpose environment, a cue could be whether the products available in the shop are in an affordable price range or not. It is therefore determined for each choice alternative whether the choice alternative's information attribute in question meets the chosen cue, or not. In addition, the cues are ranked in a hierarchy, therefore starting with the examination of the most relevant information attribute for the given decision situation and then continuing with other information attributes in descending relevance order.

During the decision making process, the two choice alternatives are assessed following the given cue hierarchy. The decision maker thereby determines, whether one of the two alternatives is favoured in the light of the information given, i.e. whether one alternative meets the cue in question and the other does not. If this is not the case, the next highest ranked information attribute is assessed and so forth until an information attribute is found which discriminates between the two alternatives and the favoured alternative is then chosen as the final decision in the decision situation. If no information attribute could be found which discriminates between the alternatives, a random alternative is chosen, [102, 108, 140].

The Take-the-Best Heuristic by Gigerenzer and Goldstein therefore represents a very efficient way to distinguish between two choice alternatives. In the most efficient case, the decision can be drawn based on only the highest ranked information attribute. The whole set of available information needs only be assessed, if no distinction could be made in the previous steps.

In the context of modelling pedestrian behaviour in complex multi-purpose environments, the CPAF's Short Time Span Adaptive Decision Making model is used in situations where the agent needs to determine whether to change their current plans or not, given emergent events. Hence, the two choice alternatives "keep the current plan" vs. "change the plan" can be assessed using the Take-the-Best Heuristic as a viable approach to these kind of decision situations. However, it is generally possible, that the agent has several alternative options available, therefore they actually need to decide between "keep the current plan" and "change the plan to plan A", "change the plan to plan B", etc. Hence, the agent not only needs to decide whether to change the plan, but also needs to make a decision among the potential multiple alternative options.

Consequently, the decision situations in which the CPAF's Short Time Span Adaptive Decision Making model is used represent a two-stage decision process. In the first stage, the agent as the decision maker needs to decide whether to make a change to their current plans. In a potential second stage, given that the agent has decided to change their plans and given that multiple alternative options are available, they need to choose one of the alternative options. However, the choice in the first stage is highly dependent on the nature of the alternative options available in the second stage.

To be able to model this two-stage decision process, the CPAF's Short Time Span Adaptive Decision Making model extends the original Take-the-Best Heuristic. Therefore, in the CPAF's Short Time Span Adaptive Decision Making model, a Take-the-Best Problem is defined as follows:

Definition 5.8: Take-the-Best Problem

Let $\gimel = (\gamma_1, \ldots, \gamma_n)$ be a non-empty discrete constraint set for $n \in \mathbb{N}$. A **Take-the-Best (TtB) Problem** is the pair $(\gimel, \Xi)$, where $\Xi = (\xi_1, \ldots \xi_m)$ is a sequence of functions with

$$\xi_j : \gimel \rightarrow \{-1, 0, 1\} \qquad \text{for all } 1 \leq j \leq m \text{ and } m \in \mathbb{N}$$

Ξ is then called the **cue sequence** of the Take-the-Best Problem $(\gimel, \Xi)$ and $\gimel$ the problem's **choice set**. An element $\xi_j \in \Xi$ is called a **cue** (cf. notion in Gigerenzer [108]) of $(\gimel, \Xi)$ and an element $\gamma_i \in \gimel$ is called a **(choice) alternative**.
A cue $\xi \in \Xi$ therefore characterises a choice alternative $\gamma \in \gimel$:

$$\begin{aligned}
\gamma \text{ matches the cue } \xi \quad &:\Longleftrightarrow \quad \xi(\gamma) = 1 \\
\gamma \text{ doesn't match the cue } \xi \quad &:\Longleftrightarrow \quad \xi(\gamma) = -1 \\
\gamma \text{ is indifferent to the cue } \xi \quad &:\Longleftrightarrow \quad \xi(\gamma) = 0
\end{aligned}$$

Analogously to the set of all optimal solutions of a Multi-Criteria Optimisation Problem problem, optimality for a Take-the-Best Problem can also be defined:

Definition 5.9: Optimality for a Take-the-Best Problem

Let $(\gimel, \Xi)$ be a Take-the-Best Problem as defined in Definition 5.8. For each cue $\xi_j \in \Xi$, a choice alternative $\gamma^* \in \gimel$ is said to be **optimal with regard to** ξ_j, if

$$\xi_j(\gamma^*) = 1 \qquad \text{and} \qquad \xi_i(\gamma^*) \in \{0, 1\} \quad \forall 1 \leq i < j$$

Therefore, the set of all optimal solutions of a Take-the-Best Problem is defined as in Definition 5.10. The Take-the-Best Problem's optimal solutions set $\mathfrak{P}_{(\daleth,\Xi)}$ is determined using Algorithm 5.1.

Definition 5.10: Optimal Solution Set for a Take-the-Best Problem

Let $(\daleth, \Xi)$ be a Take-the-Best Problem. Let

$$\mathfrak{P}_{\xi_j} := \{\gamma^* \in \daleth \mid \gamma^* \text{ is optimal with regard to } \xi_j\}$$

be the set of all optimal choice alternatives with regard to $\xi_j \in \Xi$. Let

$$k := \begin{cases} \min\{j \in \{1, \ldots, m\} \mid \mathfrak{P}_{\xi_j} \neq \emptyset\}, & \text{if } \mathfrak{P}_{\xi_1} \neq \emptyset, \\ 0, & \text{else.} \end{cases}$$

be the minimal cue index where ξ_k has got optimal choice alternatives.

The **set of all optimal solutions** of the Take-the-Best Problem $(\daleth, \Xi)$ is then defined as

$$\mathfrak{P}_{(\daleth,\Xi)} := \begin{cases} \mathfrak{P}_{\xi_k}, & \text{if } k > 0, \\ \emptyset, & \text{else.} \end{cases}$$

In the case that the optimal solution set $\mathfrak{P}_{(\daleth,\Xi)}$ of a given Take-the-Best Problem is empty, ζ will not choose a choice alternative.

A Take-the-Best Problem as defined in Definition 5.8 is used to model a given choice problem as in Definition 5.4 with choice set $\daleth$ and the choice criterion C, which states that a certain reference state (i.e. the agent's current plan) and the available choice alternatives should be compared in a time-efficient way based on a hierarchy of cues, by the CPAF's Short Time Span Adaptive Decision Making model.

The given choice problem in the Short Time Span Adaptive Decision Making model is then decided by employing the Take-the-Best Problem $(\daleth, \Xi)$, where a cue ξ_j of the hierarchical cue set $\Xi = (\xi_1, \ldots, \xi_m)$ compares the reference state given by the choice criterion C to the relevant attributes of the choice alternatives $\gamma \in \daleth$. Let therefore $\alpha : \daleth \to \mathbb{R}^m$ be an attribute function on $\daleth$ which adequately represents the hierarchical cues of the given choice criterion C and let $r \in \mathbb{R}^m$ denote the criterion's reference state. The cue functions of the corresponding Take-the-Best Problem $(\daleth, \Xi)$ are then built by comparing each choice alternative's attribute in question to the corresponding reference state: Let $\mathcal{C} = (c_1, \ldots, c_m)$ be a sequence of strict order functions:

$$c_j : \mathbb{R} \times \mathbb{R} \to \{0, 1\}, \quad c_j \in \{\omega_<, \omega_>\}$$

Algorithm 5.1 The algorithm to determine the optimal solution set $\mathfrak{P}_{(\gimel,\Xi)}$ of a Take-the-Best Problem $(\gimel, \Xi)$.

Require: Take-the-Best Problem $(\gimel, \Xi)$

temporary optimal solution set $\mathfrak{P} = \emptyset$, temporary selection set $\mathfrak{S} = \emptyset$, temporary choice set $\mathfrak{T} = \gimel$
for $1 \leq j \leq |\Xi|$ **do**
    $\mathfrak{S} = \emptyset$
    for all $\gamma \in \mathfrak{T}$ **do**
        if $\xi_j(\gamma) = 1$ **then**
            add γ to $\mathfrak{S}$
        else if $\xi_j(\gamma) = -1$ **then**
            remove γ from $\mathfrak{T}$
        end if
    end for
    if $\mathfrak{T} = \emptyset$ **then** $\{$implies $\mathfrak{S} = \emptyset\}$
        return $\mathfrak{P}$
    else if $|\mathfrak{S}| = 1$ **then**
        $\mathfrak{P} = \mathfrak{S}$
        return $\mathfrak{P}$
    else if $|\mathfrak{S}| > 1$ **then**
        $\mathfrak{T} = \mathfrak{S}$
        $\mathfrak{P} = \mathfrak{S}$
    end if
end for
return $\mathfrak{P}$

where

$$\omega_{<}\colon\ \mathbb{R}\times\mathbb{R}\to\{0,1\},\quad \omega_{<}(x,y) := \begin{cases} 1 & \text{if } x<y \\ 0 & \text{else} \end{cases} \tag{5.5}$$

$$\omega_{>}\colon\ \mathbb{R}\times\mathbb{R}\to\{0,1\},\quad \omega_{>}(x,y) := \begin{cases} 1 & \text{if } x>y \\ 0 & \text{else} \end{cases} \tag{5.6}$$

With the comparison functions $\mathcal{C}$, the ordered cue set Ξ in the CPAF's Short Time Span Adaptive Decision Making model is then defined as the component-wise comparisons of the choice alternatives' attributes to the reference state:

$$\xi_j^{c_j,r}(\gamma) := \begin{cases} 1, & \text{if } c_j(\alpha_j(\gamma), r_j) = 1 \\ 0, & \text{if } \alpha_j(\gamma) = r_j \\ -1, & \text{else} \end{cases}$$

and hence $\Xi := \Xi(\mathcal{C}, r)$.

When solving the Take-the-Best Problem $(\beth, \Xi(\mathcal{C}, r))$, the corresponding optimal solution set $\mathfrak{P}_{(\beth,\Xi(\mathcal{C},r))}$ contains all choice alternatives, that were favoured over the reference state r by the ordered cue set Ξ. Therefore, the choice candidate set of a choice problem which is modelled by the Short Time Span Adaptive Decision Making model is set to the corresponding Take-the-Best Problem's optimal solution set:

$$\mathfrak{P}^{\text{STSADM}} :\equiv \mathfrak{P}_{(\beth,\Xi(\mathcal{C},r))}$$

It is hereby possible, that the choice candidate set is empty.

From the choice candidate set, the final choice needs to be drawn. Therefore, a choice function ζ which is appropriate for the given choice problem needs to be chosen in the modelling process. If the choice candidate set is empty, then ζ chooses no choice alternative.

In summary, the CPAF's Short Time Span Adaptive Decision Making model of a given choice problem is defined as in Definition 5.11.

Definition 5.11: Short Time Span Adaptive Decision Making Model

A **Short Time Span Adaptive Decision Making (STS-ADM) model** of a choice problem with chosen parameter set

$$(\beth^{\text{STSADM}}, \alpha^{\text{STSADM}}, r^{\text{STSADM}}, \mathcal{C}^{\text{STSADM}}, \zeta^{\text{STSADM}})$$

solves the Take-the-Best Problem $(\beth^{\text{STSADM}}, \Xi^{\text{STSADM}})$ with $\Xi^{\text{STSADM}} := \Xi(\mathcal{C}^{\text{STSADM}}, r^{\text{STSADM}})$. The Short Time Span Adaptive Decision Making's choice rule to choose a choice alternative from the choice problem's choice candidate set $\mathfrak{P}_{(\daleth^{\text{STSADM}}, \Xi^{\text{STSADM}})}$ is then set as

$$\left(\zeta^{\text{STSADM}}, \mathfrak{P}_{(\daleth^{\text{STSADM}}, \Xi^{\text{STSADM}})}\right)$$

In the context of modelling complex multi-purpose environments, the CPAF's Short Time Span Adaptive Decision Making model is used in the following situations:

- The agent reacts to external conditions such as procedural processes and congestion, see Section 5.6.2.
- The agent perceives features in the environment and decides whether to change their plans based on their perception, see Section 6.4.1.
- The agent responds to an alarm by choosing an appropriate alarm response and their targeted exit, see Chapter 7.2.3.

5.5. Visual Perception Representation

Facilities in complex multi-purpose environments, e.g. a shopping mall, are equipped with large shop windows or sign-boards, which advertise the facility's services. While traversing a complex multi-purpose environment, pedestrians perceive these visual clues and thereby the advertised facilities. Upon perceiving a certain facility, the pedestrian then categorises this facility corresponding to their individual preferences and needs and determines, whether they want to respond to this stimulus. Possible responses are, that a pedestrian is attracted to the advertised facility and decides to enter it, or that the pedestrian memorises the facility and potentially at a later point decides to visit it.

In the current version of the buildingEXODUS software tool [14], the agent is capable of visually perceiving exit signs during an evacuation simulation and thereby potentially adjusting their exit route, see Section 4.5.1. The CPAF adopts this feature not only for exit signs, but also for signs that can point to the environment's goal locations in usage-cycle simulations of complex multi-purpose environments.

In a complex multi-purpose environment simulation which uses the CPAF, each modelled goal location can be assigned a sign which points to this goal location. It is postulated that the most significant information that is obtained by visual perception is information related to the environments purpose and its relation to the individual agent's needs and preferences. Therefore, if a sign pointing to a goal location in the environment – e.g. a facility or an outlet or also an exit – is perceived by the agent, the goal location with its feature attributes as well as the goals related to this goal location is memorised by the agent. In the case that the goal location in question has been already learned previously, the agent's memory of this goal location is refreshed. In the CPAF it is postulated, that signs which point to the modelled environment's facilities are perceived and evaluated as soon as the agent is physically able to see the sign in question.

The buildingEXODUS CPAF Plug-in uses the buildingEXODUS's Visibility Catchment Area for the modelled signs, cf. Xie et al. [138], Filippidis et al. [139]. For signs which point to the special goal locations of exits, the sign awareness and understanding model currently implemented in the buildingEXODUS software tool is also used for the buildingEXODUS CPAF Plug-in, cf. Xie [136].

5.6. Stimuli Representation

In the context of modelling pedestrian circulation behaviour in complex multi-purpose environments, events are defined as emergent incidents or changes to the current situation caused by various stimuli. The stimuli thereby can be both "external", i.e. cannot be influenced by the agent, and "internal", i.e. can be influenced by the agent. External events therefore include procedural operations such as a train time table or environmental influences such as the population density. Internal events on the other hand include events such as fatigue. To represent these stimuli, emotion modelling techniques have been applied in the CPAF, which monitor and classify these events as well as potentially trigger the agent's decision making entity in order to adapt to the emergent changes.

In the remainder of this thesis, the agent's representation of "internal" stimuli is referred to as their *motivations* [114] and the agent's representation of "external" stimuli is referred to as their *emotions*. Both stimuli representations are realised by internal agent parameters.

Motivations and emotions differ not only in their causality, but also in the way the agent perceives and reacts to these stimuli representations, see Figure 5.4.

The motivation parameters are updated time-continuously. Since these simulate internal stimuli, the motivation parameters depend only on the time and other internal attributes of the agent, such as physical or social attributes. Motivations can lead to the rise of new agent goals or the reactivation of formerly achieved agent goals, such as the goal to eat in response to the stimulus of being hungry.

If a goal is evoked by a motivation variable, a decision making instance is triggered which aims to add a task for satisfying this goal. The agent therefore will refer to their spatial memory for feasible goal locations where the evoked goal could be satisfied, or they will refer to their current working memory, whether the new goal can be accommodated at a goal location that is already aimed to be visited by another task on the Agent Task List. It is postulated, that the agent can make the decision on adding a new task to their itinerary or adjusting an existing task unhurriedly, because of the continuous matter of the motivation parameter. Furthermore, the agent's spatial memory is postulated to be

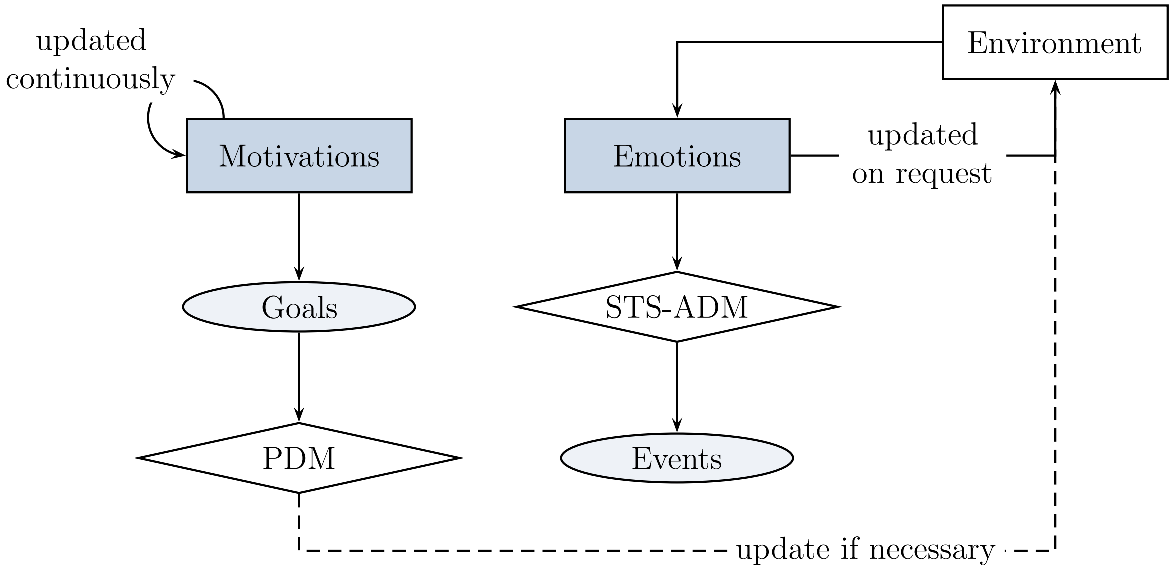


Figure 5.4.: Stimuli representation and processing

a reliable information base in this decision situation and as a result the Planned Decision Making model is employed.

Emotion parameters are updated on request, i.e. in non-regular time intervals, or if the assessment is triggered by specific actions of the agent. During the update process, the agent draws the relevant information from the environment, interprets this information and reflects the agent's individual assessment of the situation by the emotion variable in question. The environmental information is interpreted using the Short Time Span Adaptive Decision Making model, which categorises the perceived situation and adjusts the internal emotion variable accordingly. The buildingEXODUS's Urgency model (see Section 4.3.1) is an example for the modelling of the impact of the external stimuli available time and population density in a pedestrian behaviour simulation model.

Since both stimuli representations can lead to the adjustment of the agent's current plans, a hierarchy between the stimuli needs to be imposed. It is hereby postulated in this thesis, that emotions overrule motivations for the agent's decision making. In other words, emotional responses can lead to the suppression of goals that have been evoked by motivational responses. Therefore, if tasks have been added to the agent's itinerary by a motivational response, an assessment of the external circumstances is triggered by the means of updating the relevant emotional variables.

5.6.1. Motivations: Representations of Internal Stimuli

Motivation parameters are modelled as continuous monotonic increasing functions of the time τ:

$$\mu : \mathbb{R}_0^+ \longrightarrow [0,1] \ , \qquad \mu'(\tau) \geq 0 \quad \forall \tau \in \mathbb{R}_0^+$$

The initial values $\mu(\tau_0)$ at the simulation time τ_0 of the agent's entry in the environment are set individually for each agent during the simulation initialisation phase. The agent's initial motivation values are generated according to a uniform random distribution and consistent with the their Agent Goal Set (AGS):

$$\mu(\tau_0) = \begin{cases} \mathcal{U}([\mathbf{M}_{low}, 1]) & \text{if the related agent goal } g_\mu \text{ is initially active on AGS} \\ \mathcal{U}([0, \mathbf{M}_{low}]) & \text{else} \end{cases}$$

Two thresholds are used to determine the impact of the motivation onto the agent's behaviour, $\mathbf{M}_{low}$ and $\mathbf{M}_{up}$, where

$$0 \leq \mathbf{M}_{low} < \mathbf{M}_{up} \leq 1$$

$\mathbf{M}_{low}$ determines the threshold at which point the motivation shows an effect onto the agent's behaviour and $\mathbf{M}_{up}$ determines the threshold at which point the motivation exhibits a dominant impact onto the agent's behaviour. It is thereby assumed that as long as a motivation parameter $\mu(\tau)$ is smaller than the lower motivation threshold, i.e. $\mu(\tau) < \mathbf{M}_{low}$, the motivation is too weak to have an impact on the agent's behaviour. As a result, no goal is created in this case. However, once the motivation exceeds the lower threshold, i.e. $\mu(\tau) \geq \mathbf{M}_{low}$, the motivation triggers the creation of a new or the reactivation of the previously achieved related agent goal, see Figure 5.5.

If a motivation μ gives rise to an agent goal $g_\mu \in$ Agent Goal Set, the agent goal's relative importance $I(g_\mu)$ is then dependent on the strength of the motivation and the relative importance range of the underlying goal $\widehat{g} \in$ Global Goal Set with $g_\mu \lhd \widehat{g}$:

$$I(g_\mu) = \begin{cases} I_{low}(\widehat{g}) & \text{if } 0 \leq \mu < \mathbf{M}_{low} \\ \dfrac{I_{low}(\widehat{g}) - I_{up}(\widehat{g})}{\log(\mathbf{M}_{low})} \log(\mu) + I_{up}(\widehat{g}) & \text{if } \mathbf{M}_{low} \leq \mu \leq 1 \end{cases} \tag{5.7}$$

The relative importance of the related agent goal – if existent – is therefore also continuously updated each time the associated motivation is updated. As a result, the importance of an agent goal that is associated with a motivation parameter is increasing in simulation time. Consequently, the agent's goal hierarchy of their Agent Goal Set is also dynamic during the course of the simulation.

The agent performs the goal assessment for each modelled motivation, thereby potentially adding or updating multiple agent goals on their Agent Goal Set. After each motivation has been assessed and if the Agent Goal Set has been changed, the agent then needs to decide on further actions to take in order to satisfy their new or updated agent goals. As a result, the agent seeks to update existing tasks on their Agent Task List or to add new tasks to the Agent Task List to cope with the potential changes of their goals. However, the agent will only consider changing their Agent Task List, if they aren't currently engaged in a task. In

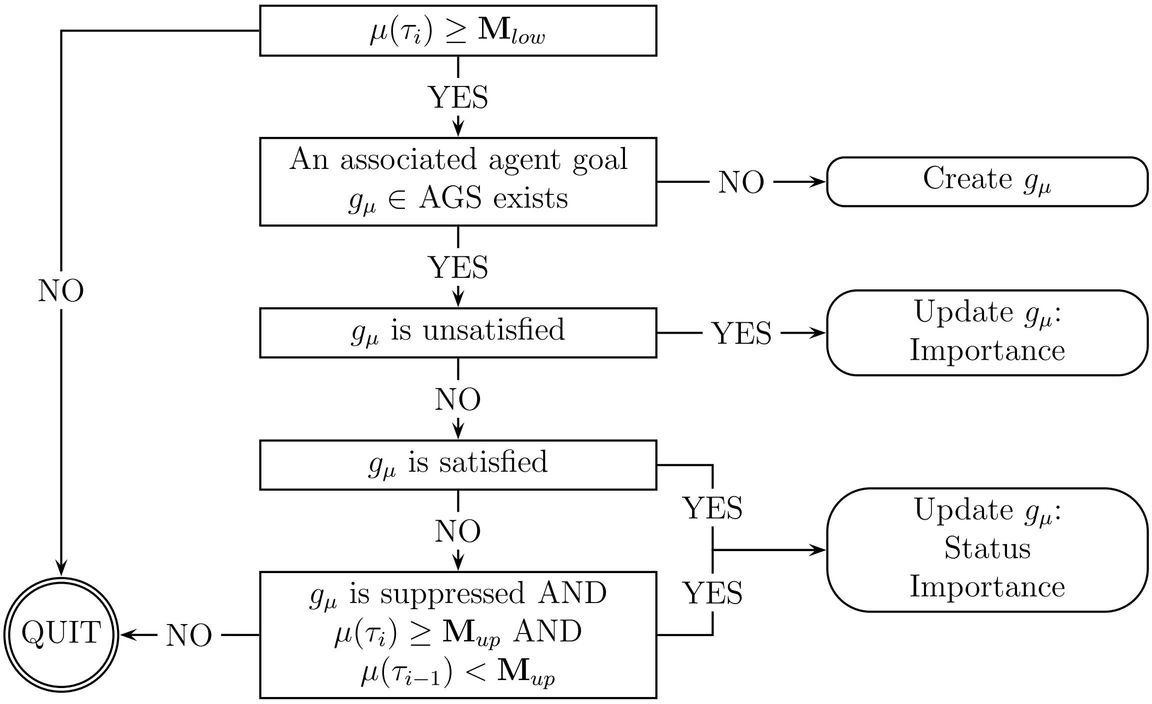


Figure 5.5.: Assessment of whether to update the Agent Goal Set, depending on the strength of the associated motivation μ at the simulation time τ_i.

this case, even if changes to the Agent Goal Set had been made, the agent will first complete their currently ongoing task before updating their Agent Task List. Nevertheless, the agent keeps updating their motivations and Agent Goal Set while performing a task.

When the agent considers to adjust existing or to add new tasks based on their motivations, they need to distinguish between two different types of motivations respectively two different types of goals: those that qualify for a compromise task and those that don't qualify for a compromise task. Hereby, a task is understood to be a compromise task if the task satisfies more than one agent goal, see Section 5.3.2. This is possible, since goal locations exists which can satisfy several goals, e.g. a coffee shop can satisfy the goals "eat" and "drink".

For this reason, let $\mathfrak{L}(\mathfrak{G})$ denote the set of all communal goal locations for a given set of agent goals $\mathfrak{G} \subseteq$ Agent Goal Set:

$$\mathfrak{L}(\mathfrak{G}) := \bigcap_{g \in \mathfrak{G}} \mathfrak{L}(g) \tag{5.8}$$

If changes to the agent's Agent Goal Set have been made regarding motivations which don't qualify for a compromise task, the agent employs an algorithm as illustrated in Figure 5.6 to determine a suitable task response.

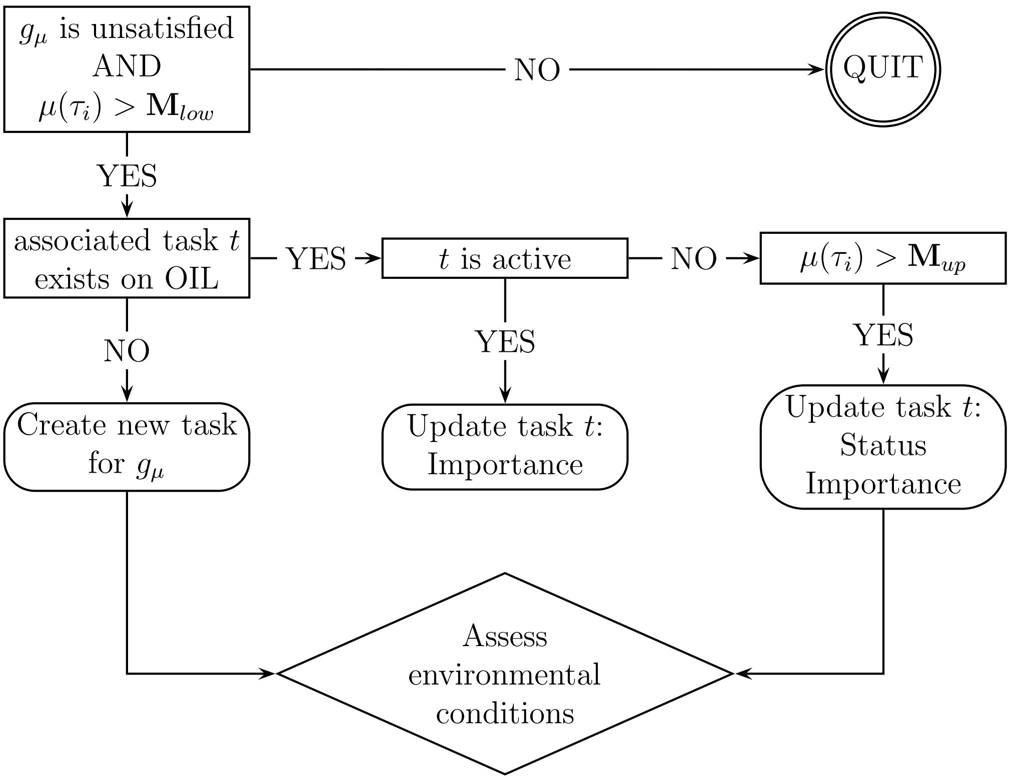


Figure 5.6.: The motivation model's assessment on whether to update an existing or create a new task for motivations μ and related goal g that doesn't qualify for compromise tasks.

Thereby, the agent assesses first whether a task associated with the unsatisfied agent goal

g_μ and the elevated motivation $\mu(\tau_i)$ at the current time step τ_i exists. If a task exists and it is active, the task's importance is updated with the current relative importance $I(g_\mu)$. If the task has previously been dismissed and is therefore not active anymore, the task is only updated if the motivation has reached an urgent state. In that case, the task is reactivated and its importance is updated. If no task associated with the still to be achieved agent goal g_μ exists on the agent's Agent Task List, they invoke Algorithm 5.2.

Algorithm 5.2 The motivation model's task creation algorithm for a set of agent goals $\mathfrak{G} \subseteq$ Agent Goal Set.

Require: set of agent goals $\mathfrak{G} \subseteq$ Agent Goal Set
identify the set of all possible compromise locations $\mathfrak{L}(\mathfrak{G})$
if $\mathfrak{L}(\mathfrak{G}) \neq \emptyset$ **then**
    $I_{max}(\mathfrak{G}) := \max_{g \in \mathfrak{G}} I(g)$
    if $U > 0$ **then**
        identify the importance-optimal position on the Agent Task List, i.e. find π^*, with $\pi_0 \leq \pi^* \leq \pi_{cr}$ so that $I(t_\pi) < I_{max}(\mathfrak{G})\ \forall \pi^* \leq \pi < \pi_{cr}$
        choose distance-optimal goal location $l^* \in \mathfrak{L}(\mathfrak{G})$ for the position π^*, see Table 5.10
    else
        choose preference-optimal goal location $l^* \in \mathfrak{L}(\mathfrak{G})$, see Table 5.10
        choose distance-optimal position π^*, $\pi_0 \leq \pi^* \leq \pi_{cr}$, for the new task on the Agent Task List, see Table 5.10
    end if
    generate new task t from $\mathfrak{G}$ and l^* with importance $I_{max}(\mathfrak{G})$ and add the new task to the Agent Task List at position π^*
end if

Algorithm 5.2 creates a new task for a given set of agent goals $\mathfrak{G} \subseteq$ Agent Goal Set. Based on the agent's level of urgency – if modelled – it determines the position π on the Agent Task List where to insert the new task and the goal location $l^* \in \mathfrak{L}(\mathfrak{G})$ which is optimal for the given state of urgency. The new task is then built from $\mathfrak{G}$ and l^* as described in Section 5.3.2.

The Algorithm 5.2 makes use of the CPAF's Planned Decision Making instances and generic choice problems depicted in Table 5.10. These Planned Decision Making instances and generic choice problems as well as a way to solve these generic choice problems are outlined in Section 6.1. In some of these Planned Decision Making instances, the additional distance function $\partial_+(\pi, l)$ is used:

$$\partial_+ : \mathbb{N} \times \text{GLS} \to \mathbb{R}, \qquad \partial_+(\pi, l) := \partial(l(t_{\pi-1}), l) + \partial(l, l(t_\pi)) - \partial(l(t_{\pi-1}), l(t_\pi))$$

For a given position π on the agent's Agent Task List and a given goal location l, $\partial_+(\pi, l)$ determines the additional distance that needs to be travelled by the agent if a task with associated goal location l is inserted into the Agent Task List before the task t_π.

Finally, if the agent assesses the possible task response for elevated motivations which

Table 5.10.: The generic choice problems and the decision making model instance used in Algorithm 5.2.

Situation in Algorithm 5.2	Model	Parameter Set	Attribute Function	see Def.
Distance-optimal goal location choice	Preference-Optimal Goal Location Choice Problem	$(\mathfrak{L}(\mathfrak{G}), \alpha, 0)$	$\alpha(l) := \partial_+(\pi^*, l)$	6.1
Preference-optimal goal location choice	Preference-Optimal Goal Location Choice Problem	$(\mathfrak{L}(\mathfrak{G}), \alpha, P)$	$\alpha(l) := F(l)$	6.1
Distance-optimal position choice	Planned Decision Making model	$(\{\pi_0, \ldots, \pi_{cr}\}, \alpha, \mathbb{1}_{\mathbb{R}})$	$\alpha(\pi) := \partial_+(\pi, l^*)$	5.7

qualify for a compromise task, they employ an algorithm as illustrated in Figure 5.7.

The algorithm used in Figure 5.7, is almost identical to the one illustrated by Figure 5.6, but instead of directly creating a new task if no associated task could be found, the agent checks for compromise actions.

When checking for compromise actions, the agent determines whether an active task exists on the Agent Task List which is associated with a motivation that is capable of a compromise action with the currently assessed agent goal g_μ. If such as task t' exists, the agent checks whether g_μ can be satisfied at the this task's location. This is necessary, since in general

$$\mathfrak{L}(g) \cap \mathfrak{L}(g') \neq \emptyset \quad \not\Rightarrow \quad \mathfrak{L}(g) = \mathfrak{L}(g')$$

for two compromise-capable agent goals g and g'.

If g_μ can be satisfied at the goal location associated with t', g_μ is then added to the task's associated agent goals $\mathfrak{G}(t')$ and its importance is updated to

$$I(t') := \max_{g \in \mathfrak{G}(t')} I(g)$$

If g_μ cannot be satisfied at the goal location associated with t', the agent determines whether an alternative goal location is known, where g_μ and all agent goals already associated with t' can be satisfied. If this is the case, t' is dismissed and a new task is generated with the agent goal g_μ and all $\mathfrak{G}(t')$ using Algorithm 5.2.

In the cases that either no task associated with a compromise-qualified agent goal for g_μ could be found on the agent's Agent Task List or if a task t' had been found but the task's location is unsuitable for g_μ and no alternative goal location for g_μ and $\mathfrak{G}(t')$ is known, the

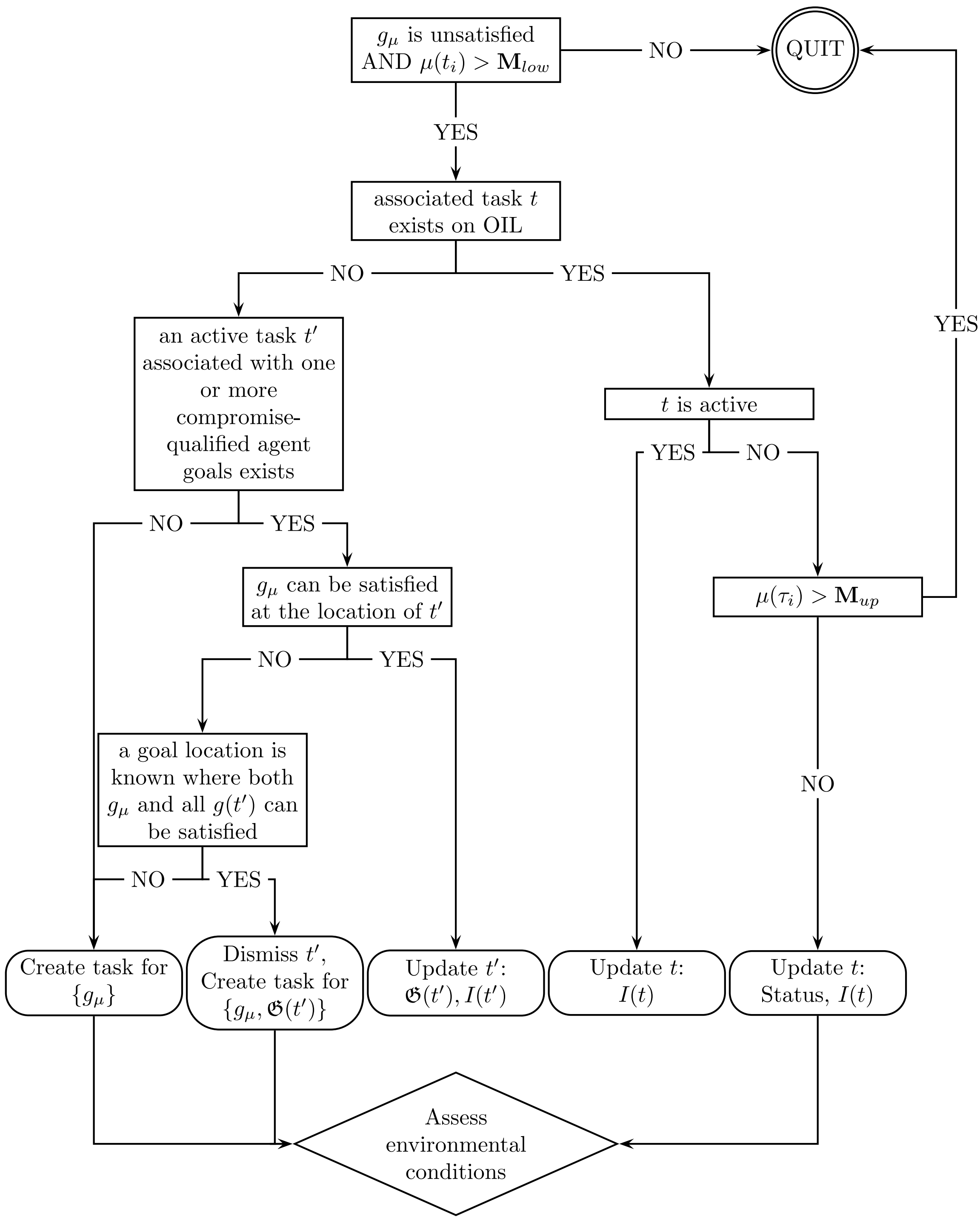


Figure 5.7.: The motivation model's assessment on whether to update an existing or create a new task for motivations μ and related goal g that qualifies for compromise tasks.

agent keeps t' and creates a new task for g_μ, again using Algorithm 5.2.

Therefore, motivations can change the agent's Agent Task List at any given time step during the simulation. Conversely, if during the simulation an agent goal associated with a motivation is satisfied by completing the associated task, the motivation function in question is then reset to zero.

If changes to the agent's Agent Task List have been made during the motivation assessment process either by having created a new task or by having reactivated a formerly dismissed task, the agent triggers an assessment of the relevant environmental conditions. The agent thereby ensures, that the motivated changes to their plans are still consistent with their current situation.

For example, the three motivation parameters depicted in Table 5.11 have been implemented in the buildingEXODUS CPAF Plug-in for demonstrating the CPAF's capabilities in a comprehensive verification case, see Chapter 9. These motivations have been chosen with respect to the goal realisations of the Global Goal Set also implemented in the buildingEXODUS CPAF Plug-in, see Table 5.5. These example motivations have been chosen to correspond to the global goals to eat, to drink and to rest.

Table 5.11.: An example for a possible list of motivation parameters for use with the Cognitive Pedestrian Agent Framework. These motivation parameters have been implemented in the buildingEXODUS CPAF Plug-in.

Motivation	Related Goal	Motivation function
hunger	"eat"	η
thirst	"drink"	θ
fatigue	"rest"	ϕ

All of the example motivation parameters depicted in Table 5.11 depend on the simulation time τ such that the pedestrian will get more hungry, thirsty or tired based on the amount of time that has elapsed since their entry in the environment and the amount of physical work that the agent has performed. Therefore, the example motivation functions η, θ and ϕ have been defined based on the agent's energy and fluid expenditure.

The energy expenditure ϵ of a pedestrian who is moving with a constant velocity v on a "normal" terrain can be approximated by the exponential function:

$$\epsilon_v = 0.023 \cdot e^{0.8127v} \qquad \left[\frac{kCal}{s}\right] \tag{5.9}$$

based on data by McArdle et al. [6], see Figure 5.8.

The fluid expenditure $\digamma$ is postulated to be linear in simulation time:

$$\digamma = \frac{2.5}{86400} \qquad \left[\frac{l}{s}\right]$$

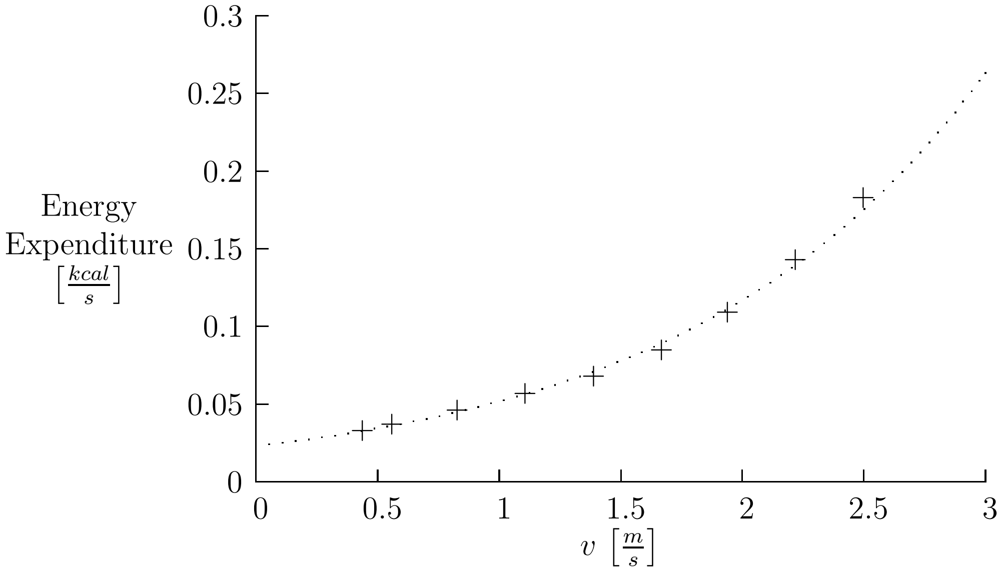


Figure 5.8.: Energy Expenditure while walking on a level surface at different speeds, McArdle et al. [6].

where the cumulative fluid expenditure over one day amounts to 2.5 l, which is the recommended daily fluid intake for a normal adult.

Over a given period of simulation time $[\tau_i, \tau_j]$, the cumulative energy and fluid expenditure therefore amounts to

$$\epsilon_{(v_1,\ldots,v_k)}(\tau_i, \tau_j) := \sum_{k=1}^{m} T_k \cdot \epsilon_{v_k} \qquad [kCal] \tag{5.10a}$$

$$F(\tau_i, \tau_j) := (\tau_j - \tau_i) \cdot F \qquad [l] \tag{5.10b}$$

where the time intervals $T_1, \ldots, T_m$ with

$$T_k := \tau_{i_k+1} - \tau_{i_k}$$

are the simulation time intervals in the period of simulation time $[\tau_i, \tau_j]$

$$\tau_i \equiv \tau_{i_1} < \tau_{i_1+1} \leq \tau_{i_2} < \tau_{i_2+1} \leq \ldots \leq \tau_{i_k} < \tau_{i_k+1} \equiv \tau_j$$

that the agent in question travels with constant velocities $v_1, \ldots, v_k$:

$$v(\tau) \equiv v_k \qquad \forall\ \tau \in [\tau_{i_k}, \tau_{i_k+1}]$$

The example motivation functions for hunger η, thirst θ and fatigue ϕ are directly related to the agent's energy expenditure ϵ respectively fluid expenditure F by discrete cumulative functions:

$$\eta(\tau) \;:=\; \min\left\{1, \eta(\tau - \mathbf{T}^{\text{TimeStep}}) + \frac{\epsilon_{v(\tau)}(\tau - \mathbf{T}^{\text{TimeStep}}, \tau)}{500\ kCal}\right\} \tag{5.11a}$$

$$\theta(\tau) \;:=\; \min\left\{1, \theta(\tau - \mathbf{T}^{\text{TimeStep}}) + \frac{F(\tau - \mathbf{T}^{\text{TimeStep}}, \tau)}{1.25\ l}\right\} \tag{5.11b}$$

$$\phi(\tau) \;:=\; \min\left\{1, \phi(\tau - \mathbf{T}^{\text{TimeStep}}) + \frac{\epsilon_{v(\tau)}(\tau - \mathbf{T}^{\text{TimeStep}}, \tau)}{250\ kCal}\right\} \tag{5.11c}$$

These definitions for the example motivation functions in the buildingEXODUS CPAF Plug-in make use of the general guideline, that a normal adult should have an energy intake of about 2000 kCal and a fluid intake of about 2.5 l per day.

5.6.1.1. Meal Times

In a complex multi-purpose environment which offers food outlets, it is not uncommon that the pedestrians feel the urge to visit these food outlets stronger during certain time periods of the day, i.e. during the culturally customary breakfast, lunch and dinner time periods. To reflect this custom, the buildingEXODUS CPAF Plug-in restricts the impact of the modelled hunger motivation on the agent's task planning dependent on the time of the day. For this reason, a meal times probability function has been incorporated into the buildingEXODUS CPAF Plug-in. This probability function determines how likely it is for the hunger motivation to trigger the creation or reactivation of the associated "eat" agent goal as described in Section 5.6.1.

With the help of the Cognitive Pedestrian Agent Framework Scenario Specification Generator (see Appendix Chapter B), the user can specify certain simulation time parameters

$$\mathfrak{T}_{meal} := \{\tau_j \mid 0 \leq j \leq 2n-1\} \quad \text{where } n \in \mathbb{N}$$

which describe the locally customary meal time periods $[\tau_{2i}, \tau_{2i+1}]$, $0 \leq i \leq n-1$ in the complex multi-purpose environment to be modelled. The meal times probability function will then be modelled as being normally distributed within the time periods $[\tau_{2i}, \tau_{2i+1}]$ for $0 \leq i \leq n-1$. Between the time periods, the meal probability function will be linearly continued.

Let therefore $f_{\mathcal{N}(\mu,\sigma^2)}$ and $F_{\mathcal{N}(\mu,\sigma^2)}$ denote the probability density function respectively the cumulative distribution function of the normal distribution $\mathcal{N}(\mu, \sigma^2)$ (see Equations A.3a and A.3b). With this notation, define for $\tau \in [\tau_{2i}, \tau_{2i+1}]$ with $0 \leq i \leq n-1$, $\tau_{2i}, \tau_{2i+1} \in \mathfrak{T}_{meal}$

the probability parameters as

$$
\begin{aligned}
\mu(\tau) &:= \frac{1}{2}(\tau_{2i} + \tau_{2i+1}) \\
\sigma(\tau) &:= \frac{1}{4}(\tau_{2i+1} - \tau_{2i}) \\
x_{min}(\tau) &:= \tau_{2i} - \frac{1}{2} \cdot \begin{cases} \min\{\tau_{2i}, (\tau_{2i+2} - \tau_{2i+1})\} & \text{if } i = 0 \\ \min\{(\tau_{2i} - \tau_{2i-1}), (\tau_{2i+2} - \tau_{2i+1})\} & \text{if } 1 \leq i \leq n-2 \\ (\tau_{2i} - \tau_{2i-1}) & \text{if } i = n-1 \end{cases} \\
x_{max}(\tau) &:= \mu(\tau) + (\mu(\tau) - x_{min}(\tau))
\end{aligned}
$$

Since the piece-wise probability functions on the constraint interval $[\tau_{2i}, \tau_{2i+1}]$ shall cumulate to 1, a scale factor is required for all $\tau \in [\tau_{2i}, \tau_{2i+1}]$:

$$A(\tau) := F_{\mathcal{N}(\mu(\tau),\sigma(\tau)^2)}(x_{max}(\tau)) - F_{\mathcal{N}(\mu(\tau),\sigma(\tau)^2)}(x_{min}(\tau))$$

In addition, define for $\tau_{2i} \in \mathfrak{T}_{meal}$, $1 \leq i \leq n-2$, the parameters of the linear continuations between the given time periods by

$$
\begin{aligned}
m(\tau_{2i}) &:= \frac{A^{-1}(\tau_{2i}) \cdot f_{\mathcal{N}(\mu(\tau_{2i}),\sigma(\tau_{2i})^2)}(x_{min}(\tau_{2i})) - A^{-1}(\tau_{2i-1}) \cdot f_{\mathcal{N}(\mu(\tau_{2i-1}),\sigma(\tau_{2i-1})^2)}(x_{max}(\tau_{2i-1}))}{x_{min}(\tau_{2i}) - x_{max}(\tau_{2i-1})} \\
b(\tau_{2i}) &:= m(\tau_{2i}) \cdot x_{min}(\tau_{2i}) - f_{\mathcal{N}(\mu(\tau_{2i}),\sigma(\tau_{2i})^2)}(x_{min}(\tau_{2i}))
\end{aligned}
$$

As a result, the meal times probability function $f_{meal}(\tau)$ at simulation time τ is then defined as:

$$
f_{meal}(\tau) := \begin{cases} A^{-1}(\tau) \cdot \frac{f_{\mathcal{N}(\mu(\tau),\sigma(\tau)^2)}(x_{min}(\tau_0))}{x_{min}(\tau_0)} \cdot \tau & \text{if } \tau < \tau_0 \\ A^{-1}(\tau) \cdot f_{\mathcal{N}(\mu(\tau),\sigma(\tau)^2)}(\tau) & \text{if } \tau \in [\tau_{2i}, \tau_{2i+1}],\ 0 \leq i \leq n-1 \\ m(\tau_{2i}) \cdot \tau + b(\tau_{2i}) & \text{if } \tau \in [\tau_{2i-1}, \tau_{2i}],\ 1 \leq i \leq n-1 \\ 0 & \text{if } \tau_{2n-1} < \tau \end{cases} \tag{5.12}
$$

The meal times probability function $f_{meal}(\tau)$ at any given simulation time τ therefore expresses the likelihood, that a medium hunger motivation leads to the creation or reactivation of the agent's "eat" goal: if the hunger motivation function $\eta(\tau)$ is in the range between the two motivation thresholds $\mathbf{M}_{low} \leq \eta(\tau) \leq \mathbf{M}_{up}$ the likelihood of the "eat" goal to be triggered is given by $f_{meal}(\tau)$. However, if $\mathbf{M}_{up} < \eta(\tau)$, the "eat" goal will always be triggered. Therefore, for the hunger motivation, the algorithm depicted in Figure 5.5 is adapted, see Figure 5.9.

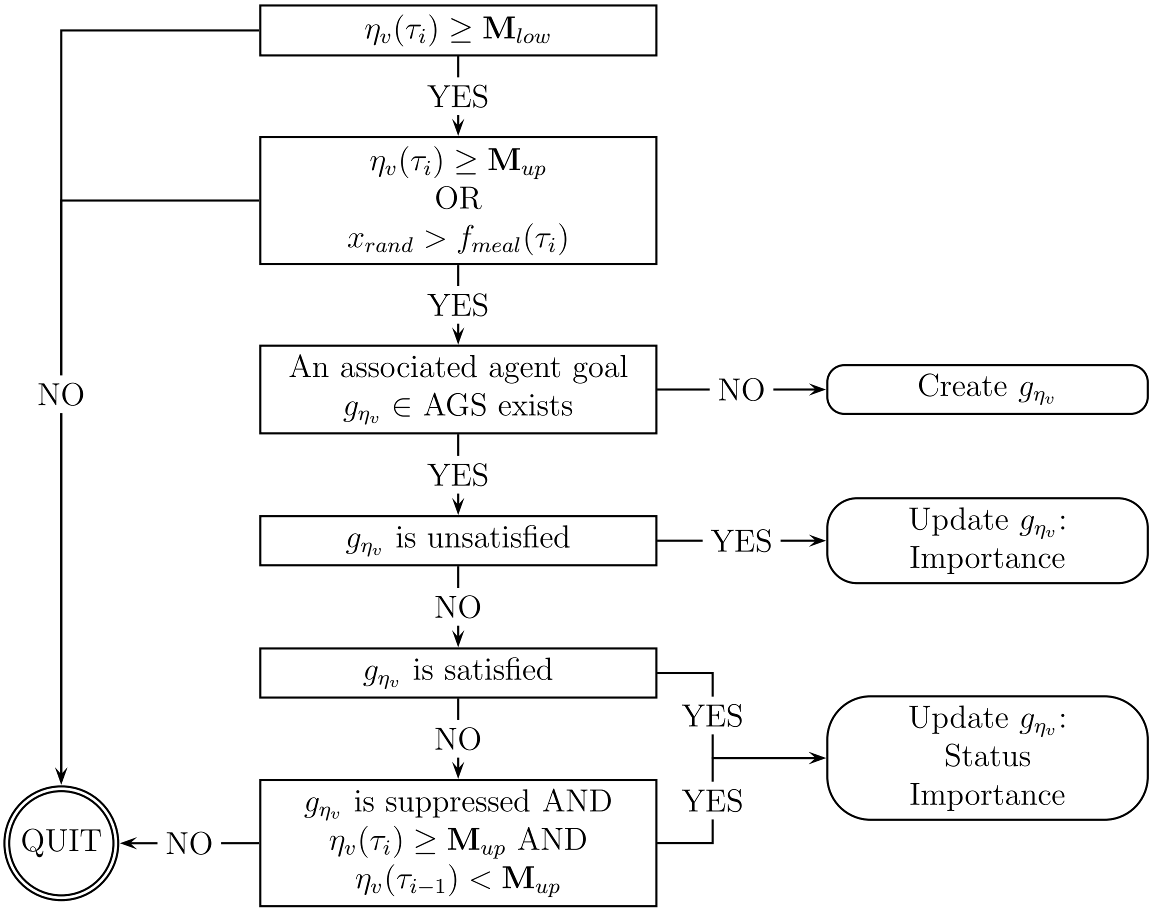


Figure 5.9.: Assessment of whether to update the Agent Goal Set, depending on the strength of the hunger motivation η and the meal times probability function f_{meal}, where x_{rand} is a random number distributed according to $\mathcal{U}[0,1]$.

5.6.2. Emotions: Reactions to External Stimuli

Emotion parameters are the agent's internal interpretation of environmental circumstances. Therefore, each emotion is represented as a function ϵ of the corresponding vector of environmental variables $E \in \mathbb{R}^n$ with $n \in \mathbb{N}$:

$$\epsilon : \mathbb{R}^n \to [0, 1] \qquad \epsilon : E \mapsto \epsilon(E)$$

An emotion parameter influences a given set of the agent's intrinsic physical, social or psychological attributes. This set is denoted as $\mathfrak{A}(\epsilon)$. The dependency on ϵ of each of the agent's attributes in question $a(\epsilon) \in \mathfrak{A}(\epsilon)$ depends on the emotion variable to be modelled. For instance, the buildingEXODUS's urgency model (see Section 4.3.1) replicates the emotional response to perceived time pressure, therefore

$$\epsilon \equiv U, \qquad U(T_a, \rho) \in \{0, 1\}, \qquad \mathfrak{A}(U) = \{D(U), P(U), v(U)\}$$

The agent responds to environmental conditions by two means: the agent's interpretation $\epsilon(E)$ of the environmental variables E is updated which affects the agent's physical, social or psychological behaviour. In addition, the environmental variable is classified into different categories, referred to as *events*, dependent on the agent's current situation. Events are discrete evaluations of the situation depicted by the environmental variable. Similarly to the influenced agent attributes $\mathfrak{A}(\epsilon)$, the type and number of events that the environmental variable E can be categorised into depends strongly on the emotion variable implemented.

The categorisation of the environmental variable into events is achieved by employing the agent's Short Time Span Adaptive Decision Making model. Consequently, for each environmental variable to be classified, the agent needs to specify their reference background regarding the environmental clue and their means of comparison of the two as described in Section 5.4.2.

Once the environmental variable has been classified into an event, the agent can respond to this emergent event by any of the following means:

- adjustment of their plans, i.e. their Agent Task List
- suppression of some of their agent goals on their Agent Goal Set, if tasks from the Agent Task List have been dismissed

In the literature survey of current pedestrian behaviour simulation models in Section 2.4, various external stimuli have been identified that are implemented in current pedestrian behaviour simulation models. As can be seen in the summary Table 2.7, the most implemented reaction to procedural processes is the reaction to time pressure. In addition, the most implemented reaction to external stimuli apart from the capability of perceiving structural information is the capability of perceiving and reacting to congestion. For this reason, the reaction to these two external stimuli has been integrated in this thesis' CPAF.

5.6.2.1. Monitoring Population Density

In complex multi-purpose environments, the individual pedestrian subconsciously monitors the surrounding population density. If at a certain point the individual judges the density to be high enough to have possible delaying effects for themselves, the pedestrian is forced to reevaluate their time planning.

The extend and accuracy to which the pedestrian monitors the surrounding population density thereby depends on the pedestrian's current situation. If they are currently travelling from one location in the environment to the next location, but are still relatively far away from their next target, the pedestrian perceives the general population density situation in the environment. However, if the pedestrian is close to their next targeted location, they will focus on those pedestrians which are also moving towards or moving from the pedestrian's assigned targeted location.

To represent these two different ways of population density evaluation, an individual agent parameter has been introduced, the *Perceived Crowd* parameter C. The way the Perceived Crowd at simulation time τ is being assessed, i.e. globally vs. locally, is dependent in the distance from the agent's current position $x_{current} \in \mathbb{E}$ to their next targeted goal location l:

$$C\colon\ \mathbb{R}_0^+ \to [0,1], \qquad C(\tau) := \begin{cases} \rho_{local}(\tau) & \text{if } \partial(x_{current}, \lambda(l)) < \overline{\partial}(\tau) \\ \rho_{global}(\tau) & \text{else} \end{cases} \tag{5.13}$$

Hereby is $\overline{\partial}(\tau) \in \mathbb{R}$ the distance which can be travelled at the current walking speed $v(\tau)$ in half the time between two updates of the population density functions Δ^{C}:

$$\overline{\partial}(\tau) := \frac{1}{2} \cdot v(\tau) \cdot \Delta^{\mathrm{C}}$$

It is postulated, that pedestrians don't continuously monitor the population density situation around them. Instead it is postulated that they will assess the surrounding population density from time to time. Consequently, the agents in the CPAF update their perceived crowd parameter in constant time intervals Δ^{C}. In the buildingEXODUS CPAF Plug-in, the Perceived Crowd update time intervals Δ^{C} can be set by the user.

Since the global population density function ρ_{global} is intended to represent a rough estimate on the overall situation within the modelled environment, ρ_{global} is defined as

$$\rho_{global}(\tau) := \frac{(\#\text{agents in the modelled environment})(\tau)}{\mid \mathbb{E} \mid} \tag{5.14}$$

On the other hand, the local population density function ρ_{local} is intended to represent the situation in the vicinity of the next targeted location. The interpretation of vicinity therefore depends on the type of the targeted goal location.

For example in the buildingEXODUS CPAF Plug-in: If the goal location is represented by a single node in buildingEXODUS , the relevant vicinity will be directly around the node. Conversely, if the goal location is represented by a compartment zone in buildingEXODUS, the relevant vicinity is the area in front of the entry to the goal location. In addition, the perceived local population density also depends on the distance of the individual agent from the targeted node respectively the entry to the compartment zone: For the perceiving agent, only those of the other agents are relevant, which are closer to the targeted goal location than the agent themselves.

In the case that the goal location l is represented by a single node in buildingEXODUS, let

$$\delta_n := \min\left\{\overline{\partial}(\tau), \partial(x_{current}, \lambda(l))\right\}$$

denote the minimum of the distance threshold $\overline{\partial}(\tau)$ and the agent's current distance from the targeted goal location node $\lambda(l)$. Furthermore, let $\mathfrak{C}_{\delta_n}(l) \subset \mathbb{E}$ denote the circle encompassing all permissible environmental locations that are within a radius of δ_n around the goal location l:

$$\mathfrak{C}_{\delta_n}(l) := \{x \in \mathbb{E} \mid \partial(x, \lambda(l)) \leq \delta_n\}$$

On the other hand, for a goal location l which is represented by a compartment zone in buildingEXODUS and therefore has got an entrance spatial location $x_{entrance}(l) \in \mathbb{E}$, let

$$\delta_c := \min\left\{\overline{\partial}(\tau), \partial(x_{current}, x_{entrance}(l))\right\}$$

denote the minimum of the distance threshold $\overline{\partial}(\tau)$ and the agent's current distance from the goal location's entrance $x_{entrance}(l)$. Let further $\mathfrak{S}_{\delta_c}(\tilde{x}, l)$ denote the semi-circle with centre $x_{entrance}(l)$ and radius δ_c in direction $\tilde{x} \in \mathbb{E}$:

$$\mathfrak{S}_{\delta_c}(\tilde{x}, l) := \{x \in \mathbb{E} \mid \partial(x, x_{entrance}(l) \leq \delta_c \;\text{ and }\; \partial(x, \tilde{x}) \leq \partial(\tilde{x}, x_{entrance}(l))\}$$

With these notations, the local population density function ρ_{local} is defined as follows in the buildingEXODUS CPAF Plug-in:

$$\rho_{local}(\tau) := \begin{cases} \dfrac{(\#\text{agents in } \mathfrak{C}_{\delta_n}(l))(\tau)}{|\mathfrak{C}_{\delta_n}(l)|} & \text{if } \Lambda(l) = \{\lambda(l)\} \\[2ex] \dfrac{(\#\text{agents in } \mathfrak{S}_{\delta_c}(x_{current}, l))(\tau)}{|\mathfrak{S}_{\delta_c}(x_{current}, l)|} & \text{if } |\Lambda(l)| > 1 \end{cases} \tag{5.15}$$

When the agent assesses the surrounding population density by updating their perceived crowd parameter C (see Equation (5.13)), they also need to decide whether the surrounding population density is considered to have a possible delaying impact on their task planning. The agent therefore needs to decide whether they should reconsider their current plans and therefore trigger an assessment of their Urgency parameter, see Section 5.6.2.2.

It is postulated, that such a decision is rather made subconsciously and reactively, and therefore the CPAF's Short Time Span Adaptive Decision Making model is used to model this decision situation. The agent needs to choose, whether the population density might have an impact on their task planning. However, it is postulated that not the current population density is a reasonable trigger for an Urgency assessment, but rather the change in the population density from the last time the Perceived Crowd parameter has been updated to the current situation is significant information:

$$(\Delta C)(\tau) := C(\tau) - C(\tau_i - \Delta^{\mathrm{C}}) \in [-1, 1]$$

Each individual pedestrian has got their own threshold at which they consider the change in population density to be remarkable. Therefore, each agent has been assigned an individual perceived crowd threshold $C^* \in [0, 1]$ based in a uniform random distribution on a perceived crowd threshold interval which has been specified by the user (see Appendix Chapter B).

To sum up, the choice problem can be stated as in Problem 5.1.

Problem 5.1: Perceived Crowd

The objective of the Perceived Crowd (PC) Problem is to decide whether the change in the perceived population density is significant as in to potentially delay the assigned plans.

This choice problem is a very simple one-dimensional choice problem and can be modelled by a Short Time Span Adaptive Decision Making model with parameter set

$$\begin{aligned}
\gimel^{\mathrm{PC}} &= \{\text{trigger Urgency assessment at time } \tau\} \\
\alpha^{\mathrm{PC}} &\colon \gimel \to [-1, 1], \quad \alpha^{\mathrm{PC}}(\text{trigger Urgency assessment at time } \tau) = (\Delta C)(\tau) \\
r &= C^* \\
\mathcal{C} &= \{>\} \\
\zeta^{\mathrm{PC}} &= \zeta_{rand}
\end{aligned}$$

The Short Time Span Adaptive Decision Making model therefore checks, whether the perceived crowd parameter at simulation time τ surpasses the former perceived crowd parameter at simulation time $\tau - \Delta^{\mathrm{C}}$ by at least the amount of the perceived crowd threshold. If this is the case, the agent decides to assess their Urgency situation at the time τ.

Assessment of Local Situation within a Goal Location

In addition to monitoring the population density in the environment, the agent also assesses the situation within their targeted goal location once they have entered it. When assessing the population density within a goal location, the agent assesses the number of other agents also occupying the given goal location with respect to the goal location's capacity. The goal location's capacity is either given for the entire goal location or – if the goal location comprises departments – by the departments' capacities.

Let denote $\rho_{\text{GL}}(l)$ denote the population density within the goal location l:

$$\rho_{\text{GL}}(l) := \frac{(\#\text{people in } \Lambda(l))}{\kappa(l)}$$

Therefore, when entering a goal location l, the agent determines at first whether the goal location comprises any departments as depicted in Table 5.3. If the goal location doesn't comprise any departments, the goal location's capacity $\kappa(l)$ is uniformly set to be 2 pedestrians per square metre of the goal location's area.

On the other hand, if the goal location comprises departments, the departments are given by an ordered list $\mathcal{D}(l) = (l_1^d, \ldots, l_n^d)$. For example for a shop goal location that is modelled with several departments, a natural realisation would be that the goal location would comprise two departments where the first one l_1^d is the selection department and the second one l_2^d is the queuing department. With this set-up, the agent would first choose a product in the selection department and then queue in order to pay for the desired product in the queuing department, see also Section 5.2.

Let therefore without loss of generality denote $\mathcal{D}(l) = (l_1^d, \ldots, l_n^d)$ the sequence of modelled departments of the goal location l. In case that the goal location hasn't been modelled with comprised compartments, the sequence is defined to contain only the goal location itself as the first entry l_1^d: $\mathcal{D}(l) := (l)$.

When entering the goal location l, the agent assesses the contained departments in the order given by $\mathcal{D}(l)$ whether there is still enough capacity in the department l_i^d, i.e. whether $\rho_{\text{GL}}(l_i^d) < 0.95$. If this is not the case for the department l_i^d, the agent checks whether l_i^d is obligatory. If the department is obligatory, the agent will skip the entire task $t(l)$ related to the targeted goal location l and will continue with their next assigned task. However, if the department l_i^d is non-obligatory, the pedestrian decides to not visit this department and continues with the assessment of the local population density ρ_{GL} for the next departments.

The agent therefore changes their plans based on the population density situation within the targeted goal location.

5.6.2.2. Reactive Behaviour to Time Pressure: Urgency

The CPAF contains a feature for modelling the agent's reaction to time pressure, the Urgency parameter (Section 4.3.1). This feature is strongly motivated by the buildingEXODUS Urgency feature, see Section 4.3.1, but the CPAF's Urgency feature contains small enhancements: The Urgency parameter in the CPAF is a continuous function dependent on the perceived time pressure; the time pressure assessment is achieved by invoking a Short Time

Span Adaptive Decision Making instance; and the definition of the time thresholds, the estimated required times, has been enhanced.

Since the CPAF's Urgency Model is used in the same way as the buildingEXODUS's Urgency model, only the differences and newly introduced parameters in the CPAF's Urgency model are described in this section. For a detailed description of the general framework of the assessment of the impact of time pressure on the agent's behaviour, see Section 4.3.1.

In the buildingEXODUS CPAF Plug-in, a new walk speed has been introduced to be able to better model pedestrian circulation behaviour. As has been described in Section 4.1.2, buildingEXODUS on its own is able to model two walk speeds for agents, a "fast" walk speed and a "normal" walk speed. In addition, the CPAF also models a "dawdle" walk speed which is intended to represent the relaxed dawdling of pedestrians when having enough or even too much time before their next critical time task, see Table 5.12 for an overview.

Table 5.12.: Walk speeds in the Cognitive Pedestrian Agent Framework, based on walk speeds in buildingEXODUS.

Symbol	Description	% of v_f	Velocity v	available in
v_f	Fast walk speed	100%	1.5 $\frac{m}{s}$	buildingEXODUS
v_n	Normal walk speed	90%	1.35 $\frac{m}{s}$	buildingEXODUS
v_d	Dawdle walk speed	40%	0.6 $\frac{m}{s}$	CPAF

As has been described in Section 4.3.1 for the buildingEXODUS Urgency model, the CPAF agent's Urgency parameter is dependent on the amount of time T_a that the agent has got still available until his next critical time task $t_{\pi_{cr}} \in \mathrm{ATL}$

$$T_a = \tau_{wait}(t_{\pi_{cr}}) - \tau$$

and appropriated time estimates, the Estimated Required Times. In the CPAF's Urgency model, the Estimated Required Times are newly defined based on the newly introduced walk speed. In addition, the CPAF's advanced evaluation of the surrounding population density as represented by the agent's Perceived Crowd parameter C (see Section 5.6.2.1) has been incorporated into the time assessment instead of the simple population density estimator ρ used in the former Urgency model.

The CPAF Urgency model's Estimated Required Time thresholds T_v^{ERT} are defined as in Equations (5.16) for a given walk speed constant v:

$$T_v^{\text{ERT}} := (1 + C) \cdot (T_W(v) + T_{MD}) \tag{5.16a}$$

$$= (1 + C) \cdot \left(\frac{1}{v} \cdot \sum_{i=\pi_0}^{\pi_{cr}-1} \partial(l(t_i), l(t_{i+1})) + \sum_{t \in \mathfrak{T}_{delay}} T_{max}(t) \right) \tag{5.16b}$$

Hereby, $\mathfrak{T}_{delay}$ denotes the set of all remaining delay type tasks on the agent's Agent Task

List:

$$\mathfrak{T}_{delay} = \{t_i \in \text{ATL} \mid \pi_0 \leq i < \pi_{cr} \text{ and } t_i \text{ is of task type “delay”}\}$$

and $T_{max}(t)$ is the maximum possible delay that the agent can experience when performing the delay task t.

T_v^{ERT} therefore represents the estimated time that the pedestrian requires to complete their remaining tasks from the current task $t_{\pi_0} \in \text{ATL}$ to their next highest critical time task $t_{\pi_{cr}} \in \text{ATL}$ if they are travelling with constant walk speed v through an environment with population density C.

$T_W(v)$ is therefore the estimated time needed to walk the goal location route starting at $l(t_{\pi_0})$ via $l(t_{\pi_0+1}), \ldots, l(t_{\pi_{cr}-1})$ to $l(t_{\pi_{cr}})$ with constant walk speed v; and $T_M D$ is the maximum possible cumulative time that the pedestrian will spent being engaged in activities at the given goal locations. By linearly scaling the resulting cumulative time with the agent's Perceived Crowd parameter, the Estimated Required Time T_v^{ERT} incorporates an estimate of the extra delay time impinged by the presence of other agents.

Every time the agent assesses their time pressure situation with the CPAF's Urgency model, they categorise their time situation according to the following process (cf. also Figure 4.5)

- If $T_{v_d}^{\text{ERT}} \leq T_a$, the agent continues as normal.
- If $T_{v_n}^{\text{ERT}} \leq T_a < T_{v_d}^{\text{ERT}}$, the agent's Urgency parameter is linearly elevated according to Equation (5.17).
- If $T_{v_f}^{\text{ERT}} \leq T_a < T_{v_n}^{\text{ERT}}$, the agent seeks for possible compromise actions. If no compromise actions are possible, they drop their least important task t and the task's associated agent goals $\mathfrak{G}(t)$ are marked as suppressed on their Agent Goal Set.
- If $0 \leq T_a < T_{v_f}^{\text{ERT}}$, the agent drops all elective tasks until their next critical time task. The elective tasks' associated agent goals on the agent's Agent Goal Set are marked as suppressed.
- If $T_a < 0$, the agent drops their next critical time task $t_{\pi_{cr}}$.

When assessing their time situation with the CPAF's Urgency model, the agent therefore decides whether to change their behaviour and plans or not based on the experienced time pressure. If the agent decides, that they need to change their behaviour and plans, they can either decide to be more persistent in following their plans, to dismiss one or all of their elective tasks that they had planned to do before their next critical time task or if their next planned critical time task isn't tenable anymore. Consequently, the time assessment of the CPAF's Urgency model can be modelled as a Short Time Span Adaptive Decision Making instance with choice set

$$\beth^{\mathrm{U}} = \{\text{“become urgent”}, \text{“dismiss one elective task”}, \\ \text{“dismiss all elective tasks”}, \text{“not enough time”}\}$$

and Short Time Span Adaptive Decision Making parameters

$$\alpha^{\mathrm{U}} : \beth \to \mathbb{R}^+ \qquad r^{\mathrm{U}} = (T_a)$$
$$\mathcal{C}^{\mathrm{U}} = \{>\} \qquad \zeta^{\mathrm{U}} = \zeta_{max}$$

where

$$\alpha^{\mathrm{U}}(\text{“become urgent”}) := \mathbf{T}^{\mathrm{ERT}}_{v_d} \qquad \alpha^{\mathrm{U}}(\text{“dismiss one elective task”}) := \mathbf{T}^{\mathrm{ERT}}_{v_n}$$
$$\alpha^{\mathrm{U}}(\text{“dismiss all elective tasks”}) := \mathbf{T}^{\mathrm{ERT}}_{v_f} \qquad \alpha^{\mathrm{U}}(\text{“not enough time”}) := 0$$

In the case, that $\zeta^{\mathrm{U}}(\mathfrak{P}_{\beth^{\mathrm{U}},\Xi(\mathcal{C}^{\mathrm{U}},r^{\mathrm{U}})}) =$ “dismiss one elective task”, the agent tries first, whether a compromise action is possible, before they decide to dismiss their least important task. Hereby, the agent first determines the set of possible compromise tasks

$$\mathfrak{T}_c := \{t_i \in \mathrm{ATL} \mid \pi_0 \le i < \pi_{cr} \text{ and } \mathfrak{G}(t_i) \text{ contains compromise-qualified agent goals}\}$$

The agent then checks for each task $t \in \mathfrak{T}_c$, whether all its associated agent goals $\mathfrak{G}(t)$ can be accomplished at the goal location of any other task $t' \in \mathfrak{T}_c \setminus \{t\}$. If this is the case, the task t is dismissed and its agent goals are associated with the task t': $\mathfrak{G}(t') \to \mathfrak{G}(t') \cup \mathfrak{G}(t)$. If not such two tasks exist in $\mathfrak{T}_c$, the agent seeks for alternative goal locations. Therefore, for each two tasks $t, t' \in \mathfrak{T}_c$, the agent refers to their Spatial Memory Set, whether they know any goal location $l \in \mathrm{SMS}$, such that $\mathfrak{G}(\{t, t'\}) \subseteq \mathfrak{G}(l)$. If such two tasks and a corresponding goal location can be found, the agent dismisses the tasks t and t' and creates a new task t_c with associated agent goal set $\mathfrak{G}(t_c) = \mathfrak{G}(\{t, t'\})$ and assigned goal location l. The newly created task t_c is then inserted at the distance-optimal position $\pi_0 \le \pi^* < \pi_{cr}$. Only if the agent couldn't find a compromise task during either of the two steps does the agent dismiss their least important elective remaining task.

While assessing the time situation with the CPAF's Urgency model, the agent adapts their Urgency parameter to the current time pressure situation, see Equation (5.17):

$$U(T_a) = \begin{cases} 0 & \text{if } \mathbf{T}^{\mathrm{ERT}}_{v_d} < T_a \\ \dfrac{T_a - \mathbf{T}^{\mathrm{ERT}}_{v_d}}{\mathbf{T}^{\mathrm{ERT}}_{v_n} - \mathbf{T}^{\mathrm{ERT}}_{v_d}} & \text{if } \mathbf{T}^{\mathrm{ERT}}_{v_n} \le T_a \le \mathbf{T}^{\mathrm{ERT}}_{v_d} \\ 1 & \text{if } T_a < \mathbf{T}^{\mathrm{ERT}}_{v_n} \end{cases} \tag{5.17}$$

The agent's Urgency parameter in the CPAF's Urgency model is therefore constant 0 for the non-urgent behaviour case, then increases linearly with decreasing T_a in the case that the agent decides to become urgent, and finally the Urgency parameter is constant to 1 for the remaining behaviour cases.

As for the buildingEXODUS Urgency model, the time pressure situation in the CPAF's Urgency model is assessed in dynamic time intervals which depend on the previously determined Estimated Required Times

$$\Delta^{\mathrm{U}}\tau = \begin{cases} \max\{\Delta^{\mathrm{U}}_{min}, \mathbf{T}^{\mathrm{ERT}}_{v_d} - \mathbf{T}^{\mathrm{ERT}}_{v_f}\} & \text{if } \mathbf{T}^{\mathrm{ERT}}_{v_d} \leq T_a \\ \max\{\Delta^{\mathrm{U}}_{min}, \mathbf{T}^{\mathrm{ERT}}_{v_d} - \mathbf{T}^{\mathrm{ERT}}_{v_n}\} & \text{if } T_a < \mathbf{T}^{\mathrm{ERT}}_{v_d} \end{cases}$$

Hereby, the CPAF's Urgency model uses a minimum time interval $\Delta^{\mathrm{U}}_{min}$ after which the agent will reassess their Urgency. This minimal time interval prevents the agent to reassess their time pressure situation in unnecessary short time intervals. In the buildingEXODUS CPAF Plug-in, $\Delta^{\mathrm{U}}_{min}$ can be set by the user.

However, if the agent has chosen to adjust their Agent Task List during their time assessment, i.e. if $\zeta^{\mathrm{U}}(\mathfrak{P}_{\beth^{\mathrm{U}},\Xi(\mathcal{C}^{\mathrm{U}},r^{\mathrm{U}})})$ is either "dismiss one elective task", "dismiss all elective tasks" or "not enough time", the Urgency is immediately assessed again in the current time step:

$$\zeta^{\mathrm{U}} \in \{\text{“dismiss one elective task”}, \text{“dismiss all elective tasks”}, \text{“not enough time”}\} \\ \implies \Delta^{\mathrm{U}}\tau = 0$$

When simulating pedestrian circulation behaviour within complex multi-purpose environments with the CPAF, the time pressure situation is not only assessed in regular time intervals, but can in addition be triggered by specific events or specific actions of the agent. Therefore, the time interval after which the agent's time pressure situation is reassessed using the CPAF's Urgency model is set to one time step $\Delta^{\mathrm{U}}\tau = \mathbf{T}^{\mathrm{TimeStep}}$ after the following situations:

- after the agent has completed one of their tasks
- when the agent has added tasks to their Agent Task List in the following situations:
  - during their motivations assessment (Section 5.6.1),
  - when having perceived a relevant spatial location (Section 6.4.1),
  - or during their Unsatisfied Desired Goal Behaviour (Section 6.4.2).
- if the time pressure assessment is triggered by the assessment of the surrounding population density (Section 5.6.2.1)

When dismissing any task during the time assessment with the CPAF's Urgency model, the agent marks all associated agent goals on their Agent Goal Set as suppressed. As has been described in Section 5.3.2, if an agent goal on the agent's Agent Goal Set is suppressed, the agent will not attempt any further actions to accomplish this goal during their sojourn in the modelled environment.

In the same way as the buildingEXODUS's Urgency model, the dependent agent parameters in the buildingEXODUS CPAF Plug-in are updated after the agent has assessed their level of Urgency with the CPAF's Urgency model. In the buildingEXODUS CPAF Plug-in, the dependent parameters are the agent's drive attribute D, patience attribute P and walk speed attribute v, see Equations (5.18):

$$P(\tau) = P_0 \cdot (2 - U(\tau)) \tag{4.1a}$$

$$D(\tau) = D_0 \cdot (0.5 + 0.5 \cdot U(\tau)) \tag{4.1b}$$

$$v(\tau) = \begin{cases} (v_n - v_d) \cdot 2 \cdot U(\tau) + v_d & \text{if } U(\tau) < 0.5 \\ (v_f - v_n) \cdot 2 \cdot (U(\tau) - 0.5) + v_n & \text{if } 0.5 \leq U(\tau) \end{cases} \tag{5.18a}$$

The dependency of the agent's drive and patience attributes are adopted from the buildingEXODUS's Urgency model, see Equations (4.1) in Section 4.3.1. However, the dependency of the agent's walk speed $v(\tau)$ has been adjusted in the buildingEXODUS CPAF Plug-in to incorporate the additional "dawdle" walk speed v_d.

5.7. Summary

This chapter has outlined the core components of the proposed Cognitive Pedestrian Agent Framework (CPAF) for the modelling of goal-directed and advanced cognitive pedestrian behaviours with a pedestrian behaviour simulation model in a model of a complex multi-purpose environment. This chapter thereby addresses Research Objective 3 in which the development of a comprehensive model for simulating purpose-related, deliberate and contextual pedestrian behaviour has been suggested. In the current pedestrian behaviour simulation models (see Chapter 2), a similar holistic and comprehensive framework could not be found. The proposed CPAF follows the concept of a cognitive architecture (see Section 3.1). All components of a cognitive architecture identified during the survey of well known cognitive architectures and depicted in Figure 3.4 are represented in the CPAF, see Figure 5.1.

In Section 5.2, the introduction of the notion of goals and goal-directed behaviour into a pedestrian behaviour simulation model has been described, therefore addressing Research Question 1. The CPAF comprises an additional layer of goal-related information both within the environment and agent model. The CPAF agent is hence capable to exhibit goal-driven behaviour by planning their sojourn in the modelled environment according to their goals.

In order to model cognitive processes, a reference background is needed for the agent. The CPAF therefore comprises an attitude and knowledge representation, which has been described in Section 5.3. The attitudes and knowledge represented in the CPAF are tailored to the task of simulating pedestrian behaviour in complex multi-purpose environments. The CPAF agents are able to compare different target locations in the environment based on their individual preferences and to store this relevant information about target locations in their knowledge component. Based on this information, the CPAF agent is capable of making informed and individual decisions with regard to which target locations they want to visit and which route they want to take.

A sophisticated decision making model has been proposed and described in Section 5.4. The CPAF's decision making model is based on theories in human decision making research, see Section 3.2.1. Together with the CPAF's knowledge component, the CPAF's decision making model therefore proposes a model to simulate purpose-related and individual pedestrian decision making, thereby addressing Research Question 2. A similar generic and sophisticated human decision making model that is based on human behaviour research has not been found in current pedestrian behaviour simulation models, see Section 2.5.

Finally, the CPAF comprises a stimuli representation (see Section 5.6) which models both the pedestrian's response to external stimuli and thereby improving their situational awareness model as well as the pedestrian's response to internally motivated stimuli. In addition, the CPAF's stimuli representation employs the CPAF's decision making entities in order to adjust their behaviour in response to the perceived stimuli, if necessary, thereby addressing Research Question 4. The CPAF's stimuli representation is based on inspirations from emotion modelling and motivational action selection models.

The CPAF is a generic framework for modelling pedestrian behaviour in complex multi-purpose environments. It has been designed to be applicable in various types of situations and therefore to be customisable to the actual use case to be studied. The CPAF thereby allows for great flexibility in specifying the environment model (goals, facilities, facility characteristics, ...) and the agent model (personal preferences, modelled motivations). Table 5.13 gives an overview of which input is required from the user to inform the components of the CPAF.

Table 5.13.: An overview of the parameters which are required to constitute the components of the Cognitive Pedestrian Agent Framework.

CPAF Component	Entity	Required Input
Environment	Goals	Global Goal Set
Environment	Goal Locations	Goal Location Set
Environment	Goal Locations	Departments
Environment	Goal Locations	Goal Location Feature Parameters F
Agent Model	Attributes	Personal Preferences P
Agent Model	Motivations	Motivations and Motivation Functions

Chapter 6:

Modelling the Pedestrian Usage-Cycle using the Cognitive Pedestrian Agent Framework

One of the main applications of the Cognitive Pedestrian Agent Framework (CPAF) as proposed in Chapter 5 is the modelling of the entire pedestrian usage-cycle in complex multi-purpose environments. The benefits of modelling the entire usage-cycle have been outlined (amongst others) by Gwynne and Kuligowski [9] in their ICE concept.

With the CPAF, the agent is capable of pursuing goal-driven behaviours, making individual plans based on their individual level of knowledge, and react to changes in the surrounding environment. These features can be used to instruct and conduct a pedestrian usage-cycle simulation of a modelled complex multi-purpose environment with a pedestrian behaviour simulation tool.

The pedestrian usage-cycle is realised with the CPAF in four stages:

Initialisation Stage: The geometry in question is analysed and the global goals and procedural processes are defined. The agent population is thereafter created including the assignment of their agent goals, personal preference attributes and previous spatial knowledge, see Section 6.2.

Ingress Phase: The individual agent's initial itinerary is set according to their assigned Agent Goal Set, Spatial Memory Set and personal preferences, see Section 6.3.

Circulation Phase: Each agent pursues their itinerary, assembles further information about the environment by visual perception and monitors internal and external events. If an emergent event occurs, the agent then decides to maintain, add or drop plans from their working memory applying their adaptive human decision making model. If an agent needs to seek further information to be able to accomplish a decision making task, they can retrieve additional information. The actual pedestrian circulation behaviour features of the CPAF which employs the CPAF's core components are described in Section 6.4.

Egress Phase: During a normal pedestrian circulation scenario, the agent finishes their planned itinerary and exits by their initially planned exit location, see Section 6.5. However, if during the circulation phase an alarm has been launched, the CPAF can be used to inform an appropriate alarm response behaviour which makes use of the agent's assembled knowledge and decision entities in order to initiate the agent's evacuation behaviour, see Chapter 7.

In addition to the four simulation stages of the pedestrian usage-cycle, this chapter also gives an overview of typical decision situations that the agents can encounter during their sojourn in the simulated environment. Section 6.1 lists these generic choice problems and describes the way these decision situations are resolved using the CPAF's intrinsic decision making component.

6.1. Generic Choice Problems

When modelling the pedestrian usage-cycle in complex multi-purpose environments with the CPAF, the agents will frequently have to solve decision situations using their modelled decision making component (Section 5.4). Some of these choice problems are generic and will be encountered in several different decision situations. In this section, the most common generic choice problems when simulating pedestrian circulation behaviour with the CPAF are stated and the way that the agent decision making component (Section 5.4) solves these generic choice problems is illustrated.

In the specific decision situations that the agent encounters during their travel in the modelled complex multi-purpose environment, the agent will hence often refer back to these generic choice problems in order to resolve the given specific decision situation. They will thereby use either their intrinsic Planned Decision Making entity, if an optimal goal location is sought, or their intrinsic Short Time Span Adaptive Decision Making entity, if the decision needs to be made in a very short time.

6.1.1. Goal Location Choice

A typical choice problem that the agents encounter during a circulation scenario in a modelled complex multi-purpose environment is that the agent has to choose between several different goal locations. This is the case for example when planning their route in the environment (Section 6.3 and Section 6.4.2), when visually perceiving a goal location that is related to their current plans (Section 6.4.1) or when any of their motivations give rise to a new goal (Section 5.6.1).

6.1.1.1. Preference-Optimal Goal Location Choice Problem

In certain specific decision situations, the agent will have to choose an optimal goal location for the given decision situation from a set of goal locations $\mathfrak{L}$, which is a subset of the environment's Goal Location Set: $\mathfrak{L} \subseteq \text{GLS}$. The optimality of a goal location thereby depends on the specific decision situation, and will be given by stating an attribute function $\alpha : \mathfrak{L} \to \mathbb{R}^m$ on the given choice set of goal locations and a corresponding set of decision preferences $p \in \mathbb{R}^m$, where the i-th component of the attribute function relates to the i-th decision preference attribute:

$$\alpha_i(l) \rightleftarrows p_i \qquad 1 \leq i \leq m$$

Such a decision situation can be modelled as a *Preference-Optimal Goal Location Choice Problem*, see Problem 6.1. Examples for a Preference-Optimal Goal Location Choice Problem in a pedestrian behaviour simulation are given in Examples 6.1 and 6.2.

Problem 6.1: Preference-Optimal Goal Location Choice Problem

Let $\mathfrak{L}$ be a given set of goal locations with attribute function $\alpha : \mathfrak{L} \to \mathbb{R}^m$ and let $p \in \mathbb{R}^m$ be a given set of decision preference attributes which corresponds to α.

The objective of the Preference-Optimal Goal Location Choice Problem is then to choose a goal location $l^* \in \mathfrak{L}$ which goal location attributes $\alpha(l^*)$ closest match the given set of preference attributes p.

Example 6.1: Preference-Optimal Shop Choice

An agent has the active need to shop for a product. In the modelled environment, the agent is aware of three shops, where they can purchase their desired product. The agent therefore chooses the shop which best matches their personal preferences.

The set of goal locations $\mathfrak{L}$ is therefore the set of the three known shops where the desired product can be purchased. The attribute function α for each shop is therefore the shop goal location's feature parameters $\alpha_i(l) := F_i(l)$ for $1 \leq 1 \leq 3$ with $F_1(l)$ representing the shop's price category, $F_2(l)$ representing the shop's brand category and $F_3(l)$ representing the shop's size category. These correspond to the agent's personal preference attributes P_1, P_2, P_3 which form the decision preference attributes p of the Preference-Optimal Goal Location Choice Problem.

Example 6.2: Distance-Optimal Exit Choice

When an alarm event occurs, the agent needs to choose the exit from their list of known exits which is as closest as possible.

The set of goal location $\mathfrak{L}$ is therefore the set of exits which are known to the agent. The attribute function $\alpha : \mathfrak{L} \to \mathbb{R}$ maps each known exit to the distance between the agent's current position and the exit and the one-dimensional decision preference attribute $p \in \mathbb{R}$ is simply $p = 0$ for representing the agent's desire to minimise the distance to the chosen exit.

Since the Preference-Optimal Goal Location Choice Problem is an optimisation problem, the Preference-Optimal Goal Location Choice Problem 6.1 is solved by employing an instance of the agent's Planned Decision Making entity. Therefore, the Planned Decision Making model's choice set, and its attribute function, objective function and scalarisation function need to be chosen for this choice problem.

The Planned Decision Making model's choice set and attribute function are the choice set and attribute function of the given Preference-Optimal Goal Location Choice Problem, $\mathfrak{L}$ and α. Since the objective of the given choice problem is to match the given decision preferences as closely as possible, a goal programming approach is valid. Therefore, the Planned Decision Making model's objective function is chosen as the function

$$h_p : \mathbb{R}^m \to \mathbb{R}^m, \qquad h_p(x) := x - p \tag{6.1}$$

for the decision preference attributes p of the given choice problem. Furthermore, the scalarisation function is chosen to determine the Euclidean distance: $z = \|.\|_2$.

By choosing these parameters for the Planned Decision Making model of the Preference-Optimal Goal Location Choice Problem, the choice alternatives are compared based on the cumulative deviation of their chosen attributes from the given decision preferences. In summary:

Model 6.1: Preference-Optimal Goal Location Choice Problem

The preference-optimal goal location $l^* \in \mathfrak{L}$ of the Preference-Optimal Goal Location Choice Problem 6.1 is determined by solving the Planned Decision Making model with the parameter set $(\mathfrak{L}, \alpha, h_p, \|.\|_2)$.

6.1.1.2. Preference-Optimal Goal Location Set Choice Problem

In certain specific decision situations, the agent might not want to choose a single goal location from a set $\mathfrak{L} \subseteq \text{GLS}$ of goal locations, but the agent might want to determine the complete set of preference-optimal goal locations $\mathfrak{L}^* \subseteq \mathfrak{L}$ for an assigned attribute function $\alpha : \mathfrak{L} \to \mathbb{R}^m$ and given corresponding decision preference attributes $p \in \mathbb{R}^m$. Such a decision situation can be modelled as a *Preference-Optimal Goal Location Set Choice Problem*, see Problem 6.2 for the problem definition and Example 6.3 for an example.

Problem 6.2: Preference-Optimal Goal Location Set Choice Problem

Let $\mathfrak{L}$ be a given set of goal locations with attribute function $\alpha : \mathfrak{L} \to \mathbb{R}^m$ and let $p \in \mathbb{R}^m$ be a given set of decision preference attributes which corresponds with α.

The objective of the Preference-Optimal Goal Location Set Choice Problem (PO-GLS-CP) is then to determine the subset $\mathfrak{L}^*$ of goal locations from the choice set $\mathfrak{L}$ which elements' goal location features closest match the set of preference attributes p.

Example 6.3: Preference-Optimal Goal Location Set Choice Problem

The agent evaluates the restaurants in a modelled environment. They are interested in all those restaurants which best match their personal preferences.

In this example, $\mathfrak{L}$ denotes the set of all restaurant goal locations in the modelled environment, $\alpha : \mathfrak{L} \to \mathbb{R}^3$ represents the restaurant goal locations feature attribute parameters $\alpha_i(l) := F_i(l)$ and the decision preferences $p \in \mathbb{R}^3$ are the agent's personal preference attributes $p_i \equiv P_i$.

Since the set of all optimal choice alternatives is sought, the Preference-Optimal Goal Location Set Choice Problem 6.2 can be modelled as a Multi-Criteria Optimisation Problem. The Multi-Criteria Optimisation Problem's choice set is the problem's choice set $\mathfrak{L}$ and as for the Preference-Optimal Goal Location Choice Problem, the Multi-Criteria Optimisation Problem's objective function f is chosen to be $f = h_p \circ \alpha$ for the Preference-Optimal Goal Location Set Choice Problem's attribute function α and the goal programming function h_p as defined in Equation (6.1). Also, the Multi-Criteria Optimisation Problem's scalarisation function is chosen to be the Euclidean distance $z^{\text{PO-GLS-CP}} := \|.\|_2$.

In summary, the Preference-Optimal Goal Location Set Choice Problem 6.2 is solved by Model 6.2:

Model 6.2: Preference-Optimal Goal Location Set Choice Problem

The set of preference-optimal goal locations $\mathfrak{L}^* \subseteq \mathfrak{L}$ of the Preference-Optimal Goal Location Set Choice Problem 6.2 is determined by solving the Multi-Criteria Optimisation Problem with the parameter $(\mathfrak{L}, h_p \circ \alpha, \|.\|_2)$.

6.1.1.3. Minimal Goal Location Set Choice Problem

In certain specific decision situations, the agent might have a set of agent goals which they want to accomplish and they have already determined for each agent goal g_i a set of suitable goal locations $\mathfrak{L}_i$ for $1 \leq i \leq n$. The agent therefore needs to choose from each of these goal location sets $\mathfrak{L}_i$ one goal location, at which they can accomplish the given agent goal g_i.

According to Remark 5.3 about compromise-qualified goals, it is possible that these goal location sets aren't disjoint and therefore one goal location can be a member of two or more of the sets $\mathfrak{L}_i$. Since visiting one goal location instead of several goal locations is far more efficient, it is postulated that an agent will always prefer choosing one goal location to accomplish several goals over choosing different goal locations for each of the agent goals.

Therefore, the problem to choose a goal location from each set $\mathfrak{L}_i$, $1 \leq i \leq n$, can be modelled as a *Minimal Goal Location Set Choice Problem (MGLS-CP)*, see Problem 6.3 and Example 6.4 for an example.

Problem 6.3: Minimal Goal Location Set Choice Problem

Let $\mathfrak{L} = \prod_{i=1}^{n} \mathfrak{L}_i$ be a given product set of given sets of goal locations $\mathfrak{L}_i$.

The objective of the Minimal Goal Location Set Choice Problem (MGLS-CP) is to choose an optimal sequence $(l_1^*, \ldots, l_n^*) \in \mathfrak{L}$, $l_i^* \in \mathfrak{L}_i$, such that the corresponding set $\mathfrak{L}^* := \{l_1^*, \ldots, l_n^*\}$ is of minimal size.

Example 6.4: Minimal Goal Location Set Choice Problem

The agent has the needs to eat and to drink something. They have therefore evaluated their known goal locations and found that they know two eating goal locations, which they equally like, the coffee shop “Coffee2Go” and at the restaurant “Simple Food”. Likewise, the agent has found two drinking goal locations of equal appeal, the coffee shop “Coffee2Go” and at the bar “Drinks and more”. When the agent finally decides where they should go to eat and drink something, they will probably decide to visit “Coffee2Go”, since they can satisfy both their eat and their drink need at this goal location.

In the notation of Problem 6.3 the product set $\mathfrak{L}$ in this case would be

$$\mathfrak{L} = \{\text{“Coffee2Go”}, \text{ “Simple Food”}\} \times \{\text{“Coffee2Go”}, \text{ “Drinks and more”}\}$$

where the optimal sequence would be $(l_1^*, l_2^*) = (\text{“Coffee2Go”}, \text{“Coffee2Go”})$ respectively the optimal set being $\mathfrak{L}^* = \{\text{“Coffee2Go”}\}$.

For a Minimal Goal Location Set Choice Problem 6.3, the choice problem's choice criterion can be reformulated such that a sequence $(l_1^*, \ldots, l_n^*) \in \mathfrak{L}$ is optimal, if the number of goal locations l_i^* within the sequence that are contained in the maximum possible number of sets $\mathfrak{L}_i$ is maximal.

Using this reformulation, the Minimal Goal Location Set Choice Problem 6.3 is solved by a Planned Decision Making model with choice set $\mathfrak{L}$. The Planned Decision Making model's attribute function $\alpha^{\text{MGLS-CP}}$ is chosen as follows:

$$\alpha^{\text{MGLS-CP}} : \mathfrak{L} \to \mathbb{R}^n, \qquad \alpha_i^{\text{MGLS-CP}}(l_1, \ldots, l_n) := \sum_{j=1}^{n} \mathbb{1}_{\mathfrak{L}_j}(l_i)$$

Therefore, $\alpha^{\text{MGLS-CP}}$ counts for each l_i within the sequence $(l_1, \ldots, l_n) \in \mathfrak{L}$ in how many sets of goal locations $\mathfrak{L}_j$ it is contained.

Let the maximum possible number of goal location sets $\mathfrak{L}_i$ that a single goal location is contained in be denoted by

$$m^{\text{MGLS-CP}} := \max_{(l_1,\ldots,l_n)\in\mathfrak{L}} \max_{1\leq i\leq n} \alpha_i^{\text{MGLS-CP}}(l_1,\ldots,l_n)$$

The Planned Decision Making model's objective function $h^{\text{MGLS-CP}}$ is then defined as

$$h^{\text{MGLS-CP}} : \mathbb{R}^n \to \mathbb{R}^n, \qquad h_i^{\text{MGLS-CP}}(x) := \begin{cases} 0, \text{if } m^{\text{MGLS-CP}} = x_i \\ 1, \text{if } m^{\text{MGLS-CP}} > x_i \end{cases}$$

Hence, $h^{\text{MGLS-CP}}$ determines for each goal location l_i in the sequence $(l_1,\ldots,l_n) \in \mathfrak{L}$, whether it is contained in the maximum possible number of sets $\mathfrak{L}_i$ (iff $h_i^{\text{MGLS-CP}}(l_1,\ldots,l_n) = 0$) or not (iff $h_i^{\text{MGLS-CP}}(l_1,\ldots,l_n) = 1$). Since the objective of the Minimal Goal Location Set Choice Problem 6.3 is to choose a sequence which contains the maximum number of goal locations that are contained in the maximum possible number of given goal location sets, the sum of all $h_i^{\text{MGLS-CP}}(l_1,\ldots,l_n)$ needs to be minimal. Consequently, the Planned Decision Making model's scalarisation function is chosen to be $\|.\|_1$.

In brief, the Minimal Goal Location Set Choice Problem 6.3 is solved by Model 6.3:

Model 6.3: Minimal Goal Location Set Choice Problem

The optimal set of goal locations $\mathfrak{L}^* = \{l_1^*, \ldots l_n^*\}$ corresponding to an optimal sequence $(l_1^*,\ldots,l_n^*) \in \mathfrak{L}$ of the Minimal Goal Location Set Choice Problem 6.3 is determined by solving the Planned Decision Making model with parameter set $(\mathfrak{L}, \alpha^{\text{MGLS-CP}}, h^{\text{MGLS-CP}}, \|.\|_1)$.

6.1.1.4. Goal Set's Preference-Optimal Goal Location Set Choice Problem

In certain decision situations, the agent will want to achieve a subset of their assigned agent goals $\mathfrak{G} \subseteq$ AGS. Therefore, they will have to choose a set of goal locations $\mathfrak{L}^* \subseteq \mathfrak{L}$ from a given set of goal locations $\mathfrak{L}$, where the agent can satisfy all of their agent goals in $\mathfrak{G}$. In these decision situations, the agent will have certain decision preferences $p \in \mathbb{R}^m$, which the corresponding attributes $\alpha(l)$ of the chosen goal locations $l \in \mathfrak{L}^*$ should meet as closely as possible.

This choice problem can be formulated as the *Goal Set's Preference-Optimal Goal Location Set Choice Problem (GS-PO-GLS-CP)*, see Problem 6.4 and Example 6.5 for an example.

Problem 6.4: Goal Set's Preference-Optimal Goal Location Set Choice Problem

Let $\mathfrak{G}$ be a given set of agent goals of size $N := |\mathfrak{G}|$, $\mathfrak{L}$ a given set of goal locations with attribute function α and $p \in \mathbb{R}^m$ a given set of decision preference attributes.

The objective of the Goal Set's Preference-Optimal Goal Location Set Choice Problem (GS-PO-GLS-CP) is then to choose a smallest subset $\mathfrak{L}^* \subseteq \mathfrak{L}$ such that for all agent goals $g \in \mathfrak{G}$ there exists a goal location $l \in \mathfrak{L}^*$ such that g can be accomplished at the location l and l is preference-optimal with regard to p.

Example 6.5: Goal Set's Preference-Optimal Goal Location Set Choice Problem

The agent plans their stay in the modelled environment. They have a list of goals that they want to accomplish, e.g. $\mathfrak{G} = \{\text{“eat”}, \text{“drink”}, \text{“shop”}\}$. The agent then chooses a list of goal locations from their experience which best match their personal preference attributes P and such that the agent has to visit the minimal amount of different goal locations in order to satisfy their agent goals. In this example, the smallest subset of goal locations $\mathfrak{L}^*$ can either be of size 3 (one goal location for each goal) or of size two (since the “eat” and the “drink” goal are compromise-qualified).

The Goal Set's Preference-Optimal Goal Location Set Choice Problem 6.4 is solved in two steps:

1. For each agent goal $g \in \mathfrak{G}$ the set of all preference-optimal goal locations $\mathfrak{L}_g \subseteq \mathfrak{L}$ is determined.
2. From all possible combinations of goal locations from the preference-optimal known goal location sets $\mathfrak{L}_g$ a combination of minimal length is chosen.

In brief, the Goal Set's Preference-Optimal Goal Location Set Choice Problem 6.4 is solved by Model 6.4:

Model 6.4: Goal Set's Preference-Optimal Goal Location Set Choice Problem

The minimal subset of preference-optimal goal locations $\mathfrak{L}^* \subseteq \mathfrak{L}$ of the Goal Set's Preference-Optimal Goal Location Set Choice Problem 6.4 such that all agent goals in $\mathfrak{G}$ can be accomplished at goal locations in $\mathfrak{L}^*$ is determined by first obtaining for each agent goal $g \in \mathfrak{G}$ the set of all preference-optimal goal locations $\mathfrak{L}_g$ by solving the Preference-Optimal Goal Location Set Choice Problem Model 6.2 with the parameter set $(\mathfrak{L} \cap \mathfrak{L}(g), \alpha, p)$. Afterwards, $\mathfrak{L}^*$ is obtained by solving the Minimal Goal Location Set Choice Problem Model 6.3 with the parameter set

$$\left(\prod_{g \in \mathfrak{G}} \mathfrak{L}_g \right)$$

6.1.2. Spatial Route Choice Problem

After the agent has chosen a set of goal locations $\mathfrak{L}^*$ by either a Preference-Optimal Goal Location Set Choice Problem Model, a Minimal Goal Location Set Choice Problem Model or a Goal Set's Preference-Optimal Goal Location Set Choice Problem Model, the agent needs to choose an order in which they want to visit the chosen goal location set and thereby a route through the environment.

A route in the environment is a sequence of permissible spatial locations in the environment:

Definition 6.1: Spatial Route

Let $\mathfrak{X} \subseteq \mathbb{E}$ be a set of targeted locations of size $n \in \mathbb{N}$, $x_s \in \mathbb{E}$ a given start location and $x_e \in \mathbb{E}$ a given end location. A **spatial route** $\mathcal{R}$ of the triple $(x_s, x_e, \mathfrak{X})$ is a sequence

$$\mathcal{R}(x_s, x_e, \mathfrak{X}) \in \{x_s\} \times \mathfrak{X}^n \times \{x_e\} \subset \mathbb{E}^{n+2}$$

defined by

$$\mathcal{R}(x_s, x_e, \mathfrak{X}) = (x_1^{\mathcal{R}}, x_2^{\mathcal{R}}, \ldots, x_{n+1}^{\mathcal{R}}, x_{n+2}^{\mathcal{R}}) := (x_s, x_1, \ldots, x_n, x_e)$$

where $(x_1, \ldots, x_n) \in \mathfrak{S}(\mathfrak{X})$ is a sequence of the set of targeted locations.

The set of all routes for the triple $(x_s, x_e, \mathfrak{X})$ is called the triple's **spatial route set** $\mathfrak{R}(x_s, x_e, \mathfrak{X})$:

$$\mathfrak{R}(x_s, x_e, \mathfrak{X}) := \{\mathcal{R}(x_s, x_e, \mathfrak{X}) = (x_s, x_1, \ldots, x_n, x_e) \mid (x_1, \ldots, x_n) \in \mathfrak{S}(\mathfrak{X})\}$$

A spatial route $\mathcal{R}(x_s, x_e, \mathfrak{X})$ is characterised based on weights which are assigned to each edge (x, x') connecting any spatial locations $x, x' \in \mathbb{E}$ in the environment, $w(x, x') \in \mathbb{R}$. The weights can involve any set of attributes relating to the edge (x, x'), such as for example the pleasantness of taking this particular edge [41] or a utility function of advanced edge attributes [132]. For the course of this thesis however, the weight attribute has been chosen to be the walking distance between the two locations:

$$w(x, x') := \partial(x, x')$$

with the walking distance metric ∂ (see Equation 5.1).

In this thesis, a spatial route $\mathcal{R}(x_s, x_e, \mathfrak{X})$ is therefore characterised based on the walking distances of each of the routes edges $(x_i^{\mathcal{R}}, x_{i+1}^{\mathcal{R}})$:

Definition 6.2: Distance-Attribute Function

Let $\mathfrak{X} \subset \mathbb{E}$ be a given set of targeted locations of size $n := |\mathfrak{X}|$, $x_s \in \mathbb{E}$ be a given start location and $x_e \in \mathbb{E}$ be a given end location.

On the spatial route set $\mathfrak{R}(x_s, x_e, \mathfrak{X})$, let α_∂ be the function defined by

$$\alpha_\partial : \mathfrak{R}(x_s, x_e, \mathfrak{X}) \to \mathbb{R}^{n+1}, \qquad \alpha_\partial(\mathcal{R}(x_s, x_e, \mathfrak{X})) := \begin{pmatrix} \partial(x_1^{\mathcal{R}}, x_2^{\mathcal{R}}) \\ \vdots \\ \partial(x_{n+1}^{\mathcal{R}}, x_{n+2}^{\mathcal{R}}) \end{pmatrix} \tag{6.2}$$

α_∂ is called the spatial route's **distance-attribute function**.

Consequently, the *Distance-Optimal Spatial Route Choice Problem (DO-SR-CP)* is defined as in Problem 6.5:

Problem 6.5: Distance-Optimal Spatial Route Choice Problem

Let $\mathfrak{X} \subset \mathbb{E}$ be a given set of targeted locations of size $n := |\mathfrak{X}|$ and let x_s respectively x_e be given start respectively end locations.

The objective of the Distance-Optimal Spatial Route Choice Problem (DO-SR-CP) is to choose a distance-optimal spatial route $\mathcal{R}^*(x_s, x_e, \mathfrak{X})$ from the set of all spatial routes $\mathfrak{R}(x_s, x_e, \mathfrak{X})$. The spatial route $\mathcal{R}^*(x_s, x_e, \mathfrak{X})$ is hereby distance-optimal if it minimises the 1-Norm of the distance attribute function α_∂

$$\|\alpha_\partial(\mathcal{R}^*(x_s, x_e, \mathfrak{X}))\|_1 = \min_{\mathcal{R}(x_s,x_e,\mathfrak{X}) \in \mathfrak{R}(x_s,x_e,\mathfrak{X})} \|\alpha_\partial(\mathcal{R}(x_s, x_e, \mathfrak{X}))\|_1 \tag{6.3}$$

for all spatial routes $\mathcal{R}(x_s, x_e, \mathfrak{X})$ contained in $\mathfrak{R}(x_s, x_e, \mathfrak{X})$.

For solving the Distance-Optimal Spatial Route Choice Problem 6.5, the CPAF comprises two alternative decision making models. The first one solves the mathematical optimisation problem given by Equation (6.3) (see Section 6.1.2.1, Model 6.5). The second approach is inspired by human path planning research (see Section 6.1.2.2, Model 6.6).

6.1.2.1. Mathematical Optimisation

The Distance-Optimal Spatial Route Choice Problem 6.5 can be solved by using a Planned Decision Making instance. The Planned Decision Making model's choice set is therefore the route set $\mathfrak{R}(x_s, x_e, \mathfrak{X})$ and since a distance-optimal route is sought, the Planned Decision Making model's attribute function is chosen to be the spatial route's distance-attribute function α_∂.

In summary, the Distance-Optimal Spatial Route Choice Problem 6.5 can be solved by Model 6.5:

Model 6.5: DO-SR-CP: Mathematical Optimisation

The distance-optimal spatial route $\mathcal{R}^*(x_s, x_e, \mathfrak{X})$ of the Distance-Optimal Spatial Route Choice Problem 6.5 is determined by solving the Planned Decision Making model with the parameter set

$$(\mathfrak{R}(x_s, x_e, \mathfrak{X}), \alpha_\partial, \mathbb{1}_{\mathbb{R}^{n+1}}, \|.\|_1)$$

6.1.2.2. Human Path Planning Heuristic

The Model 6.5 mathematically solves a Hamiltonian Path or Open Travelling Salesman Problem (e.g. [141]). These problems relate closely to the original (closed) Travelling Salesman Problem, where an imaginary salesman is asked to find the shortest possible route from their current location via a given set of other targeted locations back to their starting location.

Wiener et al. [7] and Tenbrink and Wiener [8] have studied the performance of humans and their strategies in solving the (closed) Travelling Salesman Problem in navigational and paper-based empirical trials. The participants' performance has then both been assessed by evaluating the found solution and by post-trial discourse analysis techniques.

Wiener et al. [7] have found, that – although the Travelling Salesman Problem is a NP-hard problem – human performance in solving it is close to a distance-optimal route. This result confirms, that an optimisation model is appropriate to model human route choice for fixed targets. Furthermore, Wiener et al. have also demonstrated that when human beings need to retrieve the target locations from their memory, they rely on regional-based heuristics to solve the Travelling Salesman Problem. The regional-based heuristics have been further analysed by Tenbrink and Wiener [8] using discourse analysis techniques and it has been found, that while employing regional-based strategies, humans follow a forward-backward search to solve the Travelling Salesman Problem.

Based on these empirical insights, the Distance-Optimal Spatial Route Choice Problem 6.5 can be modelled as a three-stage choice process:

Model 6.6: DO-SR-CP: Human Path Planning Heuristic

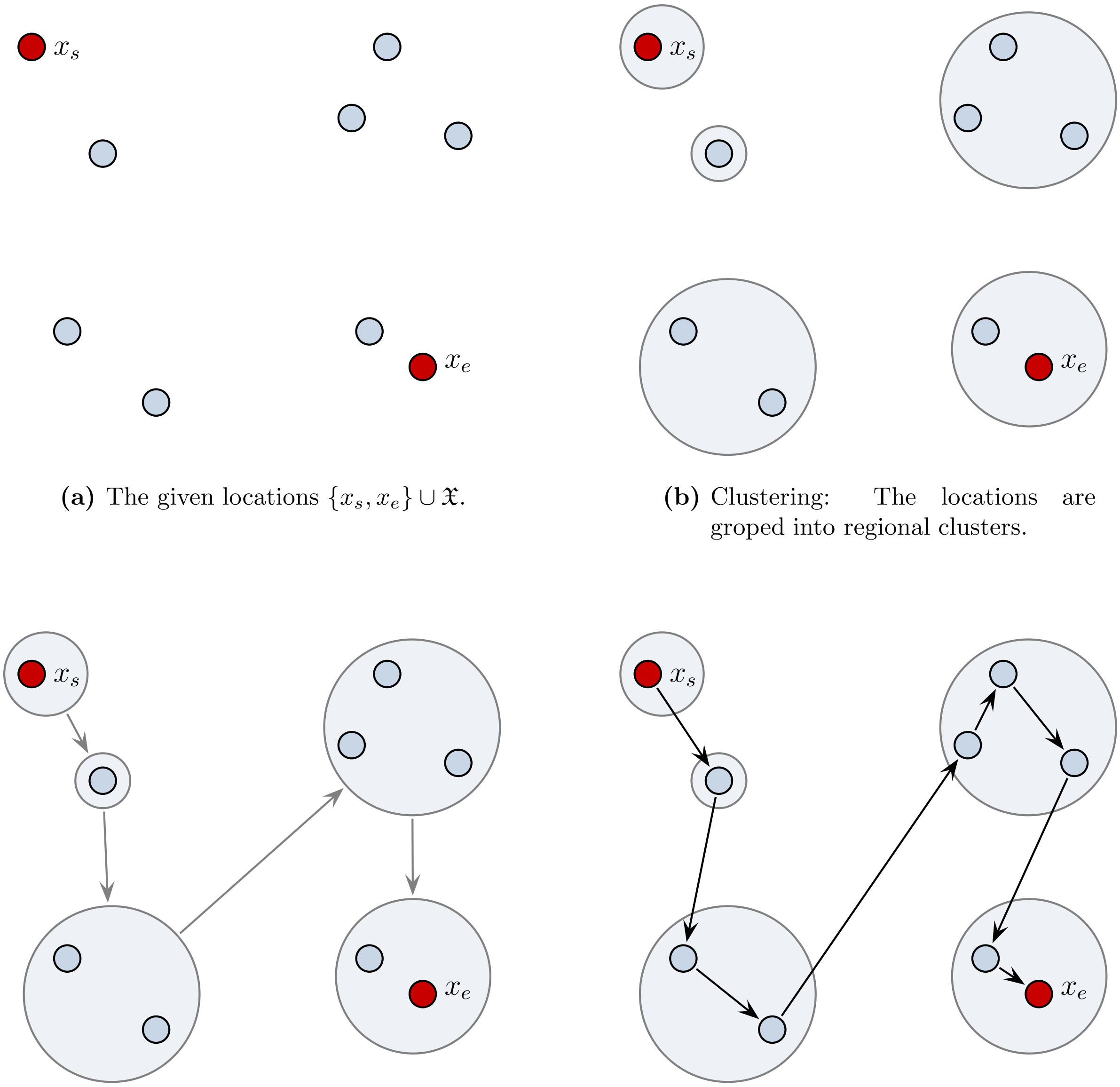
The distance-optimal spatial route $\mathcal{R}^*(x_s, x_e, \mathfrak{X})$ of the Distance-Optimal Spatial Route Choice Problem 6.5 is determined by solving the three-stage choice problem:

1. Clustering: The given locations $\mathfrak{X} \cup \{x_s, x_e\}$ are grouped into regional clusters.

2. Cluster Route Choice: A spatial location route which connects the given start location x_s to all the chosen regional clusters and to the given end location x_e is chosen using a bidirectional distance-optimal choice problem.

3. Intra-Cluster Route Choice: A distance-optimal spatial route is chosen within each regional cluster which connects the cluster's entry location, the cluster's exit location and all other remaining locations within the cluster using the Distance-Optimal Spatial Route Choice Problem Model 6.5.

The three stages of Model 6.6 can be illustrated as depicted in Figures 6.1.



(a) The given locations $\{x_s, x_e\} \cup \mathfrak{X}$.

(b) Clustering: The locations are groped into regional clusters.

(c) Cluster Route Choice: A route connection the clusters is chosen.

(d) Intra-Cluster Route Choice: Based on the cluster route a final route is chosen.

Figure 6.1.: An overview of the Human Path Planning heuristic for solving the Distance-Optimal Spatial Route Choice Problem based on insights by Wiener et al. [7] and Tenbrink and Wiener [8].

Clustering

To be able to use a regional-based heuristic for the Distance-Optimal Spatial Route Choice Problem 6.5, the set of given spatial locations $\mathfrak{X} = \{x_1, \ldots, x_n\}$ as well as the route's start location x_s and exit location x_e need to be grouped into regional clusters.

For this reason, a threshold system is determined. As a threshold, the average local walking distance between the targeted locations is used:

$$\bar{\partial}_{loc} := \frac{2}{(n+2)(n+1)} \left[\partial(x_s, x_e) + \sum_{i=1}^{n} (\partial(x_s, x_i) + \partial(x_e, x_i)) + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \partial(x_i, x_j) \right]$$

For each targeted spatial location $x \in \mathfrak{X} \cup \{x_s, x_e\}$, a spatial location cluster $\mathfrak{C}(x)$ is then defined as:

$$\mathfrak{C}(x) := \{x' \in \{x_s, x_1, \ldots, x_n, x_e\} \mid \partial(x, x') \leq \bar{\partial}_{loc}\} \qquad \forall\, x \in \{x_s, x_1, \ldots, x_n, x_e\}$$

This results in a number of duplicate clusters, since $x \in \mathfrak{C}(x') \;\Leftrightarrow\; x' \in \mathfrak{C}(x)$. Therefore, in a next step all duplicate clusters are removed, resulting in the final cluster set

$$\{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\} \qquad \text{with } 1 \leq k \leq n+2$$

A sample clustering is illustrated in Figure 6.2.

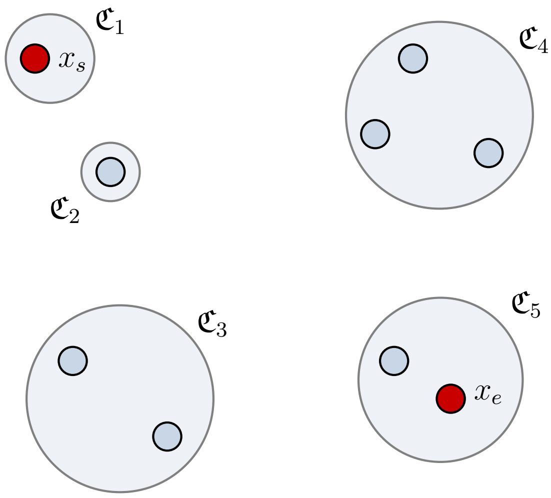


Figure 6.2.: A sample clustering of given locations $\{x_s, x_e\} \cup \mathfrak{X}$.

Cluster Route Choice Problem

In the next step of modelling the Distance-Optimal Spatial Route Choice Problem 6.5, as inspired by Tenbrink and Wiener [8], a cluster route with start spatial location x_s and end spatial location x_e which connects all regional clusters $\{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}$ is chosen. This is formulated as the *Cluster Route Choice Problem (C-R-CP)*, see Problem 6.6.

Problem 6.6: Cluster Route Choice Problem

Let $\{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}$ be a given set of regional clusters, x_s a given start location and x_e a given end location.

The objective of the Cluster Route Choice Problem (C-R-CP) 6.6 is to choose a route connecting the given regional clusters and the given start spatial location x_s and end spatial location x_e by invoking a bidirectional minimum distance algorithm.

The Cluster Route Choice Problem (C-R-CP) as defined in Problem 6.6 is modelled as a Planned Decision Making model. Therefore, each regional cluster $\mathfrak{C}_i$ is assigned a representative spatial location $\bar{x}^{\mathfrak{C}_i}$:

$$\bar{x}^{\mathfrak{C}_i} := \frac{1}{|\mathfrak{C}_i|} \sum_{x \in \mathfrak{C}_i} x$$

The Planned Decision Making model's choice set is therefore the spatial route set

$$\mathfrak{R}(x_s, x_e, \{\bar{x}^{\mathfrak{C}_1}, \ldots, \bar{x}^{\mathfrak{C}_k}\})$$

and the distance-attribute function α_∂ (see Equation 6.2) is chosen as the Planned Decision Making model's attribute function. To define the objective function of the Planned Decision Making's Multi-Criteria Optimisation Problem model, define the forward-backward index sequence as

$$\mathcal{I}_{k+1} := \left(1, k+1, 2, k, \ldots, \left\lceil \frac{k+1}{2} \right\rceil + 1\right)$$

Subsequently, define $h^{\text{CRC}} : \mathbb{R}^{k+1} \longrightarrow \mathbb{R}^{k+1}$ as the operation of the permutation matrix $H \in \mathbb{R}^{(k+1)\times(k+1)}$ with

$$H_{ij} := \begin{cases} 1 & \text{if } j = \mathcal{I}_{k+1}(i) \\ 0 & \text{else} \end{cases} \qquad h^{\text{CRC}}(x) := H \cdot x \;\Rightarrow\; h_i^{\text{CRC}}(x) = x_{\mathcal{I}_{k+1}(i)}$$

The Multi-Criteria Optimisation Problem's optimal solution set $\mathfrak{P}_{(\mathfrak{R}(x_s,x_e,\{\bar{x}^{\mathfrak{C}_1},\ldots,\bar{x}^{\mathfrak{C}_k}\}),h\circ\alpha)}$ is then obtained by applying Algorithm 6.1 on the vector set

$$(h^{\text{CRC}} \circ \alpha_\partial)(\mathfrak{R}(x_s, x_e, \{\bar{x}^{\mathfrak{C}_1}, \ldots, \bar{x}^{\mathfrak{C}_k}\}))$$

Finally, the cluster route choice's choice rule ζ^{CRC} draws a random solution from the optimal solution set obtained by Algorithm 6.1:

$$\begin{aligned} \mathcal{R}^*(x_s, x_e, \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}) &:= \mathcal{R}^*(x_s, x_e, \{\bar{x}^{\mathfrak{C}_1}, \ldots, \bar{x}^{\mathfrak{C}_k}\}) \\ := \;\; & \zeta^{\text{CRC}}(\mathfrak{P}_{(\mathfrak{R}(x_s,x_e,\{\bar{x}^{\mathfrak{C}_1},\ldots,\bar{x}^{\mathfrak{C}_k}\}),h\circ\alpha)}) = \zeta_{rand}(\mathfrak{P}_{(\mathfrak{R}(x_s,x_e,\{\bar{x}^{\mathfrak{C}_1},\ldots,\bar{x}^{\mathfrak{C}_k}\}),h\circ\alpha)}) \end{aligned}$$

Algorithm 6.1 The algorithm to find all minimal vectors of a bidirectional search problem.

Require: set of vectors $\mathfrak{X} \subset \mathbb{R}^m$
maximum entry $\mathbf{x}_{max} := \max_{x \in \mathfrak{X},\ 1 \leq j \leq m} x_j$
minimum vector $x^{min} \in \mathbb{R}^m$, $x_i^{min} := \mathbf{x}_{max}\ \forall\ 1 \leq i \leq m$
for all $x \in \mathfrak{X}$ **do**
  for $i = 1$ **to** m **do**
    if $x_i^{min} > x_i$ **then**
      $x_i^{min} = x_i$
      for $j = i + 1$ **to** m **do**
        $x_i^{min} = \mathbf{x}_{max}$
      end for
    else if $x_i^{min} < x_i$ **then**
      break
    end if
  end for
  if $i < m$ **then**
    break
  end if
end for
optimal vector set $\mathfrak{P} := \emptyset$
for all $x \in \mathfrak{X}$ **do**
  if $x - x^{min} = 0$ **then**
    $\mathfrak{P} \rightarrow \mathfrak{P} \cup \{x\}$
  end if
end for
return $\mathfrak{P}$

Figure 6.3 illustrates the outcome of the Cluster Route Choice Problem's bidirectional minimum distance Algorithm 6.1 for the sample clustering in Figure 6.2.

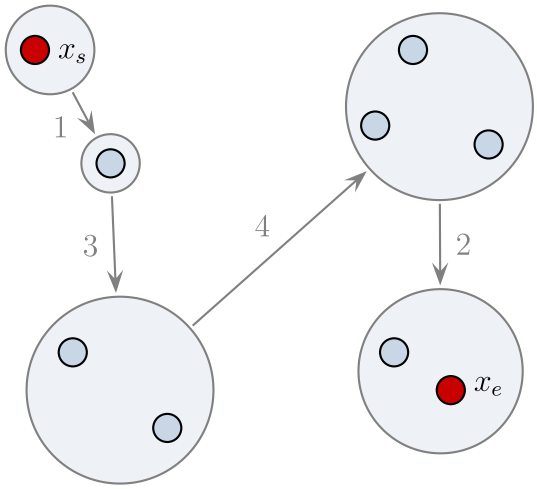


Figure 6.3.: A sample illustration of the bidirectional minimum distance algorithm of the Cluster Route Choice Problem.

Intra-Cluster Route Choice Problem

After the optimal cluster route $\mathcal{R}^*(x_s, x_e, \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\})$ has been established, the distance minimal intra-cluster routes needs to be determined. Therefore, for each cluster $\mathfrak{C} \in \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}$, a permutation of the cluster elements needs to be determined which gives the distance minimal route connecting the cluster spatial locations.

Problem 6.7: Intra-Cluster Route Choice Problem

Let $\mathfrak{C} \in \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}$ be a given spatial location cluster within the cluster route

$$\mathcal{R}^*(x_s, x_e, \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\})$$

The objective of the Intra-Cluster Route Choice Problem (IC-R-CP) is to choose a distance-minimal route $\mathcal{R}^*(x_f(\mathfrak{C}), x_l(\mathfrak{C}), \mathfrak{C}'\})$. The route's start and end location $x_f(\mathfrak{C}), x_l(\mathfrak{C}) \in \mathfrak{C}$ are given by the cluster route $\mathcal{R}^*(x_s, x_e, \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\})$ and the set $\mathfrak{C}'$ is defined as $\mathfrak{C}' := \mathfrak{C} \setminus \{x_f(\mathfrak{C}), x_l(\mathfrak{C})\}$.

For this purpose, the (minimal) distance between a spatial location and a cluster is defined as:

$$\partial(x, \mathfrak{C}) := \min_{x' \in \mathfrak{C}} \partial(x, x')$$

For any cluster $\mathfrak{C}$ in the cluster set $\{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}$, the first $x_f(\mathfrak{C})$ and the last $x_l(\mathfrak{C})$ spatial location is given by the previously determined cluster route

$$\mathcal{R}^*(x_s, x_e, \{\mathfrak{C}_1, \ldots, \mathfrak{C}_k\}) = (x_s, \mathfrak{C}_1^{\mathcal{R}}, \ldots, \mathfrak{C}_k^{\mathcal{R}}, x_e)$$

The first spatial location of the first cluster and the last spatial location of the last cluster are given by those spatial locations which have minimum distance from the start respectively end spatial locations, x_s and x_e:

$$\begin{aligned} x_f(\mathfrak{C}_1^{\mathcal{R}}) &:= x \in \mathfrak{C}_1^{\mathcal{R}} : \ \partial(x_s, x) = \partial(x_s, \mathfrak{C}_1^{\mathcal{R}}) \\ x_l(\mathfrak{C}_k^{\mathcal{R}}) &:= x \in \mathfrak{C}_k^{\mathcal{R}} : \ \partial(x, x_e) = \partial(\mathfrak{C}_k^{\mathcal{R}}, x_e) \end{aligned}$$

Further, if $|\mathfrak{C}_i^{\mathcal{R}}| = 1$ for $1 < i < k$, it is

$$x_f(\mathfrak{C}_i^{\mathcal{R}}) = x_l(\mathfrak{C}_i^{\mathcal{R}})$$

If $|\mathfrak{C}_i^{\mathcal{R}}| > 1$, the first and last spatial locations in this cluster are given by the cluster route. The bidirectional cluster route choice algorithm, $x_f(\mathfrak{C}_i^{\mathcal{R}})$ is determined before $x_l(\mathfrak{C}_i^{\mathcal{R}})$ in the first half of all clusters an $x_l(\mathfrak{C}_i^{\mathcal{R}})$ is determined before $x_f(\mathfrak{C}_i^{\mathcal{R}})$ in the second half of all the clusters. For an illustration see Figure 6.4.

If $2 \le i \le \lceil \frac{k}{2} \rceil$:

$$\begin{aligned} x_f(\mathfrak{C}_i^{\mathcal{R}}) &:= x \in \mathfrak{C}_i^{\mathcal{R}} : && \partial(x_l(\mathfrak{C}_{i-1}^{\mathcal{R}}), x) = \partial(x_l(\mathfrak{C}_{i-1}^{\mathcal{R}}), \mathfrak{C}_i^{\mathcal{R}})) \\ x_l(\mathfrak{C}_i^{\mathcal{R}}) &:= x \in \mathfrak{C}_i^{\mathcal{R}} \setminus \{x_f(\mathfrak{C}_i^{\mathcal{R}})\} : && \partial(x, x_l(\mathfrak{C}_{i+1}^{\mathcal{R}})) = \partial(\mathfrak{C}_i^{\mathcal{R}}, x_f(\mathfrak{C}_{i+1}^{\mathcal{R}})) \end{aligned}$$

and if $\lceil \frac{k}{2} \rceil < i \le k-1$:

$$\begin{aligned} x_f(\mathfrak{C}_i^{\mathcal{R}}) &:= x \in \mathfrak{C}_i^{\mathcal{R}} \setminus \{x_l(\mathfrak{C}_i^{\mathcal{R}})\} : && \partial(x_l(\mathfrak{C}_{i-1}^{\mathcal{R}}), x) = \partial(x_l(\mathfrak{C}_{i-1}^{\mathcal{R}}), \mathfrak{C}_i^{\mathcal{R}})) \\ x_l(\mathfrak{C}_i^{\mathcal{R}}) &:= x \in \mathfrak{C}_i^{\mathcal{R}} : && \partial(x, x_l(\mathfrak{C}_{i+1}^{\mathcal{R}})) = \partial(\mathfrak{C}_i^{\mathcal{R}}, x_f(\mathfrak{C}_{i+1}^{\mathcal{R}})) \end{aligned}$$

In order to determine the distance minimal intra-cluster route between the cluster's first and last spatial location, let $s+2 := |\mathfrak{C}|$ denote the size of the cluster $\mathfrak{C}$ in the Intra-Cluster Route Choice Problem 6.7 with first and last spatial location $x_f(\mathfrak{C})$ respectively $x_l(\mathfrak{C})$.

For the cluster size $|\mathfrak{C}| \in \{1, 2, 3\}$, the minimal total distance sequence with fixed start and end spatial locations can be easily determined:

$$\begin{aligned} |\mathfrak{C}| = 1 \ &: \ \mathcal{C} = (x_f(\mathfrak{C})) && \text{since } x_f(\mathfrak{C}) = x_l(\mathfrak{C}) \\ |\mathfrak{C}| = 2 \ &: \ \mathcal{C} = (x_f(\mathfrak{C}), x_l(\mathfrak{C})) \\ |\mathfrak{C}| = 3 \ &: \ \mathcal{C} = (x_f(\mathfrak{C}), x_1, x_l(\mathfrak{C})) \end{aligned}$$

If $|\mathfrak{C}| \ge 4 \Leftrightarrow s \ge 2$, the Intra-Cluster Route Choice Problem 6.7 is solved by solving the Distance-Optimal Spatial Route Choice Problem 6.5 with parameters $(\mathfrak{C}', x_f(\mathfrak{C}), x_l(\mathfrak{C}))$,

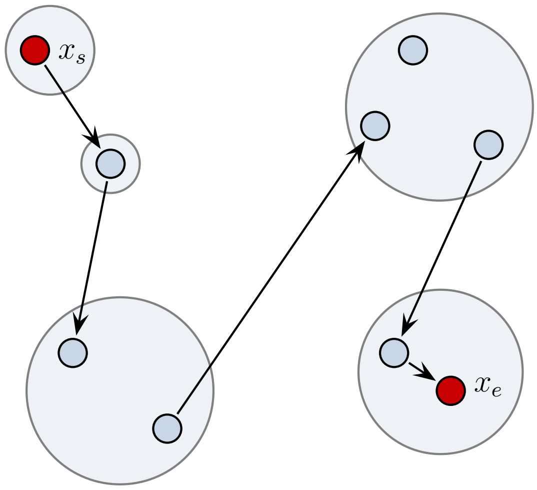


Figure 6.4.: The first and last location within each cluster of the distance-minimal intra-cluster route are given by sequentially determining the location within either the previous or the next cluster which is closest.

where $\mathfrak{C}' = \mathfrak{C} \setminus \{x_f(\mathfrak{C}), x_l(\mathfrak{C})\}$, by using Model 6.5. The resulting distance-optimal route for the cluster $\mathfrak{C}$ is denoted by

$$\mathcal{C}(x_f(\mathfrak{C}), x_l(\mathfrak{C}), \mathfrak{C}) = (x_f(\mathfrak{C}), x_1^{\mathcal{C}}, \dots, x_s^{\mathcal{C}}, x_l(\mathfrak{C})), \qquad x_i^{\mathcal{C}} \in \mathfrak{C}'$$

Final Spatial Location Route

When combining all interim results of the Cluster Route Choice Problem and the Intra-Cluster Route Choice Problem, the final distance-optimal route of the given Distance-Optimal Spatial Route Choice Problem 6.5 resulting from Model 6.6 is given as

$$\mathcal{R}^*(x_s, x_e, \mathfrak{X}) = x_s \sqcup \mathcal{C}(x_f(\mathfrak{C}_1^{\mathcal{R}}), x_l(\mathfrak{C}_1^{\mathcal{R}}), \mathfrak{C}_1^{\mathcal{R}}) \sqcup \dots \sqcup \mathcal{C}(x_f(\mathfrak{C}_k^{\mathcal{R}}), x_l(\mathfrak{C}_k^{\mathcal{R}}), \mathfrak{C}_k^{\mathcal{R}}) \sqcup x_e \tag{6.4}$$

See Figure 6.5 for an illustration.

6.1.2.3. Goal Location Route Choice Problem

The concept of a distance-optimal route on environmental locations (see Section 6.1.2) can be transferred to the environment's goal locations, the Goal Location Set (GLS).

Definition 6.3: Goal Location Route

Let $\mathfrak{L} \subseteq \text{GLS}$ be a set of targeted goal locations of size $n \in \mathbb{N}$. Let further be given a start goal location $l^s \in \text{GLS}$ and an end goal location $l^e \in \text{GLS}$. A **goal location route** $\mathcal{R}$ of the triple $(l^s, l^e, \mathfrak{L})$ is a sequence

$$\mathcal{R}(l^s, l^e, \mathfrak{L}) \in \{l^s\} \times \mathfrak{L}^n \times \{l^e\} \subset \text{GLS}^{n+2}$$

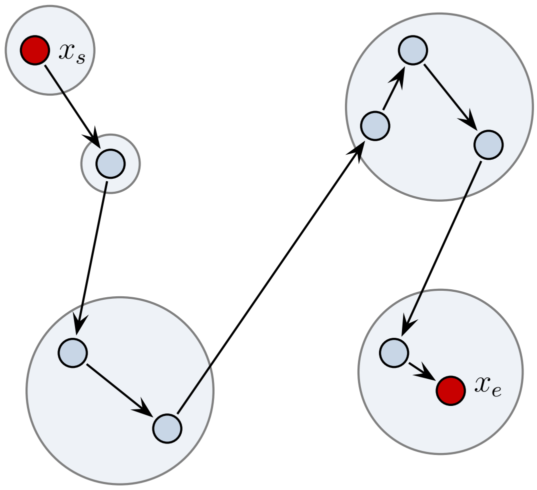


Figure 6.5.: Determining the distance-optimal route of the given Distance-Optimal Spatial Route Choice Problem 6.5 resulting from Model 6.6.

defined by

$$\mathcal{R}(l^s, l^e, \mathfrak{L}) = (l_1^{\mathcal{R}}, l_2^{\mathcal{R}}, \dots, l_{n+1}^{\mathcal{R}}, l_{n+2}^{\mathcal{R}}) := (l^s, l_1, \dots, l_n, l^e)$$

where $(l_1, \dots, l_n) \in \mathfrak{S}(\mathfrak{L})$ is a sequence of the set of targeted goal locations.
The set of all routes for the triple $(l^s, l^e, \mathfrak{L})$ is called the triple's **goal location route set** $\mathfrak{R}(l^s, l^e, \mathfrak{L})$:

$$\mathfrak{R}(l^s, l^e, \mathfrak{L}) := \{\mathcal{R}(l^s, l^e, \mathfrak{L}) = (l^s, l_1, \dots, l_n, l^e) \mid (l_1, \dots, l_n) \in \mathfrak{S}(\mathfrak{L})\}$$

In the same way as for spatial locations, the *Distance-Optimal Goal Location Route Choice Problem (DO-GLR-CP)* can be formulated as in Problem 6.8:

Problem 6.8: Distance-Optimal Goal Location Route Choice Problem

Let $\mathfrak{L} \subseteq \text{GLS}$ be a given set of targeted goal locations of size $n := |\mathfrak{L}|$, l^s respectively l^e be given start respectively end goal locations.

The objective of the Distance-Optimal Goal Location Route Choice Problem (DO-GLR-CP) is to choose a distance-optimal goal location route $\mathcal{R}^*(l^s, l^e, \mathfrak{L})$ from the route set $\mathfrak{R}(l^s, l^e, \mathfrak{L})$:

$$\mathcal{R}^*(l^s, l^e, \mathfrak{L}) \text{ distance-optimal} \quad :\Longleftrightarrow \quad \mathcal{R}^*(\lambda(l^s), \lambda(l^e), \lambda(\mathfrak{L})) \text{ distance-optimal}$$

where

$$\lambda(\mathfrak{L}) := \{\lambda(l) \mid l \in \mathfrak{L}\}$$

The Distance-Optimal Goal Location Route Choice Problem 6.8 is therefore solved by solving the related Distance-Optimal Spatial Route Choice Problem 6.5 with parameter set $(\lambda(\mathfrak{L}), \lambda(l^s), \lambda(l^e))$ using either Model 6.5 or Model 6.6. This depends on the specific decision situation.

6.1.3. Planned Goal Location Route Choice Problem

To determine a goal location route for a given situation in which the agent can unhurriedly evaluate all their available options, a *Planned Goal Location Route Choice Problem (PGLR-CP)* as defined in Problem 6.9 needs to be solved:

Problem 6.9: Planned Goal Location Route Choice Problem

Let $\mathfrak{G}$ be a given set of agent goals, $\mathfrak{L}$ a given set of goal locations with attribute function α. Let further $p \in \mathbb{R}^m$ be a given set of preference attributes and $l^s \in \mathfrak{L}$ respectively $l^e \in \mathfrak{L}$ be the given start respectively end goal location.

The objective of the Planned Goal Location Route Choice Problem (PGLR-CP) is then to choose a subset $\mathfrak{L}^{\text{PGLR-CP}} \subseteq \mathfrak{L}$ of targeted goal locations of size $n := |\mathfrak{L}^{\text{PGLR-CP}}|$ and an order $\sigma^{\text{PGLR-CP}} \in S_n$ of $\mathfrak{L}^{\text{PGLR-CP}}$ such that

- the agent can accomplish all agent goals in $\mathfrak{G}$ at the chosen goal locations $\mathfrak{L}^{\text{PGLR-CP}}$,
- the chosen goal locations $\mathfrak{L}^{\text{PGLR-CP}}$ are preference-optimal with regard to p,
- and such that the goal location route $\mathcal{R}(l^s, l^e, \mathfrak{L}^{\text{PGLR-CP}})$ is distance-optimal.

The Planned Route Choice Problem 6.9 can be solved by two means:

- Staged route choice: At first, the targeted goal locations $\mathfrak{L}^{\text{PGLR-CP}} = \{l_1, \dots, l_n\}$ are chosen. Subsequently, a distance-optimal route from the route set $\mathfrak{R}(l^s, l^e, \mathfrak{L}^{\text{PGLR-CP}})$ is chosen.
- Simultaneous route choice: The targeted goal locations and the order in which the targets are to be visited are chosen in the same decision making instance.

Both methods are valid approaches for the modelling of route planning or route choice. However, for the CPAF's planned route choice model, the staged route choice approach has been chosen.

The staged route choice comprises two independent mathematical problems, a search problem and a choice problem. The problems' choice sets are of size

$$N := \binom{|\mathfrak{L}|}{n} \qquad \text{respectively} \qquad |S_n| = n!$$

The total size of the staged route choice method is therefore $n! + N$. On the other hand, for the simultaneous route choice, the size of the problem's choice set is $n! \cdot N$. Hence for $n, N \geq 2$, the simultaneous route choice problem is more complex than the staged route choice problem.

In addition, for the staged route choice, the second stage of choosing a permutation of the previously chosen targets can be regarded as a Hamiltonian Path or an Open Travelling Salesman Problem. The performance of human beings and their methods for solving the closely related (closed) Travelling Salesman Problem has been extensively studied by Wiener et al. [7] and Tenbrink and Wiener [8]. Therefore, the results and insights of these studies can be used as an empirical basis for modelling the second stage of the staged route choice method.

For these reasons, the staged route choice method has been used for the CPAF's planned route choice model for agents with previous familiarity with the environment. The first stage is to choose a sequence of goal locations that shall be targeted based on the agent's preferences. In the second stage, a path connecting the chosen goal locations is determined using the insights from Wiener et al. [7] and Tenbrink and Wiener [8].

In the first step of the planned route choice model, the agent chooses for each of the agent goals $g \in \mathfrak{G}$ the set of preference-optimal goal locations from the set of all goal locations that can satisfy the goal g and which are contained in the given goal location set $\mathfrak{L}$. Therefore, this is a Goal Set's Preference-Optimal Goal Location Set Choice Problem 6.4 with parameters $(\mathfrak{G}, \mathfrak{L}, \alpha, p)$. Let $\mathfrak{L}^{\text{PGLR-CP}}$ denote the resulting minimal preference-optimal goal location set.

In the next stage of the Planned Goal Location Route Choice Problem 6.9, the final distance-optimal route $\mathcal{R}^*(l^s, l^e, \mathfrak{L}^{\text{PGLR-CP}})$ on the triple $(l^s, l^e, \mathfrak{L}^{\text{PGLR-CP}})$ needs to be chosen. This problem is solved by solving the corresponding Distance-Optimal Goal Location Route Choice Problem 6.8 with parameter set $(\mathfrak{L}^{\text{PGLR-CP}}, l^s, l^e)$. Since the Planned Goal Location Route Choice Problem 6.9 shall represent pedestrian way finding, the Human Path Planning Heuristic Model 6.6 is used.

6.2. Initialising a Pedestrian Circulation Simulation of a Complex Multi-Purpose Environment

During the initialisation stage of a pedestrian usage-cycle simulation incorporating the proposed CPAF, the agent population is initialised by interpreting the information available from the CPAF's environment model (see Section 5.2). Each agent is therefore assigned their initial individual set of goals that they want to accomplish during their sojourn in the environment, i.e. their initial Agent Goal Set. In addition, the CPAF provides the possibility to model different degrees of previously acquired spatial knowledge and therefore to model pedestrians which are experienced and pedestrians which are inexperienced in the modelled environment. Therefore, the agent's initial Spatial Memory Set is assigned during the initialisation stage.

In order to correctly initialise a pedestrian usage-cycle simulation of a given complex multi-purpose environment, additional information on how the agent population shall be initialised is required from the user. For this reason, a software tool which guides the user through the specification of the required parameters for the current buildingEXODUS CPAF Plug-in has been designed, the Cognitive Pedestrian Agent Framework Scenario Specification Generator. The Cognitive Pedestrian Agent Framework Scenario Specification Generator is in detail described in Appendix Chapter B. The Cognitive Pedestrian Agent Framework Scenario Specification Generator stores the acquired specifications in a Scenario Specification File which can be interpreted by buildingEXODUS (see Section 4.2) and the current buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in.

Table 6.1 lists the specifications required by the CPAF for initialising a pedestrian usage-cycle simulation. These parameters are required in addition to the parameters to constitute the components of the Cognitive Pedestrian Agent Framework as depicted in Table 5.13.

Table 6.1.: An overview of the required parameters based on which a usage cycle simulation of a complex multi-purpose environment with the Cognitive Pedestrian Agent Framework is initialised.

CPAF Component	Entity	Required Input
Agent	Ingress	Entry time
Agent	Ingress	Probability of entering the environment at goal location l_{entry}
Agent	Egress	Probability of exiting the environment at exit goal location l_{exit} for a circulation simulation
Agent Population	Goals	Probability of a goal being assigned to an agent
Agent Population	Knowledge	Personal Preference Attributes P probability distribution
Agent Population	Attributes	Perceived Crowd threshold C^* probability distribution
Agent Population	Knowledge	Previous spatial knowledge probability distribution

During the simulation initialisation process, the individual agents are therefore assigned their individual personal preference attributes (see Section 5.3.1) and their individual Perceived Crowd thresholds (see Section 5.6.2.1). These parameters are set according to probability distributions and simulation parameters provided by the user. In addition, each agent is assigned their entry point in the environment $l_{entry} \in$ GLS and their exit point $l_{exit} \in$ GLS.

Each agent is also assigned their individual initial set of agent goals, the Agent Goal Set, prior to their simulated entry in the modelled environment. This set of agent goals is derived from a subset $\mathfrak{G} \subseteq$ GGS of the global goal set. The subset $\mathfrak{G}$ is determined using the probability distributions defined by the user as a proportion of the agent population that will be equipped with an agent goal realisation $g \lhd \widehat{g}$ of the global goal $\widehat{g}$.

When assigning a certain agent goal g to an agent, the agent goal's (initial) relative importance value is drawn from a uniform random distribution on the relative importance range of $\widehat{g}$:

$$I(g) \sim \mathcal{U}([\mathbf{I}_{low}(\widehat{g}), \mathbf{I}_{up}(\widehat{g})])$$

After the agent has been assigned their individual initial Agent Goal Set, the initial motivation values are assigned based on a uniform distribution and in correspondence with the assigned Agent Goal Set. Subsequently, the agent's previous spatial knowledge of the modelled environment is populated.

6.2.1. Modelling Prior Knowledge

In complex multi-purpose environments, the pedestrian's circulation behaviour depends to a high degree on their familiarity with the environment, i.e. their spatial knowledge of the structure. The pedestrian's spatial knowledge originates from two sources. During their sojourn in the environment, the pedestrian gains spatial knowledge through perception of the environment. In addition, the pedestrian might have been to the environment previously, therefore having spatial knowledge about the environment from these previous visits. Such prior familiarity with the environment is explicitly modelled in the CPAF.

In the CPAF, different degrees of prior familiarity with the environment is reflected by the possibility to populate each agent's Spatial Memory Set with information about the environment prior to their entry into the structure. As discussed in Section 5.3.2, this prior knowledge is regarded as being permanent and thereby isn't affected by the short-term memory functionality.

When using the CPAF to model complex multi-purpose environments, the user can specify different groups of the agent population with different degrees of familiarity with the structure, thereby simulating frequent, occasional and first-time visitors to the environment in question:

Frequent visitors Very good or complete knowledge of the facilities within the environment.

Occasional visitors Different degrees of partial knowledge of the facilities within the environment.

First-time visitors No prior knowledge of the environment.

The degree of previous knowledge is determined by the user by stating a percentage of all locations in question, that shall be known to the agent group in question.

For example in a long-distance traffic facility, commuters can be simulated by frequent visitor agents, local leisure travellers can be modelled by occasional visitor agents and tourists by first-time visitor agents.

6.3. Modelling the Ingress Phase

The degree of prior familiarity with the environment (see Section 6.2.1) has got a significant impact on the pedestrians' ingress behaviour. When entering the environment, pedestrian commonly have a plan about their trip in the environment. Those pedestrians who have got prior experience with the complex multi-purpose environment in question will already have planned which facilities they want to visit and in which order. This planned itinerary is in correspondence to their needs and desires, see Section 6.3.1. On the other hand, pedestrians with no prior spatial knowledge about the complex multi-purpose environment in question need to explore the environment. They thereby actively seek for goal locations which can satisfy their needs, see Section 6.3.2.

6.3.1. Frequent and Occasional Visitors

Pedestrians with previous knowledge about the environment are able to select their route prior to their actual sojourn in the structure, thereby planning their trip to the environment. For this reason, those agents who have been equipped with prior spatial knowledge will be assigned an initial route prior to their entry into the environment. This route planning process is based on their familiarity with the structure.

Problem 6.10: Route Choice Problem for Experienced Agents

The objective of the Route Choice Problem for Experienced Agents is to choose a set of targeted goal locations $\mathfrak{L}$ from the agent's Spatial Memory Set and a route $\mathcal{R}^{\text{RCFEP}}(l_{entry}, l_{exit}, \mathfrak{L})$, such that the route from the agent's entry location l_{entry} via all targeted goal locations to the agent's assigned exit location l_{exit} is of minimal total distance.

Since the agent's previous knowledge of the environment is determined using Boolean probability distributions, it is possible that for a goal $g \in \text{AGS}$ the set of those goal locations which can satisfy g and that are known to the agent

$$\mathfrak{L}^{\text{M}}(g) = \mathfrak{L}(g) \cap \text{SMS}$$

is empty. This goal is then disregarded in the further route choice process. Let $\mathfrak{G}^{\text{M}} \subseteq \text{AGS}$ be the set of those agent goals, where for each $g \in \mathfrak{G}^{\text{M}}$ the agent is familiar with goal locations that can satisfy g from previous experience:

$$\mathfrak{G}^{\text{M}} := \{g \in \text{AGS} \mid \mathfrak{L}^{\text{M}}(g) \neq \emptyset\}$$

The process of planning an initial route for experienced agents is a Planned Goal Location Route Choice Problem 6.9 with parameters $(\mathfrak{G}^{\text{M}}, \mathfrak{L}^{\text{M}}(\mathfrak{G}^{\text{M}}), \alpha_F, P, l_{entry}, l_{exit})$, where the attribute function

$$\alpha_F\colon \mathfrak{L}^{\mathrm{M}}(\mathfrak{G}^{\mathrm{M}}) \to \mathbb{R}^s, \quad \alpha_F(l) := F(l)$$

assigns each goal location their set of goal location feature attributes, P is the agent's personal preference set and l_{entry} respectively l_{exit} denote the agent's previously assigned entry and exit goal locations.

In the case of the Route Choice Problem for Experienced Agents, the actual way finding of pedestrians which rely on their previously acquired knowledge of the structure is simulated. As has been demonstrated by Wiener et al. [7], this path planning process can be approximated by a cluster-based optimal path choice problem. Consequently, the Human Path Planning Heuristic (Model 6.6) is chosen to find the distance-optimal route of the Planned Goal Location Route Choice Problem 6.9.

Once the cluster-based distance-optimal route $\mathcal{R}^{\mathrm{RCFEP}}(l_{entry}, l_{exit}, \mathfrak{L}^{\mathrm{RCFEP}})$ has been found, tasks are created which combine the chosen goal locations $\mathfrak{L}^{\mathrm{RCFEP}}$ with their corresponding agent goals according to Algorithm 6.2. The agent's initial Agent Task List is populated with these tasks in the order of the distance-optimal route $\mathcal{R}^{\mathrm{RCFEP}}(l_{entry}, l_{exit}, \mathfrak{L}^{\mathrm{RCFEP}})$.

Algorithm 6.2 The algorithm to generate a task set $\mathfrak{T}$ based on the preference-optimal goal location set $\mathfrak{L}$ for the agent goal set $\mathfrak{G}$.

Require: agent goal set $\mathfrak{G}$, preference-optimal goal location set $\mathfrak{L}$ of size $n := |\mathfrak{L}|$

task set $\mathfrak{T} := \emptyset$

choose an order ω of $\mathfrak{L}$, $\omega(\mathfrak{L}) \in \mathfrak{S}(\mathfrak{L})$, such that the number of agent goals in the set $\mathfrak{G}$ that be accomplished at l_p is greater or equal to the number of agent goals in the set $\mathfrak{G}$ that be accomplished at l_q for $p \leq q$.

define a sequence of sets of agent goals $(\mathfrak{G}_1, \ldots, \mathfrak{G}_n)$ such that

$$g \in \mathfrak{G}_j \quad :\Longleftrightarrow \quad l_j \in \mathfrak{L}(g) \cup \mathfrak{L} \qquad \text{for } 1 \leq j \leq n$$

for $i = 1$ **to** n **do**
  if $|\mathfrak{G}_i| \neq 0$ **then**
    generate task t from goal location l_i and the agent goal set $\mathfrak{G}_i$ (see Section 5.3.2)
    $\mathfrak{T} \to \mathfrak{T} \cup \{t\}$
    for $j = i + 1$ **to** m **do**
      $\mathfrak{G}_j \to \mathfrak{G}_j \setminus \mathfrak{G}_i$
    end for
  end if
end for
return $\mathfrak{T}$

6.3.2. First-time Visitors

Agents which simulate first-time visitors of the environment don't possess any prior spatial knowledge and those agents therefore need to explore the simulated environment and actively search for goal locations at which they can accomplish their assigned initial agent goals.

To explore the environment, the first-time visitor agents use the CPAF's visual perception feature while in the environment (see Section 5.5) and an initially assigned way point route. This initial way point route is assigned to the first-time visitor agents prior to their entry into the environment during the ingress phase. The way point route is a sequence of tasks to pass by certain way point goal locations.

After having entered the environment, the agent will therefore navigate towards their first assigned way point goal location. While walking towards this way point, the goal locations adjacent to the agent's path are perceived and thereby the agent learns about goal locations at which they potentially can accomplish their assigned agent goals (see Section 5.5). By this exploration process, the first-time visitor agent will hence try to accomplish all of their assigned active agent goals. However, in the case that no goal location for a certain agent goal could be found alongside the assigned way point route, the agent will need to actively search for appropriate goal locations, see Section 6.4.2.

In the current buildingEXODUS CPAF Plug-in, the initial way point route that is assigned to first-time visitor agents consists of one task which directs the agent to the most central way point goal location $l_c \in \mathrm{WPS}$. The most central way point goal location is hereby given as the way point goal location for which the cumulative distance to all other way point goal locations is minimal:

$$\sum_{l \in \mathrm{WPS}} \partial(l_c, l) = \min_{l' \in \mathrm{WPS}} \sum_{l \in \mathrm{WPS}} \partial(l', l)$$

This very basic initial way point route has been chosen to approximate pedestrian exploration behaviour in the CPAF agents. The actual pedestrian exploration process of an unknown environment is far more complex. In reality, pedestrians that have no prior knowledge of the environment would simply not know where the most central way point would be located. Instead they will probably simply go on a walk about to explore the environment. The most central way point being assigned as the initial way point route to first-time visitor agents is an attempt to replicate the walk about behaviour with a very simplistic model in the current buildingEXODUS CPAF Plug-in. Future versions of the buildingEXODUS CPAF Plug-in could aim to represent such explorative pedestrian behaviour more accurately. For example could a future buildingEXODUS CPAF Plug-in make use of sophisticated and empirically evident way finding heuristics (see e.g. Veeraswamy [132]).

6.4. Modelling the Circulation Phase

After the ingress phase (Section 6.3) during which the agents have been assigned their initial Agent Goal Set, their initial spatial knowledge and an initial route, the agents travel through the modelled environment. During this circulation phase, the agents respond to the information and stimuli that they perceive.

In complex multi-purpose environments, the layout and structure of the environment has a high impact on the behaviour of its visitors. Pedestrians in complex multi-purpose environments extract a vast amount of information from their surrounding environment by exploring the structure, interpreting visual clues or actively seeking for missing but required information. The extracted information from the environmental structure is used by the pedestrian to re-evaluate and potentially adjust their plans and therefore their route through the environment.

Consequently, the simulation of the circulation phase of a usage-cycle simulation makes use of the structural perception capabilities provided by the CPAF. As one of the main sources of such information, an agent in the CPAF possesses the ability to visually perceive the goal locations that are modelled in the simulated environment, see Section 5.5. The agents are therefore aware of their surrounding structure and its purpose. Upon perceiving additional information, the agent can therefore decide to use this information to adjust and enhance their plans, see Section 6.4.1. In addition, agents are capable of actively seeking for required information by searching for and then enquiring information points, see Section 6.4.2. The agents are hence capable of assessing their situation and take actions in order to improve their current situation.

6.4.1. Structural Awareness: Visual Perception of Goal Locations

If the agent has perceived a goal location for the first time, they not only store its information in their knowledge component as described in Section 5.5, but they also evaluate the additional information with regard to their current plans and goal. If the perceived goal location $l_{perc} \in \text{GLS}$ is related to a currently active agent goal $g \in \text{AGS}$, i.e. $l_{perc} \in \mathfrak{L}(g)$, a decision is forced on whether the agent considers the perceived goal location for accomplishing their active goal g. In this decision situation, the two cases whether a task associated with g already exists on the agent's Agent Task List or not need to be distinguished in the modelling process.

If a task $t \in \text{ATL}$ associated with g already exists, the agent first checks, whether all goals associated with the task t can also be accomplished at the perceived goal location l_{perc}. If this is the case, the agent will check whether they prefer the perceived goal location to the task's current goal location and therefore whether to change the task's associated goal location:

Problem 6.11: Change Goal Location Choice Problem

The objective of the Change Goal Location (CGL) Choice Problem is to decide whether a given alternative goal location l_a is preferred to the given reference goal location l_r.

On the other hand, if no task associated with the active agent goal g exists on the Agent Task List, the agent needs to decide whether the perceived goal location is appropriate to accomplish g and therefore whether a task to visit l_{perc} should be added to the agent's Agent Task List:

Problem 6.12: Visit Goal Location Choice Problem

The objective of the Visit Goal Location (VGL) Choice Problem is to decide whether to visit a given goal location l or not.

Since both decisions are taken in a short amount of time while perceiving the goal location and therefore as a reaction to this perception event, the Short Time Span Adaptive Decision Making model is employed in both cases.

For the Change Goal Location Choice Problem 6.11, the choice set is the set with the one alternative goal location, $\mathfrak{L}^{\text{CGLC}} := \{l_a\}$. In this choice problem, the agent as the decision maker needs to determine whether the alternative goal location is preferred against the reference goal location, therefore the problem's attribute function α^{CGLC} is given by the absolute deviation of the alternative goal location's feature parameters from the agent's personal preference attributes:

$$\alpha^{\text{CGLC}} : \mathfrak{L}^{\text{CGLC}} \to \mathbb{R}^{s+1}, \qquad \alpha^{\text{CGLC}}(l_a) := \begin{pmatrix} |F_1(l_a) - P_1| \\ \vdots \\ |F_s(l_a) - P_s| \\ \partial(x_{current}, \lambda(l_a)) \end{pmatrix}$$

where $x_{current} \in \mathbb{E}$ is the agent's current spatial location in the environment. In the same way, the Short Time Span Adaptive Decision Making model's associated Take-the-Best Problem's cue set is built from the reference vector

$$r^{\text{CGLC}} := \begin{pmatrix} |F_1(l_r) - P_1| \\ \vdots \\ |F_s(l_r) - P_s| \\ \partial(x_{current}, \lambda(l_r)) \end{pmatrix}$$

and the sequence of comparison functions $\mathcal{C}^{\text{CGLC}} = (c_1^{\text{CGLC}}, \ldots, c_s^{\text{CGLC}})$ is given by

$$c_j^{\text{CGLC}}(l) := \alpha^{\text{CGLC}}{}_j(l) < r_j^{\text{CGLC}} \qquad \forall\ 1 \leq j \leq s,\ l \in \mathfrak{L}^{\text{CGLC}}$$

Therefore, the cues $\xi_j^{\text{CGLC}} \in \Xi^{\text{CGLC}}$ are given by

$$\xi_j^{\text{CGLC}}(l_a) = \left\{ \begin{array}{c} 1 \\ 0 \\ -1 \end{array} \right\} \iff |F_j(l_a) - P_j| \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} |F_j(l_r) - P_j| \qquad j \in \{1, \ldots, s\}$$

$$\xi_{s+1}^{\text{CGLC}}(l_a) = \left\{ \begin{array}{c} 1 \\ 0 \\ -1 \end{array} \right\} \iff \partial(x_{current}, \lambda(l_q)) \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} \partial(x_{current}, \lambda(l_r))$$

As the Short Time Span Adaptive Decision Making model's choice function the random choice function has been chosen

$$\zeta^{\text{CGLC}} := \zeta_{rand}$$

For the Change Goal Location Choice Problem 6.11, the choice candidate set as the optimal solution set of the Short Time Span Adaptive Decision Making model's Take-the-Best Problem, $\mathfrak{P}_{(\mathfrak{L}^{\text{CGLC}}, \Xi(\mathcal{C}^{\text{CGLC}}, r^{\text{CGLC}}))}$, is either empty or it contains the alternative goal location l_a. The optimal solution set is non-empty if the alternative goal location is better with regard to the agent's personal preference hierarchy. Therefore, if the choice function ζ^{CGLC} draws l_a as the non-null choice alternative, the agent has decided to prefer the alternative goal location l_a to the reference goal location l_r.

In the situation of having perceived an appropriate goal location l_{perc} for an active goal g that is currently associated to a given task $t \in \text{ATL}$, if the agent decides to prefer l_{perc} to the current $l(t)$, the task's current goal location is replaced with the perceived goal location. Furthermore, if the task t is more important than the agent's current task, t is set as the current task and therefore moved before the former current task on the agent's Agent Task List.

For the Visit Goal Location Choice Problem 6.12, the choice set is the set containing the perceived goal location, $\mathfrak{L}^{\text{VGLC}} := \{l\}$. In this choice problem, the agent as the decision maker needs to determine whether the given goal location reasonably meets their personal preferences, therefore the problem's attribute function α^{VGLC} is given by the absolute deviation of the alternative goal location's feature parameters from the agent's personal preference attributes:

$$\alpha^{\text{VGLC}} : \mathfrak{L}^{\text{VGLC}} \to \mathbb{R}^s, \qquad \alpha^{\text{VGLC}}(l) := \begin{pmatrix} |F_1(l) - P_1| \\ \vdots \\ |F_s(l) - P_s| \end{pmatrix}$$

A goal location feature parameter is postulated to reasonably match an agent's personal preference attribute, if the feature parameter is reasonably close to the preference attribute.

The interpretation of how close the feature parameter needs to be to the preference attribute depends on the agent's current Urgency. Consequently, the Short Time Span Adaptive Decision Making model's associated Take-the-Best Problem's cue set is built from the reference vector

$$r^{\text{VGLC}} := \begin{pmatrix} 2 - 2 \cdot U \\ \vdots \\ 2 - 2 \cdot U \end{pmatrix}$$

and the sequence of comparison functions $\mathcal{C}^{\text{VGLC}} = (c_1^{\text{VGLC}}, \ldots, c_s^{\text{VGLC}})$ is given by

$$c_j^{\text{VGLC}}(l) := \alpha_j^{\text{VGLC}}(l) < r_j^{\text{VGLC}} \qquad \forall\, 1 \leq j \leq s,\ l \in \mathfrak{L}^{\text{VGLC}}$$

Therefore, the cues $\xi_j^{\text{VGLC}} \in \Xi^{\text{CGLC}}$ are given by

$$\xi_j^{\text{VGLC}}(l) = \left\{ \begin{array}{r} 1 \\ 0 \\ -1 \end{array} \right\} \quad \Longleftrightarrow \quad |F_j(l) - P_j| \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} 2 - 2 \cdot U \qquad j \in \{1, \ldots, s\}$$

As the Short Time Span Adaptive Decision Making model's choice function choose the random choice function

$$\zeta^{\text{VGLC}} := \zeta_{rand}$$

For the Visit Goal Location Choice Problem 6.12, the choice candidate set as the optimal solution set of the Short Time Span Adaptive Decision Making model's Take-the-Best Problem, $\mathfrak{P}_{(\mathfrak{L}^{\text{VGLC}}, \Xi(\mathcal{C}^{\text{VGLC}}, r^{\text{VGLC}}))}$, is either empty or it contains the given goal location l. The optimal solution set is non-empty if the given goal location's feature attributes reasonably well match the agent's personal preferences. Therefore, if the choice function ζ^{VGLC} draws the given goal location l as the non-null choice alternative, the agent has decided to visit the goal location.

In the situation of having perceived an appropriate goal location l_{perc} for an active goal g that is not currently associated to a task on the agent's Agent Task List and that matches the agent's preference attributes in a reasonable manner, a new task to visit the perceived goal location and thereby accomplish the agent goal g at l_{perc} is added to the Agent Task List at the distance-optimal position.

6.4.2. Modelling Situational Awareness: the Unsatisfied Desired Goal Behaviour Model

In the CPAF, agents can not only perceive spatial information but can also demand information by enquiring information points. This information enquiry process is triggered, if the agent's spatial knowledge isn't sufficient to accomplish all of their assigned agent goals.

The CPAF's Unsatisfied Desired Goal Behaviour model is triggered for an agent, if the agent hasn't got any elective tasks left, but has still got unsatisfied agent goals $\mathfrak{G}_u$ in their Agent Goal Set:

$$\mathfrak{G}_u := \{g \in \text{AGS} \mid g \text{ is unsatisfied}\}$$

Since the agent currently doesn't possess a plan on how to accomplish these unsatisfied agent goals, they will first query their Spatial Memory Set for each unsatisfied agent goal $g \in \mathfrak{G}_u$, whether they know any goal location which can satisfy g. If the agent does know goal locations at which g can be satisfied, this agent goal is added to the set $\mathfrak{G}_u^{\text{M}} \subseteq \mathfrak{G}_u$:

$$\mathfrak{G}_u^{\text{M}} := \{g \in \mathfrak{G}_u \mid \mathfrak{L}^{\text{M}}(g) \neq \emptyset\}$$

If $\mathfrak{G}_u^{\text{M}} \neq \emptyset$, the agent will choose preference-optimal goal locations from their Spatial Memory Set in order to satisfy the currently unsatisfied goals. Therefore, the agent sorts the set of unsatisfied agent goals according to their current relative importance, starting with the most important goals:

$$\mathcal{G}_u^{\text{M}} := (g_1, \ldots, g_{|\mathfrak{G}_u^{\text{M}}|}) \text{ where } g_i \in \mathfrak{G}_u^{\text{M}} \ \forall\ 1 \leq \ i \leq |\mathfrak{G}_u^{\text{M}}| \text{ and } I(g_i) \geq I(g_j) \ i \leq j$$

In this order, the agent now chooses a preference-optimal goal location for each unsatisfied goal $g \in \mathfrak{G}_u^{\text{M}}$ and creates a new task which is added to their Agent Task List as the next task. This is a Preference-Optimal Goal Location Choice Problem 6.1 with parameter set $(g, \mathfrak{L}^{\text{M}}(\mathfrak{G}_u^{\text{M}}), \alpha^{\text{UDG Behaviour}}, p^{\text{UDG Behaviour}})$:

$$\alpha^{\text{UDG Behaviour}}\colon \mathfrak{L}^{\text{M}}(\mathfrak{G}_u^{\text{M}}) \to \mathbb{R}^s, \quad \alpha^{\text{UDG Behaviour}}(l) := \left(F_1(l), \ldots, F_s(l), 2 \cdot \frac{\partial_+(\pi, l)}{\partial_{max}}\right)^T$$

where π is the position on the Agent Task List where the new task shall be inserted and

$$p^{\text{UDG Behaviour}} := (P_1, \ldots, P_s, 0)^T$$

If $\mathfrak{G}_u^{\text{M}} = \emptyset$, i.e. the agent doesn't know any goal location where any of their unsatisfied agent goals in $\mathfrak{G}_u$ can be accomplished, they will search for an information point where they can enquire more information about the environment using Algorithm 6.3.

Once the agent has reached the way point goal location which has been assigned by the

Algorithm 6.3 The Algorithm to search for an information point goal location.

Require: set of information point goal locations that are known to the agent $\mathfrak{I} \subseteq$ SMS, set of way point goal locations WPS
1: determine the set of way points that haven't been already visited be the agent: $\mathfrak{W} \subseteq$ WPS
2: **if** $\exists l \in \mathfrak{I}\colon \partial(x_{current}, \lambda(l)) \leq 30m$ **then**
3: add task to go to the nearest information point
4: **else**
5: add task to go to the nearest non-visited way point
6: **end if**

Unsatisfied Desired Goal Behaviour Model, the pedestrian will search again for a nearest information point using Algorithm 6.3. Once the agent has reached a targeted information point, they "look up" any needed information. Thereby, their Spatial Memory Set will be enriched with all available goal locations for all their unsatisfied agent goals $\mathfrak{G}_u$. With this information, the agent adds tasks related to their unsatisfied goal locations to their Agent Task List as described above by solving Preference-Optimal Goal Location Choice Problems for each unsatisfied agent goal in the order of their current relative importance.

It is postulated, that during their trip the agent will only once try to gather missing information by visiting an information point. Therefore, once a task to go to an information point has either been completed or dismissed, the agent will not again evaluate a possible Unsatisfied Desired Goal Behaviour.

6.5. Modelling the Egress Phase

After the agent has either accomplished or suppressed any of their assigned agent goals by performing tasks at their chosen goal locations, the agent leaves the environment via their previously assigned exit goal location l_{exit} (see Section 6.2). Therefore, in a simulation of the building usage-cycle of a complex multi-purpose environment with the CPAF, agents constantly enter and leave the environment throughout the entire modelled usage-cycle period.

Using this generic egress behaviour, the CPAF allows for the modelling of more specific types of egress scenarios. For example, scenarios can be modelled where each pedestrian can be assigned a mode of transport in order to leave the environment. This feature allows for the modelling of public transport links attached to the modelled complex multi-purpose environment such as bus stations of shopping centres or even the modelling of entire transport terminals such as airports. This special egress behaviour will be demonstrated in Chapter 9 by the example of a railway station terminal simulation.

On the other hand, the CPAF can be used to simulate evacuation scenarios in response to alarms during a normal circulation scenario. The CPAF's knowledge and decision making components thereby allow the agents to choose their evacuation strategy based on their individually obtained information and their history with the modelled structure as has been proposed by Gwynne and Kuligowski [9]. This possible egress behaviour is described in Chapter 7.

6.6. Summary

In this chapter, the application of the Cognitive Pedestrian Agent Framework (CPAF) as described in Chapter 5 to the simulation of a building usage-cycle as proposed by Gwynne and Kuligowski [9] has been illustrated. This entire chapter therefore addresses Research Objective 5.

In Section 6.1, generic choice situations that an agent faces during a simulation of a building's usage-cycle have been discussed and the solution algorithms to each choice problem which incorporates the CPAF decision making models Planned Decision Making and Short Time Span Adaptive Decision Making have been described in detail.

During the simulation of a usage-cycle, the pedestrian agent repeatedly needs to choose target locations which they want to visit in order to satisfy their current needs. In Section 6.1.1, models for modelling the pedestrian's target choice in a pedestrian behaviour simulation model are proposed. Pedestrians in a complex multi-purpose environment not only choose their target locations but actually their route in the environment. Section 6.1.3 therefore addresses how humans choose a route connecting several target locations and how this behaviour can be modelled in a pedestrian behaviour simulation model. A way for solving such a route choice problem in a given environment is the Human Path Planning Heuristic introduced in Section 6.1.2.2. The Human Path Planning Heuristic incorporated in the CPAF is based on empirical human behaviour research by Wiener et al. [7]. The Human Path Planning Heuristic is the first known framework that incorporates an attempt to realise the research insights by Wiener et al. in a pedestrian behaviour simulation tool.

The agent's trip planning prior to their entry into a modelled complex multi-purpose environment which is based on their experience with the environment has been discussed in Section 6.3 and modelled by solving the appropriate generic choice problems. The methods described in Section 6.3 thereby use the functionalities of the CPAF and hence specifically address how pedestrian target and route choice can be modelled in a pedestrian behaviour simulation tool, see Research Question 5.

A way to model the agent's structural and situational awareness during a pedestrian circulation scenario using the functionalities provided by the proposed CPAF has been depicted in Section 6.4. In particular, the CPAF's visual perception model introduced in Section 5.5 and its application to structurally stimulated decision making detailed in Section 6.4.1 addresses how the CPAF agents are capable of perceiving structural information from the modelled environment. The perceived information is evaluated with respect to the agent's current goals and plans and thereby classified with regard to the agent's current context and situation. Based on this evaluation, the agent can act in concordance with their current aims, see Research Question 4. Similarly, the Unsatisfied Desired Goal Behaviour detailed in Section 6.4.2 demonstrates how CPAF agents determine a lack of knowledge to satisfy their needs and choose appropriate actions to resolve this problem.

Chapter 7:

Modelling Experiential Alarm Response Behaviour using the Cognitive Pedestrian Agent Framework

Understanding the behaviour of pedestrians during the time period between an alarm event until the point in time when the individual pedestrian initiates their travel to a suitable exit, the individual pedestrian's *alarm response behaviour*, has drawn more and more attention over the past decade in the Fire Safety Engineering and Evacuation Modelling community [142–149].

The pedestrian's alarm response behaviour and its preconditions have got a significant impact on the individual's as well as the overall evacuation performance. When discussing the alarm response behaviour of pedestrians, it is distinguished between three phases in time, see Figure 7.1.

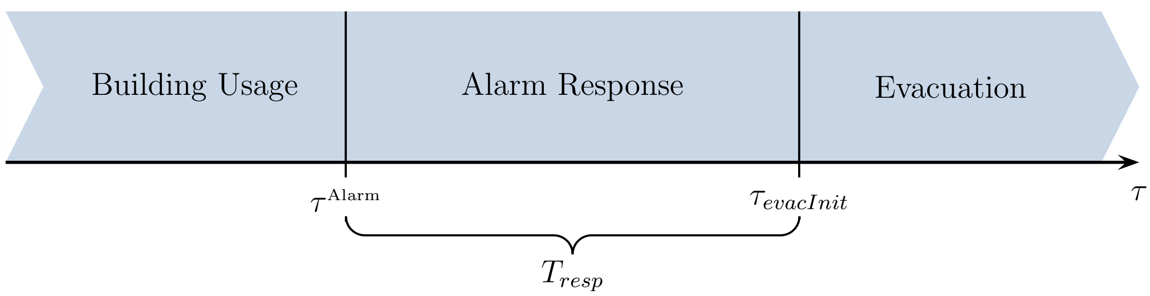


Figure 7.1.: The three phases of pedestrian behaviour when including a simulated alarm.

The first phase is the normal building usage up to the sounding of the alarm at the time τ^{Alarm}, see Figure 7.1. The pedestrians circulate in the environment and follow their plans and intentions. Upon the sounding of the alarm, each pedestrian enters their alarm response phase. During the alarm response phase, each individual pedestrian decides on which exit they shall target for their evacuation and what the pedestrian wants to do until they initiate their evacuation, their *pre-evacuation activities*. Subsequently, the pedestrian performs their chosen pre-evacuation activities until their *evacuation initiation time* $\tau_{evacInit}$ which marks the end of the pedestrian's alarm response phase, see Figure 7.1. The duration of the pedestrian's alarm response phase is then called the individual pedestrian's *response time*

$$T_{resp} := \tau_{evacInit} - \tau^{\text{Alarm}}$$

At the time $\tau_{evacInit}$, the pedestrian therefore enters their final evacuation phase where the pedestrian initially navigates from their currently occupied location in the environment towards the exit that they have chosen during their alarm response phase. Further during the evacuation phase, the pedestrian might adapt their route, but this behaviour shall not be discussed in this thesis.

From an observer's point of view, the decision processes that the individual pedestrian undertakes during their alarm response phase are not perceivable, but only the results of these decision processes, the pedestrian's emergent behaviour during and after their alarm response phase, is observable. The pedestrian's observable alarm response behaviour therefore comprises the pedestrian's pre-evacuation activities, their response time T_{resp}, their evacuation starting location and their initially targeted exit.

When simulating the evacuation of a certain structure, these four parameters need to be decided upon for each individual agent prior to the start of the evacuation simulation. An appropriate representation of these parameters is heavily dependent on the amount of specific empirical data available about the environment in question from e.g. evacuation trials or data from actual evacuations. In the case of an absence of reliable data, the set-up of the alarm response behaviour parameters is down to the user's level of expertise [150]. Inaccuracy or false assumptions might lead to an underestimation of the total evacuation time needed as well as false predictions of possible bottlenecks within the environment.

Most evacuation modelling tools provide the user with an automated set-up of the parameters mentioned above. These automatically generated suggestions are based on randomisation (as e.g. for the agents' evacuation starting locations), or on global probability distributions that have been deduced from the knowledge available in the academic literature or self-conducted evacuation trials.

Nevertheless, especially in structures such as complex multi-purpose environments, the actual intentions and experience of the individual agent have a crucial impact on their cognitive processes during the alarm response phase. These cognitive processes determine the individual agent's emergent alarm response behaviour. By employing (global) probability distributions to externally impose an alarm response behaviour on the individual agent, any real human response behaviour can only be approximated and oversimplified.

The Cognitive Pedestrian Agent Framework (CPAF) can be deployed to address these concerns and enhance the modelling of the agents' alarm response behaviour in an evacuation simulation. In order to demonstrate this possible application of the presented CPAF, an Alarm Response Behaviour Model has been designed and implemented in the buildingEXODUS CPAF Plug-in. The Alarm Response Behaviour Model presented in this chapter is inspired from the current research understanding of how pedestrians behave during their response phase. However, this model is not based on any empirical data and as such does not claim to be reproducing actual pedestrian behaviours. Instead, the model is a proof of concept for the use of the CPAF when modelling experiential alarm response behaviour.

As in reality, the alarm response behaviour model in the buildingEXODUS CPAF Plug-in tries to build upon the CPAF agent's intrinsic goal, knowledge and decision making representations to allow the modelled alarm response behaviour to be not externally imposed but to be a natural result of the agent's preconditions. For this purpose, the buildingEXODUS CPAF Plug-in has been designed to model the complete phase transition process as depicted in Figure 7.1 and thereby to allow the transition from a building usage-cycle simulation to a building evacuation simulation.

During the initially modelled building usage phase in the buildingEXODUS CPAF Plug-in, the simulated pedestrians use the environment as intended, following their goals and plans. The agents thereby acquire additional spatial information about the environment and engage in activities. At a pre-specified point in time $\tau^{\text{Alarm}} \in \mathbb{R}^{+}$, a simulated emergency alarm is operated. The agents will then choose from their available knowledge a target exit (see Section 7.1), potentially delay their evacuation because of urgent or highly rated pre-evacuation activities and will then start to evacuate from their current position at an individual point in time $\tau_{evacInit}$. The agent's response time T_{resp} and their individual pre-evacuation activities during the alarm response phase is thereby modelled by one of the buildingEXODUS CPAF Plug-in's alarm response phase models, see Section 7.2.

In the buildingEXODUS CPAF Plug-in, the agents are therefore aware of their current behavioural state, i.e. whether they are currently circulating, responding or evacuating. Depending on their current behavioural state, some of the buildingEXODUS CPAF Plug-in's components are automatically enabled or disabled for the individual agent. While in the circulation behavioural state all modelled components of the buildingEXODUS CPAF Plug-in are at the agent's disposal, the following components of the buildingEXODUS CPAF Plug-in are disabled while the agent is either in the response or in the evacuation behavioural state:

- the motivations as the realisation of the agent's internal stimuli (see Section 5.6.1),
- the emotions as the realisation of the agent's evaluation of external stimuli (see Section 5.6.2),
- the assessment of the surrounding population density as one representation of external

stimuli (see Section 5.6.2.1),

- the Unsatisfied Desired Goal Behaviour (see Section 6.4.2)

The agent, independent of their current behavioural state, is always able to make decision using their decision making model (see Section 5.4) and to perceive their surrounding environment (see Section 5.5) and thereby respond to perceived goal locations (see Section 6.4.1).

7.1. Exit Choice

At the beginning of the agent's response phase, the agent chooses an exit which they will target once they enter the evacuation behavioural state. For this, the agent in the buildingEXODUS CPAF Plug-in will use the information stored in their Spatial Memory Set, which has been obtained by either previous experience with the modelled environment in question or by perception during their travels in the simulation's previous building usage phase.

The agent chooses an exit which is known to them and therefore stored in their Spatial Memory Set. Upon choosing an exit, the agent tries to retrieve all available exits from their memory. Because of the CPAF's short-term memory feature (see Section 5.3.2), the agent might not be able to recall all of the exits available in their Spatial Memory Set. This simulates the behaviour, that if an agent has perceived an exit during their travels in the modelled environment, it is possible that they can't recall this exit during the exit choice stage because they may have forgotten about this exit.

In the buildingEXODUS CPAF Plug-in's exit choice model, it is postulated that the original experience source of the exits stored in the agent's Spatial Memory Set makes a difference in how this exit information is treated in order to choose a targeted exit. It is postulated, that during a situation of elevated stress as posed by an occurring alarm event, the agent will rely more on familiar information than recently attained information. This postulate is in accordance with the theory developed by the bounded rationality theory on human decision making (see Section 3.2.1.3) and especially the Recognition Heuristic of the Adaptive Toolbox [97].

In the buildingEXODUS CPAF Plug-in's exit choice model, the agent will therefore in the first step evaluate only those exits, which are known to them by previous experience with the modelled structure and subsequently compare this information to the exits that have been perceived during their current circulation travels. Let therefore $\mathfrak{E}_{exp}$ denote the set of all exit goal locations which are known to the agent from previous spatial experience with the modelled environment and similarly let $\mathfrak{E}_{perc}$ denote those exit goal locations known to the agent only by perception during the circulation stage of the current simulation:

$$\mathfrak{E}_{exp} := \{l \in \mathfrak{L}^{\mathrm{M}}(\text{“exit”}) \mid l \text{ is known from previous experience}\}$$
$$\mathfrak{E}_{perc} := \{l \in \mathfrak{L}^{\mathrm{M}}(\text{“exit”}) \mid l \text{ is known only from visual perception}\}$$

The agent first evaluates the exits which are known to them from previous experience based on the distance from their current spatial location in the environment $x_{current} \in \mathbb{E}$ to these exits. Since the exits to be assessed are known from previous experience and are therefore treated as being readily and reliably available, the agent employs a Planned Decision Making model instance in order to choose the exit which is closest to their current position. This is a Preference-Optimal Goal Location Choice Problem 6.1 with parameter set $(\mathfrak{E}_{exp}, \alpha^{\text{EE}}, p^{\text{EE}})$ where

$$\alpha^{\text{EE}} \colon \mathfrak{E}_{exp} \to \mathbb{R}_0^+, \quad \alpha^{\text{EE}}(l) := \partial(\lambda(l), x_{current}), \qquad p^{\text{EE}} = 0$$

This problem is solved using Model 6.1, which results in the distance-optimal exit goal location known from previous experience $l_{exp} \in \mathfrak{E}_{exp}$.

In the next step of the buildingEXODUS CPAF Plug-in's exit choice model, the agent assesses all those exits known to them from visual perception by taking the distance-optimal exit from previous experience as a reference. Since this assessment takes into account those exits that are purely retrieved from short-term memory and under the stressful situation of an ongoing alarm signal, the CPAF's Short Time Span Adaptive Decision Making model is applied [102].

The perceived exits in $\mathfrak{E}_{perc}$ are compared to the distance-optimal and thereby closest exit from previous experience l_{exp} based on two criteria. The first criterion is whether the perceived exit is closer to the agent than l_{exp}. If more than one perceived exit is closer than l_{exp}, those perceived exits which have been last perceived not too long ago are preferred. As a measure of reference, the simulation time $\tau_{\text{HT}} \in \mathbb{R}^+$ is used with

$$\tau_{\text{HT}} := \tau^{\text{Alarm}} - \frac{1}{2} \cdot \left(\tau^{\text{Alarm}} - \tau^{\text{Entry}}\right)$$

where τ^{Entry} is the agent's entry time in the modelled environment. τ_{HT} therefore marks the simulation time halfway between the agent's entry in the environment and the current time τ^{Alarm} of the modelled alarm.

Consequently, for each exit $l \in \mathfrak{E}_{perc}$, the perceived exit choice's attribute function is defined by

$$\alpha^{\text{PEC}} \colon \mathfrak{E}_{perc} \to \mathbb{R}^2, \qquad \alpha^{\text{PEC}}(l) := \begin{pmatrix} \partial(x_{current}, \lambda(l)) \\ \tau_l^{\text{Perc}}(\tau^{\text{Alarm}}) \end{pmatrix}$$

where $\tau_l^{\text{Perc}}(\tau)$ denotes the time that the exit l has last been perceived at simulation time τ.

In summary, the agent assesses their purely perceived exits $\mathfrak{E}_{perc}$ by solving the Short Time Span Adaptive Decision Making problem with parameter set

$$\left(\mathfrak{E}_{perc}, \alpha^{\text{PEC}}, \begin{pmatrix} \partial(x_{current}, \lambda(l_{exp})) \\ \tau^{\text{HT}} \end{pmatrix}, \begin{pmatrix} \omega_< \\ \omega_> \end{pmatrix}, \zeta_{rand}\right)$$

where $\omega_<$ and $\omega_>$ are the comparison functions defined by the Equations 5.5 and ζ_{rand} is the random choice function depicted in Table 5.9.

If one of the perceived exits meets the specified criteria, i.e. if

$$\zeta^{\text{PEC}}(\mathfrak{P}_{(\mathfrak{E}_{perc},\Xi^{\text{PEC}})}) =: l_{perc} \neq \mathbf{0}$$

the agent chooses this perceived exit l_{perc} as their initial target exit. If no perceived exit meets the criteria, the distance-optimal exit known from previous experience l_{exp} is chosen.

Once the agent has entered the evacuation behavioural state, the agent will therefore initially target their chosen exit. However, since the agent is able to perceive alternative exits on their way to their assigned exit, it is possible that they may decide to target a different exit on route, see Section 6.4.1.

7.2. Response Phase Modelling

Most state-of-the-art evacuation modelling tools (see Table 2.9) realise the simulation of the pedestrian alarm response behaviour by randomly assigning each agent a response time T_{resp} and a fixed evacuation starting location, where the agent will typically stand still until their response time has elapsed. The agent's individual response time is mainly set according to cumulative probability distributions which have been obtained from empirical studies and / or published resources. This approach thereby disregards the underlying processes taking place during the individual's alarm response phase and externally impose all relevant parameters. As a consequence, this method is heavily dependent on the user's level of understanding of the scenario in question.

Some evacuation modelling tools such as buildingEXODUS [14] offer – in addition to the above described method – the possibility to either manually or randomly assign certain pre-evacuation activities to specific agents which they than need to complete prior to initiating their evacuation. Thereby, the agent's response time and their evacuation starting location are the emergent result of having completed all assigned pre-evacuation activities. The draw back with this approach is the generation of these pre-evacuation activities which is down to the level of expertise of the user. In addition, the assignment of pre-evacuation activities is complex and laborious in the current buildingEXODUS version.

The buildingEXODUS CPAF Plug-in provides an alternative approach for modelling the pedestrian response phase. With the features available in the CPAF (see Chapter 5) and the buildingEXODUS CPAF Plug-in's possibility to model the transition from a building usage to an evacuation simulation (see beginning of Chapter 7), the agents' response phase behaviour can be generated as a logical result of the agents' previous building usage behaviour, as has been proposed by Gwynne and Kuligowski [9].

In order to allow for studying the outcomes of different modelling strategies, three response phase models have been developed in the buildingEXODUS CPAF Plug-in. All of these response phase models have in common, that they benefit – to different extents – from the modelling of the transition from a building usage simulation to an evacuation simulation. As a consequence, in all response phase models within the buildingEXODUS CPAF Plug-in, the agents' evacuation starting locations are never externally imposed, but rather a result of either the individual agent's building usage behaviour or their pre-evacuation activities. Hence, the buildingEXODUS CPAF Plug-in's response phase models present methods of determining the remaining two response phase parameters to the agent: their pre-evacuation activities and their response time.

The three response phase models in the buildingEXODUS CPAF Plug-in can be grouped into two categories, the Imposed Response Time Models (see Section 7.2.2) and the Predicted Response Phase Model (see Section 7.2.3).

The buildingEXODUS CPAF Plug-in's Imposed Response Time Models imposes for each individual agent the duration of their response phase, their response time, according to a global probability distribution. During their response phase, the agent than exhibits one of the modelled pre-evacuation activities, see Section 7.2.1, which are either imposed or predicted from the previous building usage behaviour.

By contrast, in the buildingEXODUS CPAF Plug-in's Predicted Response Phase Model, neither a response time nor the agent's pre-evacuation activities are imposed on the agent. Instead, the Predicted Response Phase Model allows the agent's pre-evacuation activities to be the emergent result of the agent's previous building usage. The agent therefore employs a decision making instance to decide upon their pre-evacuation activities based on their current situation and their response time is an emergent result of the predicted pre-evacuation activities, see Section 7.2.3.

Since only very little research and empirical studies are available which investigate the processes involved in the pedestrians' alarm response phase, the buildingEXODUS CPAF Plug-in's alarm response phase models presented in this thesis aims to demonstrate the possible impact of the CPAF's components rather than to propose a sophisticated alarm response framework. Therefore, the CPAF's response phase models presented in this section are designed to study the different outcomes of different possible response model strategies.

For the buildingEXODUS CPAF Plug-in, the user can specify which of the building-EXODUS CPAF Plug-in's response phase models is used for a certain scenario by using the appropriate input features in the Cognitive Pedestrian Agent Framework Scenario Specification Generator. In addition, the user can specify the parameters necessary for each response model.

7.2.1. Modelling Pre-Evacuation Activities

The kind of behaviour and especially activities pedestrians exhibit during the time period between the perception of the alarm and the commencement of the travel to an exit is drawing more and more attention in the Fire Safety Engineering community [143, 146, 151].

During empirical studies [143, 152–154], a broad range of different pre-evacuation activities has been observed, such as pedestrians carrying on with their agenda, pedestrians investigating the potential alarm cause, pedestrians standing still and waiting, or pedestrians seeking other pedestrians. Each of these activities can have several purposes. For example if a pedestrian is trying to investigate the potential cause of the alarm, the pedestrian might want to help eliminating the alarm cause or they might simply be curious. In the same way, if pedestrians are seeking other pedestrians during the response phase, motivations of the individual pedestrian might be totally different. Where one pedestrian might want to help these other pedestrians, the other pedestrian might themselves be seeking help from other more experienced pedestrians, or the pedestrian simply wants to reunite with a group with which they have been travelling before the alarm has been operated.

As can be seen from this basic enumeration, modelling possible pre-evacuation activities is a complex task which will always present a rough approximation of the actual pedestrian response behaviour. However, by studying different response phase models with different parameters, the resulting what-if scenarios can provide additional insight into potential pedestrian response behaviour.

7.2.2. Imposed Response Time Models

The buildingEXODUS CPAF Plug-in's Imposed Response Time Models are user-specified probabilistic response time models. In other words, the duration of the agent's response phase is determined by the realisation of the response time random variable

$$T_{resp} = \tau_{evacInit} - \tau^{\text{Alarm}}$$

The response time random variable T_{resp} follows a global probability distribution that the user can specify. In the current buildingEXODUS CPAF Plug-in and the Cognitive Pedestrian Agent Framework Scenario Specification Generator, the user can employ a log-normal distribution

$$T_{resp} \sim \mathcal{L}_{[0,z]}(\mu, \sigma^2) \qquad z \in \mathbb{R}^+ \cup \{\infty\}, \mu, \sigma \in \mathbb{R}^+$$

with parameters z, μ and σ. However, research suggests, that a log-normal distribution is an appropriate distribution to approximate the response time T_{resp} [155].

The assigned response time T_{resp} thereby sets the agent's evacuation initiation time $\tau_{evacInit}$, at which the agent will switch from the response behavioural state to the evacuation behavioural state and therefore at which point in time the agent will terminate their assigned pre-evacuation activities and start to travel towards their previously chosen exit (as described in Section 7.1).

In the current version of the buildingEXODUS CPAF Plug-in's Imposed Response Time Model, two basic possible alarm pre-evacuation activities have been implemented: upon perceiving the alarm, the agents will either stand still and wait or they will continue with their current agenda that had been obtained from the previously modelled building usage-cycle (see Sections 6.3 and 6.4).

The simulation of the "stationary" activity is realised by assigning a delay type task of duration T_{resp} to the agent which they need to complete at their current location. Therefore, the agent's spatial location at the time τ^{Alarm} of the sounded alarm is their evacuation starting location. On the other hand, the "carry-on" activity is simulated by simply allowing the agent to further pursue their tasks until their individual response time has elapsed, i.e. $\tau = \tau_{evacInit}$, and therefore their evacuation starting locations is dependent upon this pre-evacuation activity and T_{resp}.

The two Imposed Response Time Models in the current version of the buildingEXODUS CPAF Plug-in, the Imposed-Time Imposed-Activities Response Phase Model and the Imposed-Time Predicted-Activities Response Phase Model, differ in the way that the modelled pre-evacuation activities "carry-on" or "stationary" are assigned to the agent once the response time T_{resp} and thereby the agent's evacuation initiation time $\tau_{evacInit}$ have been set.

If the Imposed-Time Imposed-Activities Response Phase Model is used for an alarm response simulation, a discrete probability distribution needs to be specified by the user in the Cognitive Pedestrian Agent Framework Scenario Specification Generator which then determines the likelihood that an agent enacts in one of the modelled pre-evacuation activities:

$$p(a) \in [0,1] \quad \text{and} \quad \sum_{\substack{\text{pre-evacuation} \\ \text{activity } a}} p(a) = 1$$

Consequently, in the Imposed-Time Imposed-Activities Response Phase Model a pre-evacuation activity is imposed on each agent based upon this probability distribution.

By contrast, in the Imposed-Time Predicted-Activities Response Phase Model, the agent decides upon an appropriate pre-evacuation activity based on their current situation and plans using their decision making entity. Since the agent is supposed to make this kind of decision subconsciously and in a situation of elevated stress posed by the sounding of the alarm signal, the Short Time Span Adaptive Decision Making model is used to simulate this response behaviour decision situation [102].

The Short Time Span Adaptive Decision Making model to simulate the pre-evacuation activity decisions takes the current situation and therefore the "carry-on" pre-evacuation activity as the reference option. This reference option is then evaluated against the alternative to exhibit the "stationary" pre-evacuation activity:

$$\gimel^{\mathrm{ITPA}} = \{\text{stationary}\}$$

Since the decision on the agent's pre-evacuation activity considers only a very limited time frame, it is postulated that the agent will make this decision based only on the importance of their currently ongoing task $t_{\pi_0} \in \mathrm{ATL}$. Therefore, the agent should decide not to change their plans if their current plan is highly important to them. Thus, the choice alternative to exhibit the "stationary" pre-evacuation activity is represented by the following attribute function

$$\alpha^{\mathrm{ITPA}} \colon \gimel^{\mathrm{ITPA}} \to [0, 100], \quad \alpha^{\mathrm{ITPA}}(\text{stationary}) := \mathbf{I}^*$$

where the constant value $\mathbf{I}^*$ is postulated to represent the importance threshold for highly important tasks and can by specified by the user within the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

The agent therefore evaluates in this Short Time Span Adaptive Decision Making instance with parameter set

$$(\gimel^{\mathrm{ITPA}}, \alpha^{\mathrm{ITPA}}, I(t_{\pi_0}), \omega_>, \zeta_{rand})$$

whether the importance of their current task $I(t_{\pi_0})$ is less than the importance threshold $\mathbf{I}^*$. If this is the case, then the agent will change their behaviour to exhibit the "stationary" pre-evacuation activity. Otherwise, the agent will simply continue with their current plans until their response time $\tau_{evacInit}$ has been reached.

7.2.3. Predicted Response Phase Model

Contrary to the Imposed Response Time Models in Section 7.2.2, the Predicted Response Phase Model determines the agent's pre-evacuation activities during their response phase and their response time T_{resp}, from the agent's current situation.

The agent assesses their current situation by subconsciously evaluating the features of their currently ongoing task $t_{\pi_0} \in \mathrm{ATL}$, and choosing one of the modelled pre-evacuation activities based on this evaluation. The agent's response phase is then finished as soon as the agent has completed their chosen pre-evacuation activities. For this reason, the agent's response time T_{resp} and vice versa their evacuation initiation time $\tau_{evacInit}$ are dependent on the chosen pre-evacuation activity.

It is postulated, that the most important features of the current task t_{π_0} for the agent's alarm response considerations are the following:

- the task's status, i.e. whether the task has already been started and therefore whether $\tau_{start}(t_{\pi_0}) > 0$,
- the task's importance $I(t_{\pi_0})$ to the agent,

- the distance remaining to the task's assigned goal location $l(t_{\pi_0})$

$$d(t_{\pi_0}) := \begin{cases} \partial(x_{current}, \lambda(l(t_{\pi_0}))) & \text{if } \tau_{start}(t_{\pi_0}) \leq 0 \\ 0 & \text{else} \end{cases}$$

- the ratio of the time that the agent has already been performing the task t_{π_0} to the time that the agent is assigned to perform the task

$$r_{t_{\pi_0}} := \begin{cases} \dfrac{\tau^{\text{Alarm}} - \tau_{start}(t_{\pi_0})}{\tau_{end}(t_{\pi_0}) - \tau_{start}(t_{\pi_0})} & \text{if } \tau_{start}(t_{\pi_0}) > 0 \\ 0 & \text{else} \end{cases}$$

Since the agent's response time T_{resp} is not set beforehand, the pre-evacuation activities in the Predicted Response Phase Model don't have a fixed end time when the pre-evacuation activity is terminated and the travel towards the chosen exit is initiated. For this reason, the pre-evacuation activities modelled in the Predicted Response Phase Model differ from those pre-evacuation activities modelled in the Imposed Response Time Models, the main difference being that in the Predicted Response Phase Model no "stationary" pre-evacuation activity is modelled, because this would require the specification of the length of time that the agent should remain at a certain location.

The pre-evacuation activities available in the Predicted Response Phase Model are listed in Table 7.1. As depicted, the pre-evacuation activities that are available to the agent are dependent on the currently ongoing task's type and its status.

Table 7.1.: The possible pre-evacuation activities dependent upon the type and status of the current task t_{π_0}.

t_{π_0} Task Type	t_{π_0} Task Status	Possible Activities
wait	started	continue until $\tau = \tau_{term}$
	not started	abort
way point	not started	abort
delay	started	terminate now
		continue as planned
	not started	rush
		abort

As depicted in Table 7.1, the situation whether the agent needs to choose an appropriate pre-evacuation activity or whether the pre-evacuation activity is a direct consequence of the currently ongoing task, is dependent upon the currently ongoing task's type and status.

Since critical time tasks are only completed at an absolute point in time, it is necessary for the Predicted Response Phase Model to assign this type of tasks a specific end time τ_{term}, if the agent has already started this task. The end or termination time τ_{term} shall therefore be smaller than or equal to the task's original end time τ_{wait}:

$$\tau^{\text{Alarm}} \leq \tau_{term} \leq \tau_{wait}$$

This is achieved by modelling a task duration random variable

$$T_{term} := \tau_{term} - \tau^{\text{Alarm}}$$

which is distributed according to a log-normal distribution.

$$T_{term} \sim \mathcal{L}\left(\ln(T_{wait}) - \ln\left(2\sqrt{5}\right), \ln\left(\tfrac{5}{4}\right)\right) \tag{7.1}$$

Hereby denotes $T_{wait} := \tau_{wait} - \tau^{\text{Alarm}}$ the remaining amount of time after the alarm time τ^{Alarm} that the agent would normally have waited. The parameters μ and σ^2 have been chosen such that that the probability that T differs from its mean value $\mu_{T_{term}}$ by more than $\mu_{T_{term}}$ is less than $\frac{1}{4}$:

$$P\left(|T_{term} - \mu_{T_{term}}| \geq \mu_{T_{term}}\right) \leq \frac{1}{4}$$

With the Chebyshev's inequality, this leads to the following conditions on the mean $\mu_{T_{term}}$ and standard deviation $\sigma_{T_{term}}$ of T_{term}:

$$\begin{aligned} \mu_{T_{term}} &= \tfrac{1}{4} \cdot T_{wait} \\ \sigma_{T_{term}} &= \tfrac{1}{2} \cdot \mu_{T_{term}} \end{aligned}$$

With these conditions, the parameters of the log-normal distribution can be obtained as depicted in Section A.3.2.

In the case that the agent's currently ongoing task is a critical time task, the agent's pre-evacuation activity is dependent on whether the critical time task has already been started. In the case that the task t_{π_0} has already been started, the chosen pre-evacuation activity is to continue the task t_{π_0} until the newly assigned termination time T_{term} has elapsed. On the other hand, if the critical time task t_{π_0} has not been started yet, the task is immediately aborted. This alarm response behaviour in the case that t_{π_0} is a critical time task is postulated based on the assumptions, that pedestrians that are already waiting for an important event will continue waiting and thereby observing the future situation for a certain time despite the occurred alarm event.

In the case that the agent's currently ongoing task t_{π_0} is of the delay type, the agent in the Predicted Response Phase Model can decide between two possible pre-evacuation activities if they have already started the task t_{π_0} and two further possible pre-evacuation activities

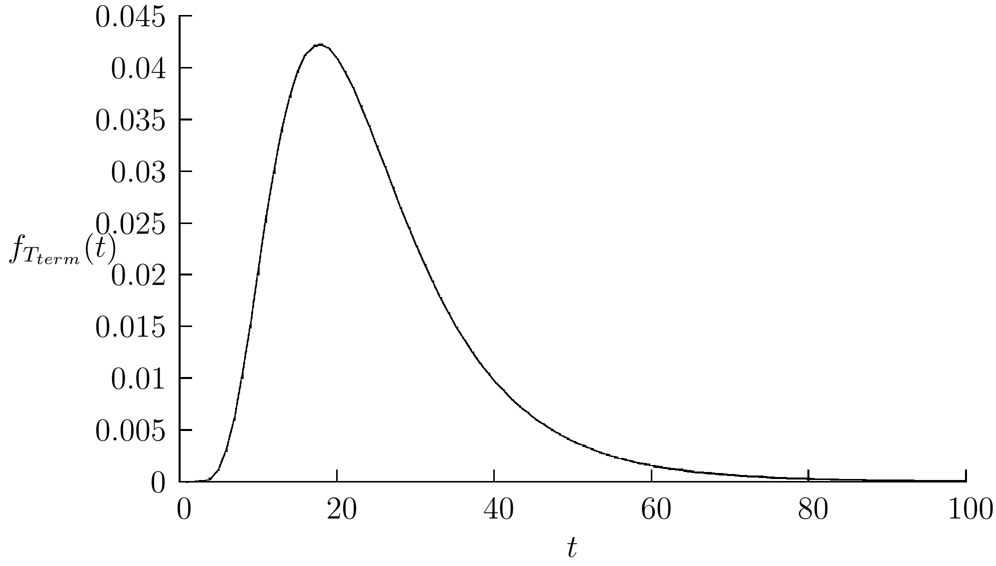


Figure 7.2.: An example probability distribution of T_{term} for $T_{wait} = 100$.

if the task t_{π_0} has not been started. In the former case, the agent can either choose to terminate the task immediately or to continue performing the task as planned. In the latter situation, the agent has either the possibility to abort the task or to rush the task. The "rush" pre-evacuation activity thereby halves the task's assigned minimum duration time T_{min} and maximum duration time T_{max}:

$$T_{min} \to \frac{1}{2} \cdot T_{min}, \qquad T_{max} \to \frac{1}{2} \cdot T_{max}$$

In the Predicted Response Phase Model, the agent decides which of the modelled pre-evacuation activities depicted in Table 7.1 they will perform during their response phase if the task t_{π_0} is of the delay type by employing the Short Time Span Adaptive Decision Making model. This is a sound approach (as has already been argued in Section 7.2.2), since in the elevated stress situation upon perceiving an alarm signal, a pedestrian is likely to make use of their heuristical decision making approaches.

The realisation of the Short Time Span Adaptive Decision Making model that the agent employs in this situation is thereby dependent upon the currently ongoing task's status, its importance $I(t_{\pi_0})$ and the task performance time ratio $r_{t_{\pi_0}}$. The complete pre-evacuation activity decision process is summarised in Algorithm 7.1.

Thereby, in Algorithm 7.1, the parameters $\mathbf{I}_1^*, \mathbf{I}_2^*, \mathbf{r}_1^*, \mathbf{r}_2^*$ are global constants specified by the user which depict two thresholds for the task's importance and two thresholds for the task performance time ratio which hold the following conditions:

$$0 < \mathbf{I}_2^* < \mathbf{I}_1^* \leq 100 \qquad \text{and} \qquad 0 \leq \mathbf{r}_1^* < \mathbf{r}_2^* \leq 1 \tag{7.2}$$

The decision tree as depicted in Algorithm 7.1 consisting of several instances of the Short

Algorithm 7.1 Algorithm to determine an appropriate pre-evacuation activity in the Predicted Response Phase Model for a delay type task $t_{\pi 0}$
.

Require: task importance $I(t_{\pi 0})$, distance to task $d(t_{\pi 0})$, task performance time ratio $r_{t_{\pi 0}}$, distance to chosen exit d_{exit}

if $d(t_{\pi 0}) = 0$ **then** {task has been started}
  if $I(t_{\pi 0}) > \mathbf{I}_1^*$ **and** $r_{t_{\pi 0}} > \mathbf{r}_1^*$ **then**
    continue task
  else if $I(t_{\pi 0}) > \mathbf{I}_2^*$ **and** $r_{t_{\pi 0}} > \mathbf{r}_2^*$ **then**
    continue task
  else
    terminate task
  end if
else {task has not been started}
  if $d(t_{\pi 0}) \leq d_{exit}$ **and** $I(t_{\pi 0}) > \mathbf{I}_2^*$ **then**
    rush task
  else
    abort task
  end if
end if

Time Span Adaptive Decision Making model is put forward as a way to simulate the agent's consideration process whether they should continue or still attempt their current task $t_{\pi 0}$ despite the occurred alarm event, or abort the task. It is therefore postulated, that if the agent has already started the task $t_{\pi 0}$, they will reason how important the task is to them and how much of the assigned task time $\tau_{end}(t_{\pi 0}) - \tau_{start}(t_{\pi 0})$ they have already completed. The conditions in Equation (7.2) therefore ensure that the agent will continue more important tasks based on a lower completed task performance time ratio. Less important tasks require a higher completed task performance time ratio on order for the agent to decide to continue the currently ongoing task. On the other hand, if the delay type task $t_{\pi 0}$ has not been started, the agent is postulated to reason whether the task's location is close in relation to their chosen exit and whether the task is to some extent important to them, in order to decide to still try and rush their currently ongoing task.

Finally, if the agent's ongoing task $t_{\pi 0}$ is of the way point type, this task is an auxiliary task in order to further explore the modelled environment (see Section 6.4.2), and therefore it is postulated that way point tasks are aborted immediately upon alarm perception.

7.3. Summary

In this chapter, the possible application of this thesis' Cognitive Pedestrian Agent Framework (CPAF) described in Chapter 5 to the simulation of experiential alarm response has been outlined. To demonstrate the benefits of the CPAF for modelling experiential alarm response in a pedestrian behaviour simulation, an alarm response model has been realised in the buildingEXODUS CPAF Plug-in and described in this chapter. This chapter thereby specifically addresses Research Objective 5 and Research Question 6.

The simulation of alarm response behaviour which is based on individual goals and experiences has been achieved in the buildingEXODUS CPAF Plug-in by simulating the transition from the circulation phase of a building usage-cycle simulation to an evacuation phase. By these means, the knowledge and plans that the individual pedestrian has gathered during the ingress and circulation phase of the building usage-cycle simulation (see Sections 6.3 and 6.4) are at their disposal to make an informed and individual decision on their evacuation strategy.

In Section 7.1, a model on how a pedestrian might choose an appropriate target exit is exemplified. This exit choice model is based on the individual agent's familiarity with the structure and therefore their Spatial Memory Set (see Section 5.3.2). The agent's Spatial Memory Set thereby comprises knowledge from previous experience with the structure (see Section 6.2.1) and perceived spatial information (see Section 5.5). From this knowledge base, the agent is then able to choose an appropriate target exit by employing their intrinsic decision making capabilities (see Section 5.4).

In Section 7.2, three approaches for modelling the agent's alarm response phase have been exemplified. Two approaches are dependent on user input (see Section 7.2.2), whereas the third approach entirely benefits from the information that is at the individual agent's disposal from the previously modelled building usage-cycle simulation and their intrinsic plans and decision making capabilities (see Section 7.2.3). All three approaches assign the individual agent a point in time at which they initiate their travel towards their chosen exit and an activity that the agent performs during their response phase, thereby implicitly setting the agent's evacuation starting location.

Table 7.2 lists the specifications required by the buildingEXODUS CPAF Plug-in for simulating experiential alarm response behaviour.

Table 7.2.: An overview of the required parameters based on which the experiential alarm response behaviour can be modelled with the buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in.

buildingEXODUS CPAF Plug-in Feature	Required Input
Alarm Response	Time of the Alarm Event
Alarm Response	Response Phase Model and Response Phase Model Parameters

Chapter 8:

Model Demonstration: Functional Verification Cases

Pedestrian behaviour simulation models are mathematical models and as such try to reproduce and approximate real human behaviour as closely as possible. However, as for any (mathematical) model of real world situations, the results produced by pedestrian behaviour simulation models are only approximations of real world outcomes, and they are highly dependent on the set-up of the modelling scenario and the model itself. Therefore, the results produced by pedestrian behaviour simulation models always need to be assessed with respect to the given problem statement and the model's set-up.

In this chapter, the components of the Cognitive Pedestrian Agent Framework (CPAF) are demonstrated and verified by simulating certain scenarios with the buildingEXODUS CPAF Plug-in. In Section 8.1, some utilities that are required to realise a pedestrian usage cycle simulation with the buildingEXODUS CPAF Plug-in and some standards for the simulation process are introduced. In Sections 8.2 to 8.8, the individual features of the buildingEXODUS CPAF Plug-in are exemplified in small functional verification cases. The functional verification cases use a simple geometry and set-up in order to demonstrate the impact of the buildingEXODUS CPAF Plug-in's various features (as described in Chapters 5, 6 and 7). The results of each functional verification case are then assessed with regard to the initial set-up and the expectations on the model's performance.

8.1. Utilities for the Model Demonstration

In this section, some basic utilities and conventions for the modelling of an environment are stipulated. These utilities and conventions facilitate the set-up of the subsequent demonstration.

8.1.1. Required Inputs for a pedestrian behaviour simulation with the Cognitive Pedestrian Agent Framework

The parameters required for a pedestrian behaviour simulation with the CPAF are listed in Table 8.1. These represent a summary to the information provided in Tables 5.13 and 6.1.

Table 8.1.: An overview of the parameters which are required for a pedestrian behaviour simulation with the Cognitive Pedestrian Agent Framework.

CPAF Component	Entity	Required Input
Environment	Goals	Global Goal Set
Environment	Goal Locations	Goal Location Set
Environment	Goal Locations	Departments
Environment	Goal Locations	Goal Location Feature Parameters F
Agent Model	Attributes	Personal Preferences P
Agent Model	Motivations	Motivations and Motivation Functions
Agent	Ingress	Entry time
Agent	Ingress	Probability of entering the environment at goal location l_{entry}
Agent	Egress	Probability of exiting the environment at exit goal location l_{exit} for a circulation simulation
Agent Population	Goals	Probability of a goal being assigned to an agent
Agent Population	Knowledge	Personal Preference Attributes P probability distribution
Agent Population	Attributes	Perceived Crowd threshold C^* probability distribution
Agent Population	Knowledge	Previous spatial knowledge probability distribution

By stating these parameters, the user can adjust the pedestrian behaviour simulation to their intended use case in their chosen environment. The CPAF thereby allows for a great flexibility in tailoring the model to the exact scenario to be modelled. This includes the environment model (goal, goal locations, feature parameters, ...) and the components of the CPAF's agent model (personal preferences, motivations). Further, the user can specify the scenario parameters and the details of the agent population to be modelled.

8.1.2. Standard Parameters of the buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in

As has already been described in the relevant chapters, the buildingEXODUS CPAF Plug-in makes use of specific examples for the required CPAF inputs. Table 8.2 therefore summarises the references to the example CPAF inputs used for the buildingEXODUS CPAF Plug-in.

Table 8.2.: References to the realisations of the required Cognitive Pedestrian Agent Framework parameters used in the Cognitive Pedestrian Agent Framework buildingEXODUS Plug-in.

CPAF Component	Input	Reference
Environment	Global Goal Set	Table 5.5
Environment	Departments	Table 5.3
Environment	Goal Location Feature Parameters	Table 5.2
Agent Model	Personal Preference Attributes	Table 5.6
Agent Model	Motivations	Table 5.11

In order to simulate motivational and goal-driven behaviour, the goal information represented in the CPAF needs to be linked to the spatial representation of outlets and facilities within the underlying pedestrian behaviour simulation tool, in the case of this thesis buildingEXODUS. As has been described in Section 5.2, an environment's facilities and outlets are represented by either single nodes or compartment zones in buildingEXODUS (see Section 4.1.1). By linking these spatial components to the goals represented in the buildingEXODUS CPAF Plug-in, these spatial locations then represent goal locations where the agents can then satisfy the associated goals.

In the current buildingEXODUS CPAF Plug-in, this linkage process is based on a keyword search, where the goals that are assigned to a facility depend on the name that has been given to the facility's spatial representation in buildingEXODUS. Based on its name, the facility is then identified with a certain goal location type. Examples for these goal locations types include e.g. restaurants or gift shops. Based on a facility's assigned goal location type, it is assigned appropriate goals from the Global Goal Set. Table 8.3 illustrates which goal is automatically associated with which goal location type in the current buildingEXODUS CPAF Plug-in.

In the remainder of this chapter, the goal location types listed in Table 8.3 will be referred to when describing the set-up of a geometry in buildingEXODUS.

8.1.3. Controlling the buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in Features

For the purpose of studying the impact of the CPAF's individual features on the simulation of the pedestrian usage-cycle of a given environment, the user can elect to disable selected features in the current buildingEXODUS CPAF Plug-in in order to reduce complexity. Table 8.4 lists the features which can be enabled respectively disabled by the user and their dependencies on other buildingEXODUS CPAF Plug-in features.

As can be seen in Table 8.4, the buildingEXODUS CPAF Plug-in's Trip Planning feature is required for all other advanced features. This is due to the fact, that if the agents aren't

Table 8.3.: A list of goals used for the Cognitive Pedestrian Agent Framework verification cases and their allocation to different goal location types.

Goal	Goal Category	Possible types of associated goal locations
"eat"	Activity	coffee shops, restaurants, food-on-the-go facilities, food shops
"drink"	Activity	coffee shops, food-on-the-go facilities, bars, food shops
"rest"	Activity	chairs, seating areas
"shop"	Activity	shopping facilities such as stationery shops, fashion shops, gift shops or beauty shops
"service"	Activity	service facilities
"information"	Navigation	information points
"way point"	Navigation	way points, junctions

Table 8.4.: The features of the current buildingEXODUS Cognitive Pedestrian Agent Framework Plug-in that can be enabled respectively disabled by the user and their dependencies.

Feature	Section / Chapter	Required buildingEXODUS CPAF Plug-in Features
Trip Planning	6.3	–
Structural Awareness	5.5, 6.4.1	Trip Planning
Urgency	5.6.2.2	Trip Planning
Perceived Crowd	5.6.2.1	Trip Planning, Urgency
Unsatisfied Desired Goal Behaviour	6.4.2	Trip Planning
Motivations	5.6.1	Trip Planning
Meal Times	5.6.1.1	Trip Planning, Motivations
Short Term Memory	5.3.2	Trip Planning
Alarm Response	7	Trip Planning

assigned routes, they will not enter and interact with the modelled environment. Alternatively to using the buildingEXODUS CPAF Plug-in's Trip Planning feature, the agents can also be assigned a route by other means, see Section 4.2. However, these routes will be externally imposed on the agents not be based on their assigned goals.

8.1.4. Data Analysis Tools

To analyse the complex results of a pedestrian usage-cycle simulation with the current buildingEXODUS CPAF Plug-in, various methods are employed. In this section the data analysis tools of the buildingEXODUS's footfall representation and the data analysis using box-an-whisker graphs are briefly introduced.

Footfall Analysis

The buildingEXODUS software tool provides the possibility to illustrate the level of usage of a modelled environment by visual means, the so called *footfall* representation, Galea et al. [14]. The buildingEXODUS's footfall representation is comparable to a temperature or gas contour fill as used in fire simulation, see for example Wang et al. [156, Figure 12]. For the footfall analysis, buildingEXODUS collects data on the usage of the single nodes of which the environment is built. For each single node i, a cumulative footfall value ν_i is therefore determined:

$$\nu_i := \frac{N_i}{\max\{1, \frac{N}{2}\}} \tag{8.1}$$

where N_i is the total number of agents that walked over the node i during the simulation and N is the total number of agents in the simulation.

After the end of a simulation run, buildingEXODUS is then capable to produce cumulative footfall images. In these footfall images, each node in the environment is coloured according to their level of footfall, see Table 8.5.

Table 8.5.: Colour keys to the buildingEXODUS footfall images [14, Figure 7-21]

ν_i	Colour of node i
$\nu < 0.0001$	□
$0.0001 \leq \nu < 0.11$	■
$0.11 \leq \nu < 0.22$	■
$0.22 \leq \nu < 0.33$	■
$0.44 \leq \nu < 0.55$	■
$0.55 \leq \nu < 0.66$	■
$0.66 \leq \nu < 0.88$	■
$0.88 \leq \nu$	■

The footfall images of simulation runs therefore provide the basis for a qualitative discussion of the agents' environment usage behaviour throughout the simulation.

Box-and-Whisker Graphs

Box-and-Whisker Graphs are non-parametric data analysis tools in descriptive statistics [157]. A box-and-whisker graph thereby illustrates the distribution of empirical data without making any assumptions on the data's underlying distribution. It consists of a box depicting the empirical data's interquartile range and lines connected to the box, the "whiskers", see Figure 8.1.

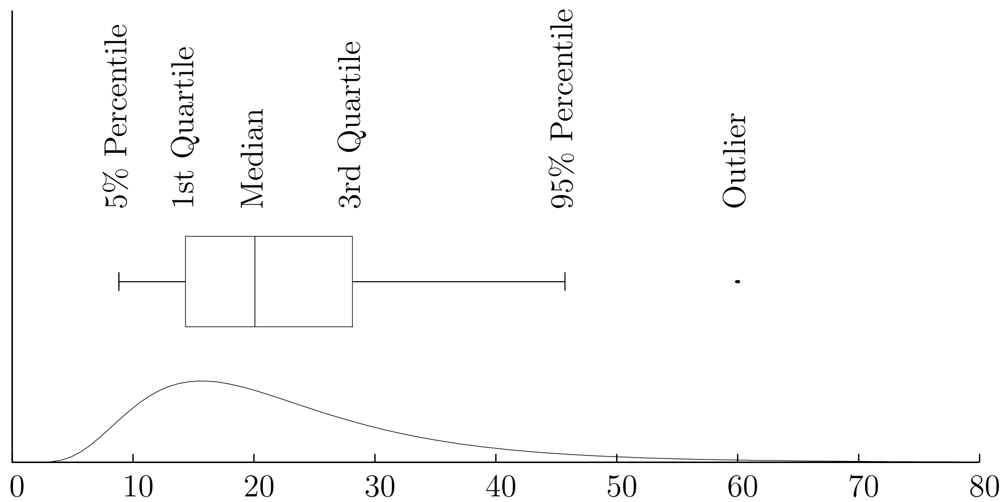


Figure 8.1.: A sample distribution of a random variable and the corresponding box-and-whisker graph.

As can be seen in Figure 8.1, the median of the empirical data's distribution is indicated by a line dividing the interquartile box in two halves. Thereby, the skewness of the underlying empirical data's distribution can be seem from a box-and-whiskers graph. To define to which value of the empirical data distribution the whiskers extend is down to the user. For the purpose of this thesis, the whiskers will be drawn from the interquartile box to the 5th respectively 95th percentile. Any values of the empirical data that don't lie in the range of the whiskers are indicated by dots and named outliers.

8.2. Trip Planning

The Trip Planning Simulation Verification Case aims to illustrate the most basic features of the CPAF. As has been described in Section 6.3, the CPAF provides the capability to simulate the trip planning of pedestrians, that are familiar, to different degrees, with the structural layout of the environment. Their differences in previous experience impacts the way they plan their route. Non-experienced pedestrians need to explore the environment, whereas those pedestrians that are familiar with the environment will choose a cluster-based distance-optimal route [7]. The purpose of the Trip Planning Simulation Verification Case is therefore to demonstrate the effects of different levels of environment familiarity on the CPAF agents' trip planning.

8.2.1. Geometries

For the Trip Planning Verification Case, two different geometries have been used. The first geometry emphasises the effect of different goal location features on the agents' goal location choice, see Sections 5.2.3 and 6.1.1. The second geometry emphasis the effect of the route choice algorithm on the agents' way planning, see Section 6.3.1. The first geometry is therefore referred to as the "Goal Location Choice (GLC)" geometry, whereas the second geometry is referred to as the "Route Choice (RC)" geometry.

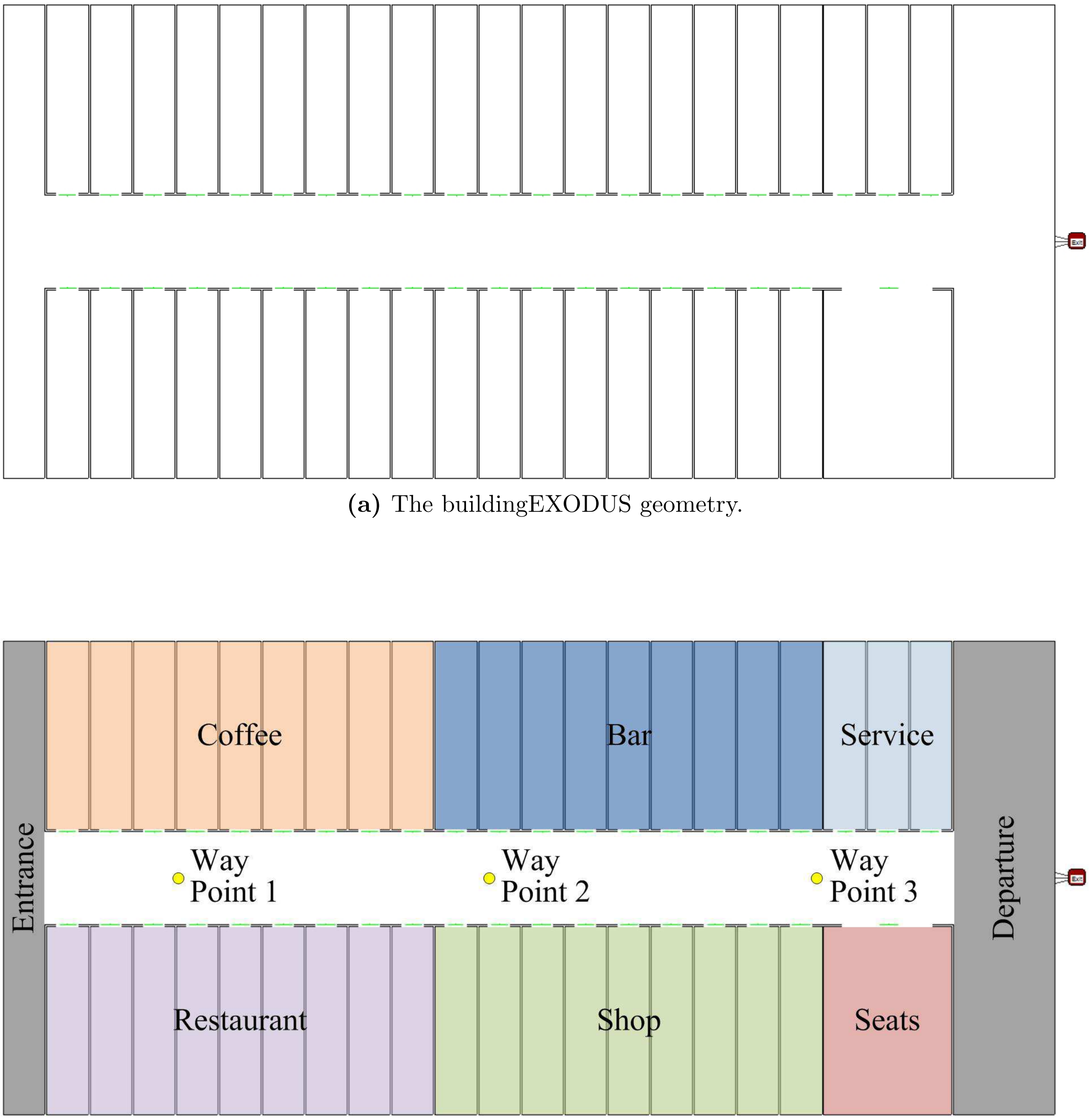
"Goal Location Choice (GLC)" geometry

The "Goal Location Choice" geometry, comprises in total 42 goal locations. 39 of these goal locations are represented in buildingEXODUS by compartment zones, which simulate rooms in the environment, see Figure 8.2a. The remaining three goal locations are way point goal locations, and are represented by nodes in buildingEXODUS.

Of the 39 compartment zone goal locations, two are the environment's entrance (far left) and departure locations (far right), see Figure 8.2b. During any simulation involving the "Goal Location Choice" geometry, all agents will be generated in the entrance goal location and will eventually exit the environment by passing the departure goal location and exiting via the only available external exit on the far right. The three way point goal locations are displayed as yellow dots in Figure 8.2b.

The remaining 37 compartment zone goal locations represent locations in the modelled environment where the agents can satisfy activity goals. These goal locations are arranged on both sides of the corridor connecting the entrance and departure goal location. The goal locations are grouped by their type. There are goal locations which represent coffee shops, bars, service facilities, restaurants, shopping facilities and seating areas. Each goal location type is represented by several different goal locations in order to be able to represent different combinations of the goal location feature attributes, see Section 5.2.3. Since the agents can therefore choose from a wide range of possible goal locations, they can choose those goal locations which optimally match their personal preferences, see Section 5.3.1.

In the current buildingEXODUS CPAF Plug-in, each goal location can be assigned three goal location features attributes, a price, brand and size attribute, see Table 5.2. Each of these feature attributes can attain one out of three possible values. Modelling each possible combination of the goal location features attributes for the coffee, bar, service, restaurant, shop and seat goal locations would therefore require to model a 54 activity goal locations. However, the effect of the agents choosing goal locations based on the goal location feature parameters and their personal preferences can also be demonstrated by a reasonable subset of these combinations. It can be reasonably assumed, that the brand attribute is irrelevant



(a) The buildingEXODUS geometry.

(b) The geometry with goal location type labels.

Figure 8.2.: The "Goal Location Choice (GLC)" verification case geometry.

to model decision-related attributes of service facilities. And it is also reasonable to assume, that a seating area is also not represented by a certain brand or price category. Finally, it has been decided for this verification case geometry, that the size attribute of any goal location should not be used for distinction. This implies that all goal locations that represent a certain goal location type are of the same size.

As a result, in the “Goal Location Choice” geometry, the seating area goal location type is represented by only one goal location. Service facilities are represented by three goal locations, one per each possible “price” attribute category. For the coffee, bar, restaurant and shopping facilities, each goal location type is represented by nine goal locations, one for each possible combination of the admissible “price” and “brand” feature attributes.

“Route Choice (RC)” geometry

The “Route Choice (RC)” geometry comprises a total number of 45 goal locations. 38 of these goal locations are represented by compartment zones in buildingEXODUS, whereas seven goal locations are represented by nodes in buildingEXODUS, see Figure 8.3a.

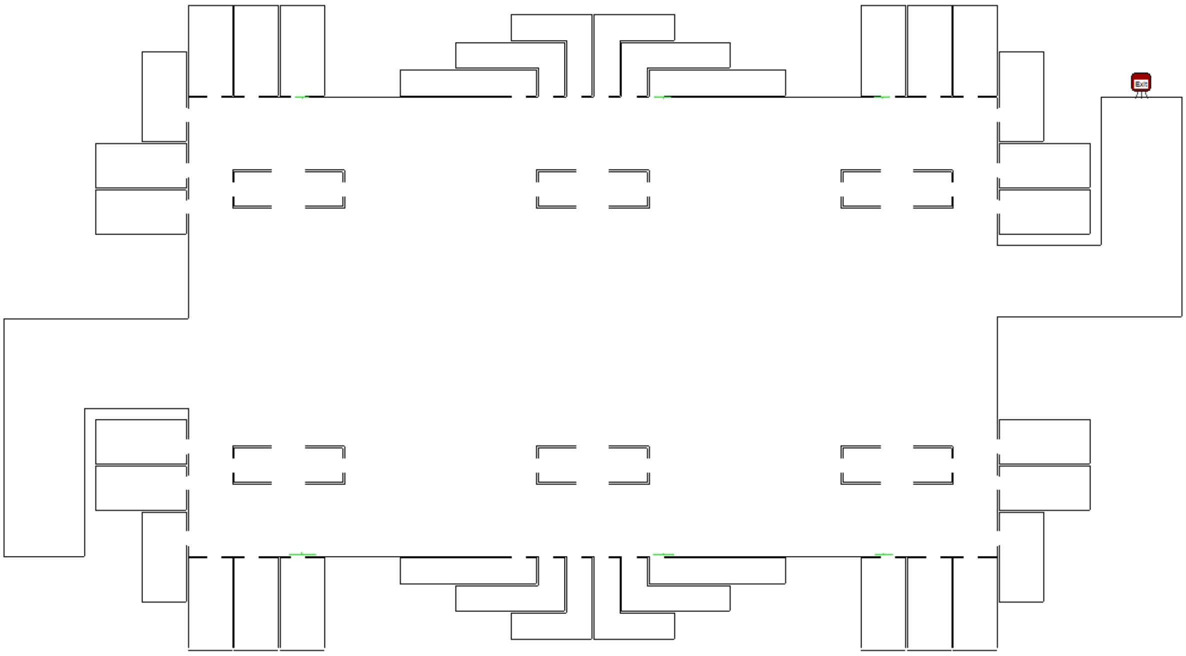
Of the 38 compartment zone goal locations, two are the environment’s entrance (far left) and departure locations (far right), see Figure 8.3b. During any simulation involving the “Route Choice” geometry, all agents will be generated in the entrance goal location and will eventually exit the environment by passing the departure goal location and exiting via the only available external exit on the top right. The seven way point goal locations are displayed as yellow dots in Figure 8.3b.

The remaining 36 compartment zone goal locations are all associated with one or more activity goals. They are arranged in six regional clusters. Each regional cluster comprises one goal location of the types bar, coffee shop, restaurant, shopping facility, service facility and an information point facility. This aims at promoting and emphasising the agents cluster-based distance-optimal route choice algorithm, see Section 6.3.1.

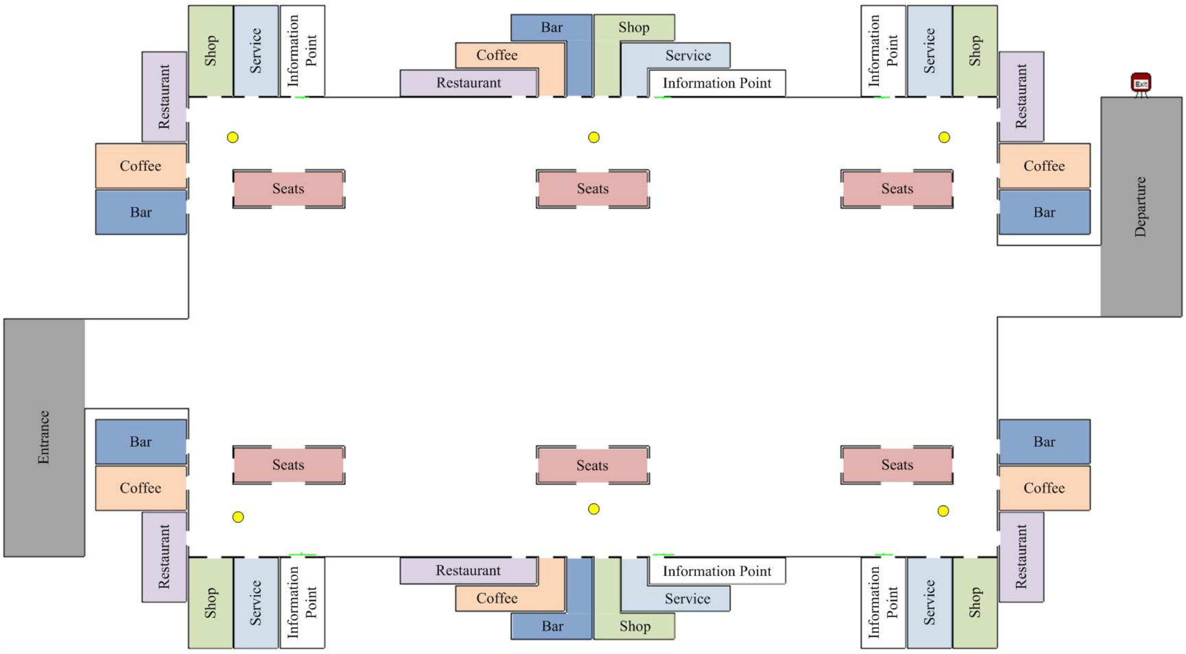
Since the “Route Choice” geometry is used mainly to demonstrate the agents’ way finding capabilities, all goal locations have been assigned the same goal location feature attributes. Each goal location is of the same size attribute and they have each been assigned the middle price and brand attribute, see Table 5.2. Consequently, the goal locations are indistinguishable for the agents in terms of their feature attributes. The only criterion for the agents’ trip planning is hence the distances between the different goal locations.

8.2.2. Scenarios

For the Trip Planning Verification Case, three scenarios have been designed. In each of the three scenarios, the agents are assigned a complete set of all five currently available activity goals, see Table 8.3. All activity goals can be accomplished by the agents at the designated goal locations both within the “Goal Location Choice” and the “Route Choice” geometry, see Table 8.3, Figure 8.2b and Figure 8.3b. In addition, each agent in all three scenarios is



(a) The buildingEXODUS geometry.



(b) The geometry with goal location type labels.

Figure 8.3.: The "Route Choice (RC)" verification case geometry.

randomly assigned a personal price and brand preference attribute, according to a uniform random distribution on the set $\{0, 1, 2\}$, see Section 5.3.1. In addition, each agent has been assigned a size preference attribute, which matches the size attribute of the modelled goal locations in the "Goal Location Choice" respectively "Route Choice" geometry.

The three scenarios differ in the amount of prior knowledge that is assigned to the agent population, see Table 8.6.

Table 8.6.: An overview of the Trip Planning Simulation demonstration scenarios with regard to the amount of assigned prior knowledge.

Scenario	Geometry	Percentage of Population with X% Prior Knowledge				
		0%	20%	50%	70%	100%
Full Prior Knowledge	GLC	–	–	–	–	100%
No Prior Knowledge	GLC	100%	–	–	–	–
Route Choice	RC	20%	15%	20%	15%	30%

The Trip Planning Verification Case is intended to demonstrate the basic way planning capability of the CPAF, see Section 6.3. Therefore, as has been described in Section 8.1.3, all other advanced buildingEXODUS CPAF Plug-in features depicted in Table 8.4 such as structural perception or short term memory have been disabled for this verification case.

In the verification case scenario "Full Prior Knowledge" of the Trip Planning Verification Case, all agents are assigned a complete prior knowledge of the "Goal Location Choice" environment. As has been described in Section 6.3.1, the agents should therefore choose a set of goal locations, where each goal location optimally matches their personal preference attributes. By the design of the "Goal Location Choice" geometry, each agent should therefore choose one goal location for each of their assigned activity goals, where the goal locations price and brand feature attribute matches their personal preferences. Consequently, the outcome of the "Full Prior Knowledge" verification case scenario should prove, that each agent has visited five activity goal locations, which optimally match their personal preferences. Thereby, each agent in the "Full Prior Knowledge" scenario should satisfy all of their assigned activity goals.

In the verification case scenario "No Prior Knowledge" of the Trip Planning Verification Case, all agents are assigned no prior knowledge of the "Goal Location Choice" geometry. As has been described in Section 6.3.2, the agents will therefore plan to explore the environment by following a way point route. Since in the current buildingEXODUS CPAF Plug-in, the way point route is determined by sending the agents to the most central way point, each agent in the "No Prior Knowledge" scenario should be directed to way point number 2, see Figure 8.2b. Since the buildingEXODUS CPAF Plug-in's Structural Perception feature has been disabled for the Trip Planning Verification Case, the agents won't be able to perceive and thereby explore any of the goal locations along there route. Consequently, all agents should finally have followed only their initial route to way point number 2, and then exit the environment. Thereby, no agent should have completed any of their assigned goals.

In the verification case scenario “Route Choice” of the Trip Planning Verification Case, the agents are assigned a certain level of prior knowledge about the used “Route Choice” geometry according to the probability distribution stated in Table 8.6. Based on their individual prior knowledge, each agent will then choose for each of their assigned activity goals one of the goal locations that they are familiar with. After having chosen their set of goal locations, the agents will then choose a cluster-based distance-optimal route connecting the chosen goal locations. If however an agent has not been assigned any prior knowledge, they will choose a way point route to the most central way point in the middle of the geometry, see Figure 8.3b. The results of the “Route Choice” demonstration scenario should therefore demonstrate the route choice algorithms described in Section 6.3. The results should also reflect, that the agents are only capable of choosing goal locations with which they are familiar from some prior knowledge, since the buildingEXODUS CPAF Plug-in’s Structural Perception capability has been disabled in the Trip Planning verification case. As a result, those agents with no assigned prior knowledge will not be able to satisfy any of their assigned activity goals. Those agents with incomplete assigned prior knowledge might be incapable of satisfying some of their assigned agent goals, due to the potential lack of environment familiarity.

8.2.3. Results

In all scenarios of the Trip Planning Verification Case, a total number of 100 agents have been generated per simulation run. The agents enter the simulated environments via the respective entrance goal locations and are assigned to leave the environment via the respective departure goal locations.

“Full Prior Knowledge” Scenario

The results of the “Full Prior Knowledge” scenario confirm, that each agent has a complete Spatial Memory Set at the end of the simulation run, containing all 42 modelled goal locations in the “Goal Location Choice” geometry. This was to be expected since the amount of prior knowledge that had been assigned to each agent in the beginning of the simulation was deterministically set to contain all the information available in the given geometry.

In the beginning of the simulation, every agent was therefore able to choose goal locations for all their assigned five agent goals. All agents thereby chose goal locations which optimally matched their given personal preferences, see Tables 8.7.

As can also be seen in Table 8.7b, the restaurant and bar goal locations have not been visited by any agents. This is due to the fact, that at restaurant goal locations, the agents can only satisfy their goal to “eat”, and that at bar goal locations, the agents can only satisfy their goal to “drink”. However, in all scenarios of the Trip Planning Verification Case, all

Table 8.7.: Average results for the distribution of personal preferences and the corresponding choice of goal locations based on their feature attributes. The results have been obtained from 10 simulation runs of the "Full Prior Knowledge" scenario of the Trip Planning Verification Case.

(a) Proportion of agent population that have been assigned a certain value of the Personal Preferences parameters by the Cognitive Pedestrian Agent Framework buildingEXODUS Plug-in.

Value	Price Preference P_1	Brand Preference P_2	Size Preference P_3
0	30.5% ± 4.95%	33.4% ± 2.32%	100.0% ± 0.00%
1	34.7% ± 2.98%	34.6% ± 4.72%	–
2	34.8% ± 4.18%	32.0% ± 3.16%	–

(b) Proportion of agent population that chose a goal location with given feature attributes during the Trip Planning stage.

Goal Location Type	Value	Price Attribute F_1	Brand Attribute F_2	Size Attribute F_3
Coffee	0	30.5% ± 4.95%	33.4% ± 2.32%	100.0% ± 0.00%
	1	34.7% ± 2.98%	34.6% ± 4.72%	–
	2	34.8% ± 4.18%	32.0% ± 3.16%	–
Shop	0	30.5% ± 4.95%	33.4% ± 2.32%	100.0% ± 0.00%
	1	34.7% ± 2.98%	34.6% ± 4.72%	–
	2	34.8% ± 4.18%	32.0% ± 3.16%	–
Restaurant	0	–	–	–
	1	–	–	–
	2	–	–	–
Bar	0	–	–	–
	1	–	–	–
	2	–	–	–
Service	0	30.5% ± 4.95%	–	100.0% ± 0.00%
	1	34.7% ± 2.98%	–	–
	2	34.8% ± 4.18%	–	–

agents have been assigned both goals to "eat" and to "drink". Since in the "Goal Location Choice" geometry, goal locations are simulated which can satisfy both of these goals, the coffee shop goal locations (see Table 8.3), each agent has chosen to rather visit a coffee shop goal location than visiting both a restaurant and a bar goal location to satisfy their "eat" and "drink" goals.

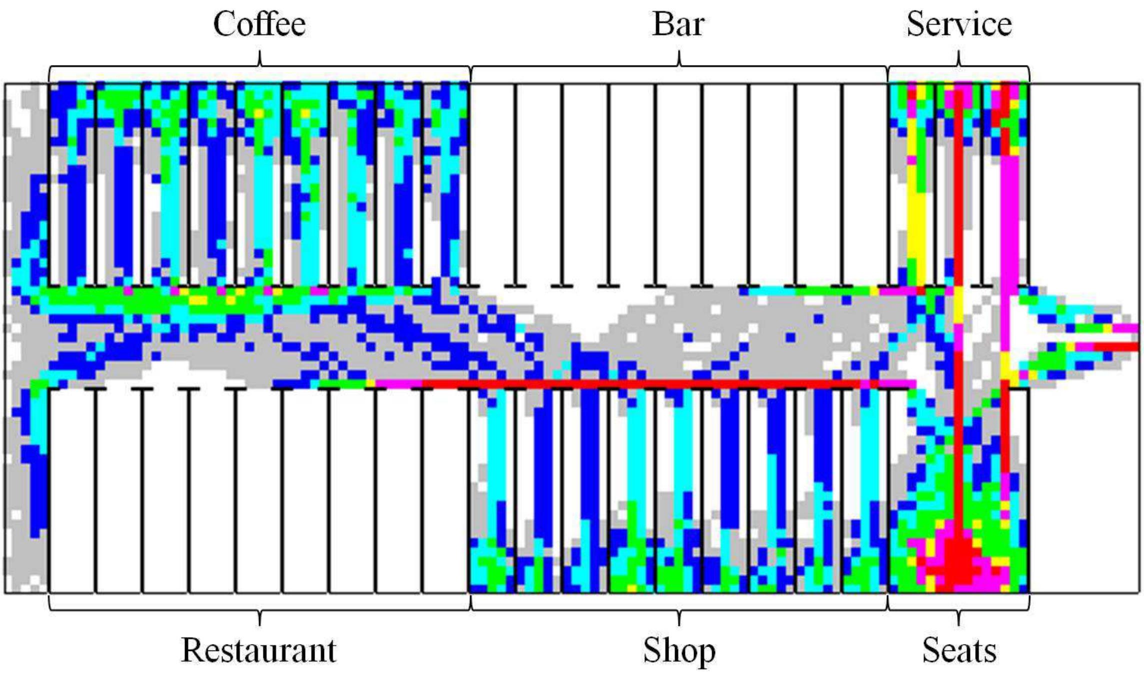


Figure 8.4.: The cumulative footfall of the agent population in a simulation run of the "Full Prior Knowledge" scenario of the Trip Planning Verification Case. See Table 8.5 for a key to the footfall colour codes.

A cumulative footfall image has been produced from the "Full Prior Knowledge" scenario for each of 10 individual simulation runs, see Figure 8.4 for a random example image. The variability in the cumulative footfall throughout the 10 individual simulation runs of the "Full Prior Knowledge" scenario is very little. As has been expected, high levels of footfall have been observed in the goal locations representing the only available seating area on the bottom right of the "Goal Location Choice" geometry. As can be seen by comparing the cumulative footfall image to Figure 8.2b, all nine goal locations representing coffee shops on the top left have been used uniformly in this simulation run. The same holds for the nine goal locations representing shopping facilities and the three goal locations representing service facilities. Also apparent in the footfall image is, that no agent has used any restaurant or bar type goal location.

After having chosen their initial itineraries, all agents in the "Full Prior Knowledge" scenario completed all of their planned tasks. As a result, all agents have completed all five of their five assigned activity goals.

“No Prior Knowledge” Scenario

In contrast to the “Full Prior Knowledge” scenario, no agent in the “No Prior Knowledge” scenario has been assigned any prior knowledge about the used “Goal Location Choice” geometry. All agents in this scenario are therefore required to explore the environment in order to achieve their assigned goals. According to the procedure described in Section 6.3.2, each agent should be sent initially to the most central way point to start their environment exploration. As has already been noted in Section 6.3.2, this is only a very simplistic model of the pedestrian exploration process. Future enhancements of the buildingEXODUS CPAF Plug-in could implement more sophisticated algorithms to represent pedestrian exploration behaviour more realistically.

The results of the “No Prior Knowledge” scenario confirm, that all agents are initially sent to the goal location Way Point 2, see Figure 8.2b. The goal location Way Point 2 is the most central of the three way points available in the geometry.

Since in the Trip Planning Verification Case, the buildingEXODUS CPAF Plug-in’s capability to perceive structural information has been disabled, no agent should be able to acquire any structural information during the course of the simulation via perception. This is confirmed by the results of the “No Prior Knowledge” scenario, as all agents are only aware of their entrance and departure goal locations. The agents are therefore unable to visit any of the coffee, restaurant, bar, service, shop or seating facilities along their travel, simply because of a lack of information. This can also be seen in the footfall image, see Figure 8.5.

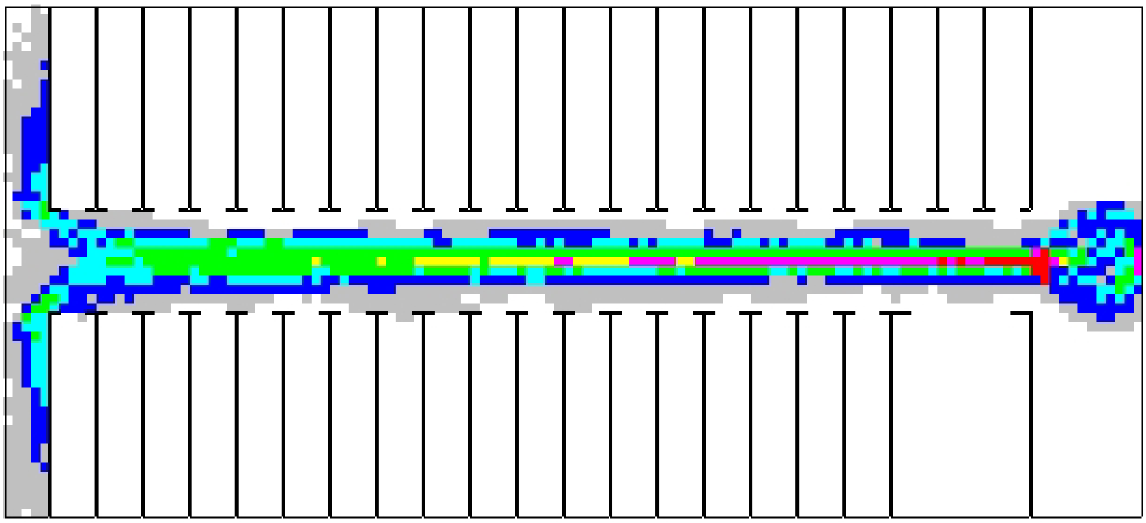


Figure 8.5.: The cumulative footfall of the agent population in a simulation run of the “No Prior Knowledge” scenario of the Trip Planning Verification Case. See Table 8.5 for a key to the footfall colour codes.

“Route Choice” Scenario
The agents in the “Route Choice” scenario of the Trip Planning Verification Case are assigned different individual levels of prior knowledge, see Table 8.6. For easier reference in the discussion of this verification case, the different level of prior knowledge available to the individual agent is referred to as their *Prior Knowledge Group*. From the scenario descriptions depicted in Table 8.6, five Prior Knowledge Groups have been used for this verification case. All agents assigned to the first group (subsequently referred to as Group A) are assigned no prior knowledge of the environment. On the other hand, all agents assigned to the second Prior Knowledge Group (subsequently referred to as Group B) are aware of 20% of all facilities available in the environment prior to the start of the simulation.

Prior to any simulation run of this verification case, each agent is randomly assigned to one Prior Knowledge Group. The probability for an agent to be assigned to a certain Prior Knowledge Group is depicted in Table 8.6. The averaged results of 10 simulation runs of this scenario case depicted in Table 8.8 demonstrate, that the assignment of the agent population to the Prior Knowledge Groups match the parameters depicted in Table 8.6.

Table 8.8.: The average proportion of the agent population over 10 simulations runs within a given Prior Knowledge Group in the “Route Choice” scenario of the Trip Planning Verification Case.

Prior Knowledge Group	Group A	Group B	Group C	Group D	Group E
X% Prior Knowledge	0%	20%	50%	70%	100%
Proportion of agent population	19.7% ± 3.27%	12.8% ± 3.33%	21.0% ± 2.11%	15.4% ± 5.40%	31.1% ± 4.15%

All agents which have been assigned by the buildingEXODUS CPAF Plug-in to the Prior Knowledge Group A and which therefore have no prior knowledge about the environment are incapable of satisfying any of their assigned activity goals. This is because they simply don’t know of any facility in the environment where they could achieve their goals. Since the structural perception feature has been disabled for the purpose of this verification case, these agents are also unable to perceive the facilities in the environment.

Regarding the agents in the other Prior Knowledge Groups, it can however not be expected, that these agents on the other hand were able to satisfy all of their assigned activity goals. This is because the probability, that an agent in a given Prior Knowledge Group other than Group A doesn’t know about any goal location where a certain goal can be satisfied is still greater than zero. Table 8.9 shows the average results from 10 simulation runs of the proportion of agents within the Prior Knowledge Groups that were able to satisfy a given number of their assigned activity goals.

As can be seen from Table 8.9, for each activity goal, the sum of the average proportion of agents that were able to satisfy and those that were not able to satisfy the particular goal

Table 8.9.: An overview of the average activity goal performance of the agent population, categorised by their assigned Prior Knowledge Group.

Goal	Status	Prior Knowledge Group (X% Prior Knowledge)				
		Group A	Group B	Group C	Group D	Group E
		0%	20%	50%	70%	100%
Eat	Satisfied	–	11.7% ± 2.54%	21.0% ± 2.11%	15.4% ± 5.40%	31.1% ± 4.15%
	Unsatisfied	19.7% ± 3.27%	1.1% ± 1.60%	–	–	–
Drink	Satisfied	–	12.0% ± 3.16%	21.0% ± 2.11%	15.4% ± 5.40%	31.1% ± 4.15%
	Unsatisfied	19.7% ± 3.27%	0.8% ± 1.23%	–	–	–
Shop	Satisfied	–	9.4% ± 3.06%	21.0% ± 2.11%	15.4% ± 5.40%	31.1% ± 4.15%
	Unsatisfied	19.7% ± 3.27%	3.4% ± 0.97%	–	–	–
Rest	Satisfied	–	9.7% ± 2.31%	20.8% ± 2.20%	15.4% ± 5.40%	31.1% ± 4.15%
	Unsatisfied	19.7% ± 3.27%	3.1% ± 1.73%	0.2% ± 0.42%	–	–
Service	Satisfied	–	9.7% ± 2.50%	20.8% ± 2.10%	15.4% ± 5.40%	31.1% ± 4.15%
	Unsatisfied	19.7% ± 3.27%	3.1% ± 1.45%	0.2% ± 0.42%	–	–

matches the average results for the assignment of the Prior Knowledge Groups depicted in Table 8.8.

As can be further seen from Table 8.9, those agents that were assigned to the Prior Knowledge Group A (no prior knowledge) were not able to satisfy any of their assigned activity goals as expected. However, even agents in those Prior Knowledge Groups that had a non-zero probability to be familiar with the environment, it is still possible for these agents to be not familiar with any goal location for a given activity goal. As a result these agents were not able to satisfy the activity goal in question. This behaviour is possible because of the probabilistic nature of the prior knowledge assignment. In the “Route Choice” environment, the activity goals “eat” and “drink” can be accomplished at twelve goal locations, and the activity goals “shop”, “rest” and “service” can be accomplished at six goal locations. As a consequence for an agent who has been assigned to Group B with 20% prior knowledge and who has been assigned the “service” activity goal, the probability for this agent not to be familiar with any goal location where they can accomplish the goal “service” is $(1 - 0.2)^6 \approx 0.26$. Hence, in a quarter of these cases, the agents will not be familiar with any service goal location. Table 8.10 gives an overview of the probabilities for any agent that has been assigned to a certain Prior Knowledge Group to not be familiar with any of the goal locations where a certain activity goal can be accomplished.

Table 8.10.: An overview of the probability that an agent in a given Prior Knowledge Group is not familiar with any goal location.

Goals	Prior Knowledge Group (X% Prior Knowledge)				
	Group A	Group B	Group C	Group D	Group E
	0%	20%	50%	70%	100%
Eat, Drink	100%	6.87%	0.02%	$\approx$ 0%	0%
Shop, Rest, Service	100%	26.21%	1.56%	$\approx$ 0%	0%

These probabilities are in correspondence to the proportions of the agent population per Prior Knowledge Group that were unable to satisfy a particular assigned activity goal in Table 8.9.

The results of the “Route Choice” scenario also illustrate the impact of the cluster-based distance-optimal route choice algorithm detailed in Section 6.3.1. A randomly chosen example route is depicted in Figure 8.6. The blue highlighted goal locations in Figure 8.6 indicate the goal locations that the agent has chosen during the goal location choice phase. The goal location numbering illustrate the order in which the agent has planned to visit the chosen goal locations.

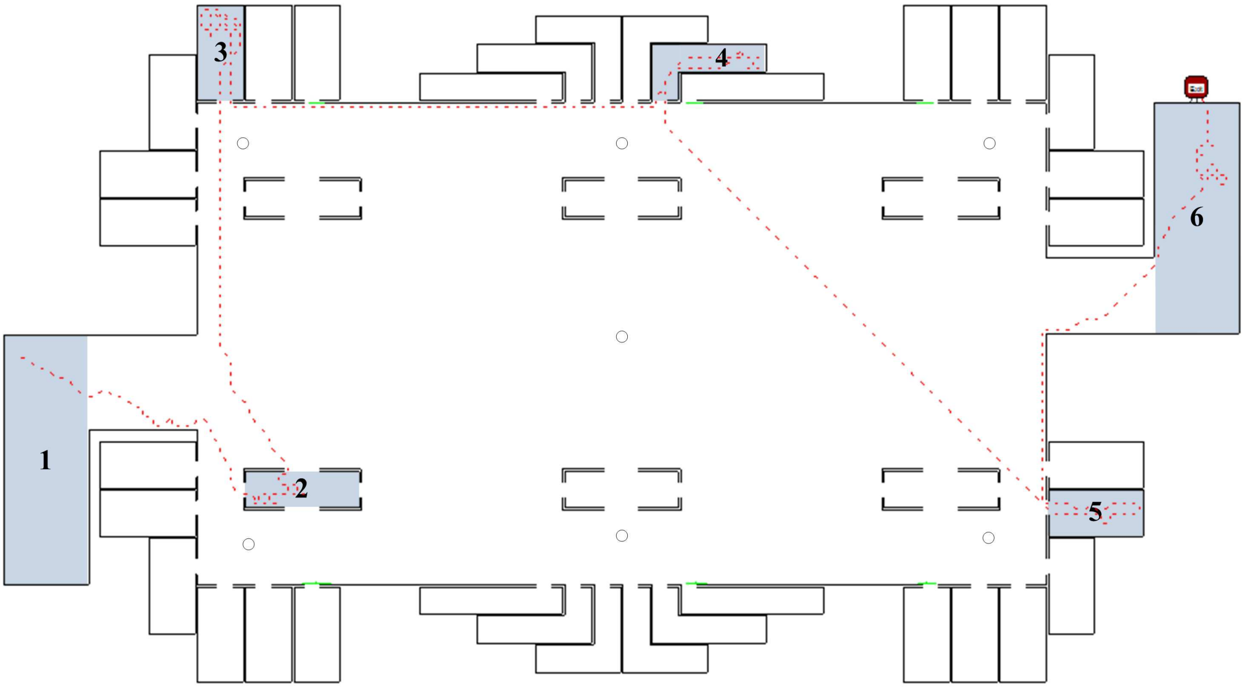


Figure 8.6.: An example route from a simulation run of the "Route Choice" scenario of the Trip Planning Verification Case.

8.2.4. Summary

The Trip Planning Verification Case demonstrates the impact of individual prior spatial knowledge on the agents' way planning as well as the actual trip planning algorithm described in Sections 6.3 and 6.1.3. It demonstrates the CPAF agents' ability to choose goal locations appropriate to fulfill their individual goals and to match their individual preferences, see Section 6.1.2. It also demonstrates the CPAF's Human Path Planning Heuristic (Section 6.1.2.2), which is based on the regional path planning heuristic by Wiener et al. [7].

The Trip Planning Verification Case thereby addresses Research Question 5 by demonstrating how the CPAF Trip Planning feature simulates pedestrian choice of their targeted locations and path within a complex multi-purpose environment.

8.3. Structural Awareness

The Structural Awareness Verification Case aims to illustrate the ability of the CPAF agents to perceive information about their environment and to alter their plans based on the perceived information. As has been described in Section 5.5, the agents in the CPAF are capable of perceiving goal locations. During the perception process, the agents attain relevant information about the perceived goal location. This information is then memorised for potential later use. In addition, the agents can also react to the perception event by potentially altering their plans, i.e. electing to visit the perceived goal location (Section 6.4.1). The purpose of the Structural Awareness Verification Case is therefore to demonstrate the informed learning capabilities and the reactive decision making to perceived structural information.

8.3.1. Geometry

The Structural Awareness Verification Case uses the "Goal Location Choice" geometry described in Section 8.2.1. However, for the Structural Awareness Verification Case, the "Goal Location Choice" geometry has been enhanced by adding signs pointing to the modelled activity goal locations. Therefore, as has been described in Section 5.5, the agents are now able to visually perceive any activity goal location within the "Goal Location Choice" geometry.

8.3.2. Scenario

For the Structural Awareness Verification Case, the buildingEXODUS CPAF Plug-in's structural perception feature has been enabled. However, all other advanced buildingEXODUS CPAF Plug-in features (see Table 8.4) have been disabled, to better demonstrate the desired effects. Each agent in the Structural Awareness Verification Case is assigned a complete set of all five activity goals.

All agents have been assigned a random price, brand and size personal preference. The agents in the Structural Awareness Verification Case are particularly characterised by the fact, that all agents are initialised to be having no prior knowledge about the modelled environment. As a result, all agents will have to explore the environment and will thereby try to find goal locations where they can accomplish their assigned activity goals.

Due to the agents in this verification case being able to explore the environment and the layout of the underlying geometry, it is expected that all agents at the end of the simulation have a full knowledge of the available activity goal locations, i.e. a complete Spatial Memory Set. Furthermore, for each available activity goal one or more goal locations exist in the underlying "Goal Location Choice" geometry where the activity goal can be accomplished. As a result it is further expected, that each agent will have satisfied all of their assigned activity goals by the end of the simulation in the Structural Awareness Verification Case. It is further expected that the agents choose such goal locations to satisfy their activity goals which match their personal preferences reasonably well.

8.3.3. Results

The expectations are confirmed by the results of the Structural Awareness Verification Case. Each agent has obtained a complete knowledge of the structure and also each agent was able to satisfy all of their assigned activity goals. In order to achieve their activity goals, the agents perceive and evaluate the available goal locations within the geometry. If more than one goal location is perceived for a given goal, the agent chooses the goal locations which provides a better match for their personal preferences. This can result in the agent changing their itinerary multiple times during the course of the simulation, see Table 8.11.

Table 8.11.: The proportion of the agent population that changed their plans a given number of times because of the Cognitive Pedestrian Agent Framework buildingEXODUS Plug-in's structural perception feature in the Structural Awareness Verification Case.

Number of Plan Changes	Proportion of Agent Population
0	6 %
1	20 %
2	44 %
3	27 %
4	3 %

A cumulative footfall image of the Structural Awareness Verification Case has also been produced, see Figure 8.7. As can be seen from the footfall data, for each assigned activity goal at least one goal location where this activity goal can be accomplished has been visited by the agents. It has to be noted, that the agents did have a tendency to visit the leftmost goal locations for each activity goal. Of the coffee shop goal locations on the top right, the three goal locations most to the left have been visited by the agents. Of these three, the leftmost coffee shop goal location has been visited the most. A similar tendency can be observed for the service goal locations on the top right and the shop goal locations on the middle right. For the restaurant goal locations (bottom left), only the leftmost restaurant goal location has been visited by agents.

This behaviour can be explained by the agents' decision making mechanism for visiting a goal location when exploring the environment, see Section 6.4.1, and the fact that the agents are traversing the geometry from left to right. The agents will choose goal locations that reasonably well match their personal preferences to accomplish their assigned activity goals. The agents are therefore not looking for an exact match to their personal preferences as they had done in the same geometry in the "Full Prior Knowledge" scenario of the Trip Planning Verification Case (see Section 8.2). But instead goal locations are chosen which match the agents personal preferences within a given range using the CPAF's lexicographic Short Time Span Adaptive Decision Making model.

According to the decision making mechanism for the CPAF's structural perception and exploration feature described in Section 6.4.1, the agents will follow their initially assigned way point route and evaluate all goal locations that they encounter on their way. If one of the agent's assigned agent goals can be accomplished at a perceived goal location, the agent's behaviour depends on whether they already have a task related to that agent goal on their Agent Task List or not.

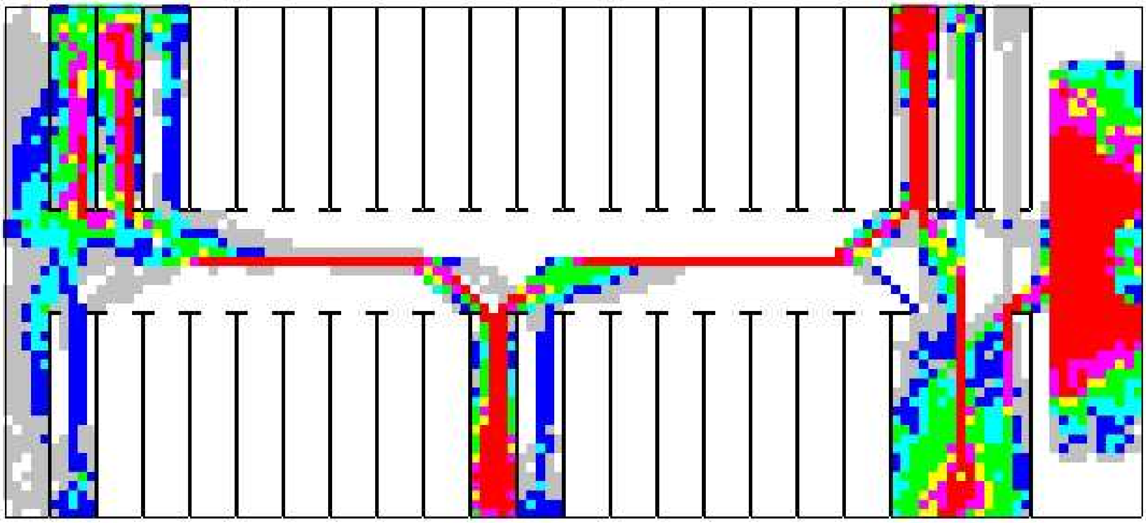


Figure 8.7.: The cumulative footfall of the agent population in a simulation run of the Structural Awareness Verification Case. See Table 8.5 for a key to the footfall colour codes.

If the agent has not yet a task to satisfy the agent goal in question on their Agent Task List, the agent will evaluate whether the perceived goal location l_{perc} matches their personal preferences reasonably well. In the current version of the buildingEXODUS CPAF Plug-in, the decision on whether a goal location matches the agent's personal preference attributes in the Structural Awareness Verification Case is made according to the following logic (see Section 6.4.1 for the generic decision making model description):

1. If the price feature attribute differs from the agent's price preference parameter by less than 2
$$|F_1(l_{perc}) - P_1| < 2$$
than the goal location is evaluated to reasonably match the agent's personal preferences.

2. Else if the price feature attribute differs from the agent's price preference parameter by 2 than the brand feature parameter is evaluated. In this case if the brand feature attribute differs from the agent's brand preference parameter by less than 2
$$|F_1(l_{perc}) - P_1| = 2 \quad \wedge \quad |F_2(l_{perc}) - P_2| < 2$$
than the goal location is evaluated to reasonably match the agent's personal preferences.

3. Else if the price feature attribute differs from the agent's price preference parameter by 2 and if the brand feature attribute differs from the agent's brand preference parameter

by 2 than the size feature parameter is evaluated. In this case if the size feature attribute differs from the agent's size preference parameter by less than 2

$$|F_1(l_{perc}) - P_1| = 2 \quad \wedge \quad |F_2(l_{perc}) - P_2| = 2 \quad \wedge \quad |F_3(l_{perc}) - P_3| < 2$$

than the goal location is evaluated to reasonably match the agent's personal preferences.

If the perceived goal location is evaluated to reasonably match the agent's personal preference attributes, the agent will add the task to visit the perceived goal location to their Agent Task List.

If on the other hand the agent already has a task planned to satisfy the agent goal in question, the agent will evaluate whether the perceived goal location provides a better match to their personal preferences than the currently planned goal location. In the current version of the buildingEXODUS CPAF Plug-in, the decision in the Structural Awareness Verification Case is made according to the following logic (see Section 6.4.1 for the generic decision making model description):

1. If the deviation of the price feature attribute of the perceived goal location l_{perc} to the agent's personal price preference is smaller than the deviation of the price feature attribute of the currently planned goal location l_{plan} to the agent's personal price preference
$$|F_1(l_{perc}) - P_1| < |F_1(l_{plan}) - P_1|$$
than the perceived goal location is preferred over the currently planned goal location.

2. Else if the deviation of the price feature attribute of the perceived goal location l_{perc} to the agent's personal price preference is equal to the deviation of the price feature attribute of the currently planned goal location l_{plan} to the agent's personal price preference than the brand feature parameter is evaluated. In this case if the deviation of the brand feature attribute of the perceived goal location l_{perc} to the agent's personal brand preference is smaller than the deviation of the brand feature attribute of the currently planned goal location l_{plan} to the agent's personal brand preference
$$|F_1(l_{perc}) - P_1| = |F_1(l_{plan}) - P_1| \quad \wedge \quad |F_2(l_{perc}) - P_2| < |F_2(l_{plan}) - P_2|$$
than the perceived goal location is preferred over the currently planned goal location.

3. Else if the deviation of the price feature attribute of the perceived goal location l_{perc} to the agent's personal price preference is equal to the deviation of the price feature attribute of the currently planned goal location l_{plan} to the agent's personal price preference and the deviation of the brand feature attribute of the perceived goal location

l_{perc} to the agent's personal brand preference is equal to the deviation of the brand feature attribute of the currently planned goal location l_{plan} to the agent's personal brand preference

$$|F_1(l_{perc}) - P_1| = |F_1(l_{plan}) - P_1| \quad \wedge \quad |F_2(l_{perc}) - P_2| = |F_2(l_{plan}) - P_2|$$

than the size feature parameter is evaluated. Since in the case of the Structural Awareness Verification Case, all goal locations have the same size feature attribute value of 0, the evaluation of the perceived goal location's size feature parameter against the planned goal location's size feature parameter will always yield, that the perceived goal location's size is not a better match to the agent's personal size preference than the size feature parameter of the planned goal location. Therefore, the perceived goal location is never preferred to the already planned goal location if their last feature attribute, their size feature attribute, is considered.

If the perceived goal location is preferred over the currently planned goal location, the agent will dismiss the task to visit the currently planned goal location and in addition will add the task to visit the just perceived goal location to their Agent Task List.

To illustrate the agents' behaviour in the Structural Awareness Verification Case, the behaviour of an example agent is discussed in more detail. The chosen agent's personal preference attributes were

$$P_1 = 2 \text{ (price preference)}, \quad P_2 = 1 \text{ (brand preference)}, \quad P_3 = 0 \text{ (size preference)}$$

Table 8.12 shows details about the agent's Agent Task List and Figure 8.8 shows the final path that the agent took during the simulation.

Table 8.12.: The Agent Task List of an agent in the Structural Awareness Verification Case. Their personal preference attributes were $P_1 = 2,\ P_2 = 1,\ P_3 = 0$.

$\pi(t)$	Goal Location	Feature Attributes	Goals	Final Status	Creation Time	Dismissal Time
1	restaurant-B0-P0	$(0,0,0)^T$	"eat"	dismissed	8.5s	14.2s
2	restaurant-B0-P1	$(1,0,0)^T$	"eat"	dismissed	14.2s	16.8s
3	coffee-B0-P2	$(2,0,0)^T$	"eat, drink"	completed	16.8s	–
4	waypoint2	–	"way point"	completed	ingress	–
5	shop-B0-P0	$(0,0,0)^T$	"shop"	completed	973.7s	–
6	service-P2	$(2,-,0)^T$	"service"	completed	1363.2s	–
7	seats	–	"rest"	completed	1363.8s	–
8	departure	–	–	completed	ingress	–

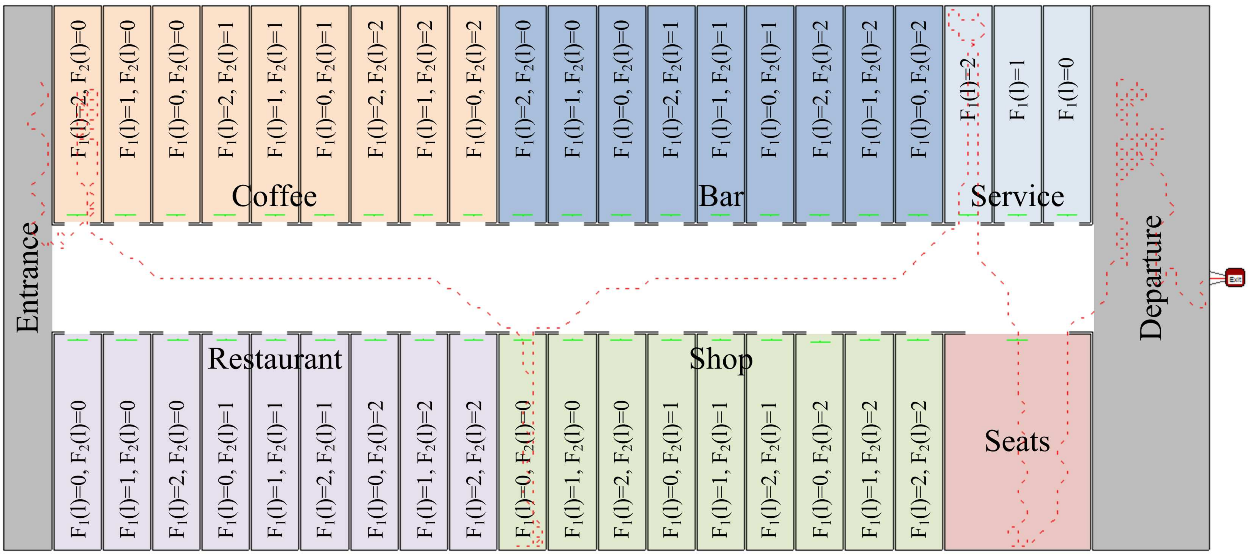


Figure 8.8.: The path of an agent in the Structural Awareness Verification Case. Their personal preference attributes were $P_1 = 2,\ P_2 = 1,\ P_3 = 0$.

As can be seen in Figure 8.8, the agent's starting location was at the upper part of the entrance goal location. From there, the agent proceeded towards their assigned way point in the middle of the simulated geometry's corridor. While heading towards the entrance to the corridor, the first goal location that was perceived by the agent was the leftmost restaurant goal location "restaurant-B0-P0". This restaurant goal location had been assigned a price feature attribute of 0 and a brand feature attribute of 0 (see also Figure 8.8). In general, agents can satisfy "eat" agent goals at restaurant goal locations.

Up until now, the agent has not planned a task to accomplish their assigned "eat" agent goal yet. They therefore evaluate whether "restaurant-B0-P0" matches their personal preferences reasonably well. The agent starts by evaluating the price attribute. The goal location's price feature attribute differs from the agent's price preference attribute by exactly 2. Hence, the agent moves on to evaluate the brand attribute. The goal location's brand feature attribute differs from the agent's brand preference attribute by 1 which is less than 2. The agent therefore now decides, that the goal location "restaurant-B0-P0" reasonably well matches their personal preferences and adds the corresponding task to accomplish their "eat" agent goal at "restaurant-B0-P0" to their Agent Task List.

The second goal location that is perceived by the agent is the next restaurant goal location "restaurant-B0-P1". This goal location had been assigned a price feature attribute of 1 and a brand feature attribute of 0. Since the agent can also satisfy their "eat" agent goal at this just perceived goal location, the agent evaluates whether they would like to change their plans to satisfy their "eat" agent goal at "restaurant-B0-P1" instead of at "restaurant-B0-P0". The agent thereby starts by comparing the deviations of the goal locations' price feature attribute from their personal price preference attribute. For the "restaurant-B0-P0" goal location, the deviation is 2 whereas for the just perceived "restaurant-B0-P1" goal location the deviation is 1. Consequently, the just perceived goal location provides a better match to the agent's price preference attribute than the planned goal location. The agent thereby decides to rather visit the just perceived "restaurant-B0-P1" goal location to accomplish their "eat" agent goal than the previously planned "restaurant-B0-P0" goal location.

The next goal location that is perceived by agent while traversing the environment on their way to their first task is "coffee-B0-P2". At coffee goal locations, the agents can accomplish their "eat" as well as their "drink" agent goals. The agent therefore evaluates again, whether they should rather visit the newly perceived "coffee-B0-P2" goal location to accomplish their "eat" agent goal than the currently planned "restaurant-B0-P1" goal location. The "coffee-B0-P2" goal location had been assigned a price feature attribute of 2 and a brand feature attribute of 0. Since again the newly perceived "coffee-B0-P2" goal location provides a better match to the agent's price preference attribute than the currently planned "restaurant-B0-P1" goal location, the agent alters their Agent Task List again to now visit the "coffee-B0-P2" goal location to accomplish their "eat" goal. The agent further realises that they can also accomplish their assigned "drink" agent goal at the "coffee-B0-P2" goal location and therefore enhances their planned task to now accomplish both agent goals at the just perceived goal location.

While heading towards the "coffee-B0-P2" goal location to accomplish their planned task to eat and drink, the agent perceives the next goal coffee goal location "coffee-B0-P1". However, since this newly perceived goal location doesn't provide a better match to the agent's personal preferences, the agent doesn't alter their Agent Task List and instead proceed to start their planned task at goal location "coffee-B0-P2". After having accomplished their task at the "coffee-B0-P2" goal location, the agent moves towards their assigned way point in search for other goal locations where they can accomplish their still outstanding agent goals to shop, to rest and to visit a service facility. On their way to the way point, the agent at first only encounters other restaurant and coffee goal locations. After having past their way point, the agent perceives the first bar goal location "bar-B0-P2". At bar goal locations, the agents can satisfy "drink" agent goals. Since the agent has already satisfied their "drink" agent goal together with their "eat" agent goal at the goal location "coffee-B0-P2", the agent is therefore not interested in any bar goal location either.

The next goal location that the agent perceives is the leftmost shop goal location "shop-B0-P0" with a price and a brand feature attribute of both 0. Since the agent has got no plan yet where to accomplish their "shop" agent goal, the agent evaluates again whether this perceived goal location reasonably well matches their personal preferences. Again, since the goal location's price feature attribute and its brand feature attribute differ from the agent's price and brand preference attribute by 2 respectively 1, the agent decides that the "shop-B0-P0" goal location provides a reasonably good match to their preferences. Therefore, they add the task to accomplish their "shop" agent goal at "shop-B0-P0" to their Agent Task List.

Consequently, the agent immediately starts heading towards the "shop-B0-P0" goal location. By this change of direction, the agent is now not able anymore to perceive the next shop goal location "shop-B0-P1" on the right hand side of the targeted shop goal location "shop-B0-P0". This can be seen when overlaying the footfall data in the Structural Awareness Verification Case with the Visibility Catchment area of the "shop-B0-P1" goal location, see Figure 8.9.

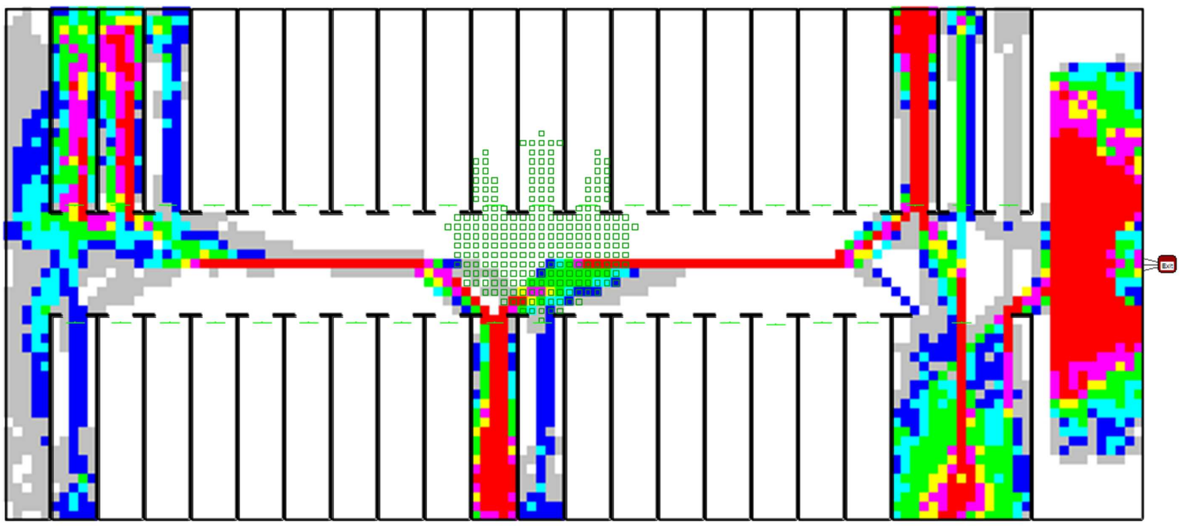


Figure 8.9.: An overlay of the footfall image of the Structural Awareness Verification Case and the Visibility Catchment Area of the second shop goal location from the left "shop-B0-P1".

The example agent follows a path in the most direct way to the "shop-B0-P0" goal location. As can be seen in Figure 8.9, the agent thereby follows a path close to the red highlighted and hence most frequented path. They thereby do not enter the green marked Visibility Catchment area of "shop-B0-P1". As a consequence, although "shop-B0-P1" would prove a better match to the agent's price preference attribute than the targeted "shop-B0-P0", the agent visits the worse goal location because of a lack of structural knowledge at the time.

After having finished their shopping task, the agent further proceeds towards the right hand side of the geometry. On their way, they perceive the service goal location "service-P2" and the seating area on the lower right. The agent chooses these goal locations to accomplish their outstanding "service" and "rest" agent goals, before departing the geometry via the departure goal location.

8.3.4. Summary

The Structural Awareness Verification Case demonstrates the CPAF's feature of enabling the agents to perceive structural information about the environment and to alter their plans based on the perceived information. It demonstrates the CPAF's advanced environment representation and the CPAF agents' capability of perceiving this advanced information about their environment, see Section 5.5. It also demonstrates how the CPAF agents make use of this information by relating it to their individual goals and their individual plans and how the CPAF agents thereby are capable of making informed decisions about altering their current plans, see Section 6.4.1.

The Structural Awareness Verification Case hence addresses Research Question 4 by demonstrating how the CPAF Structural Awareness feature simulates pedestrian adaptive behaviour to newly learned structural information.

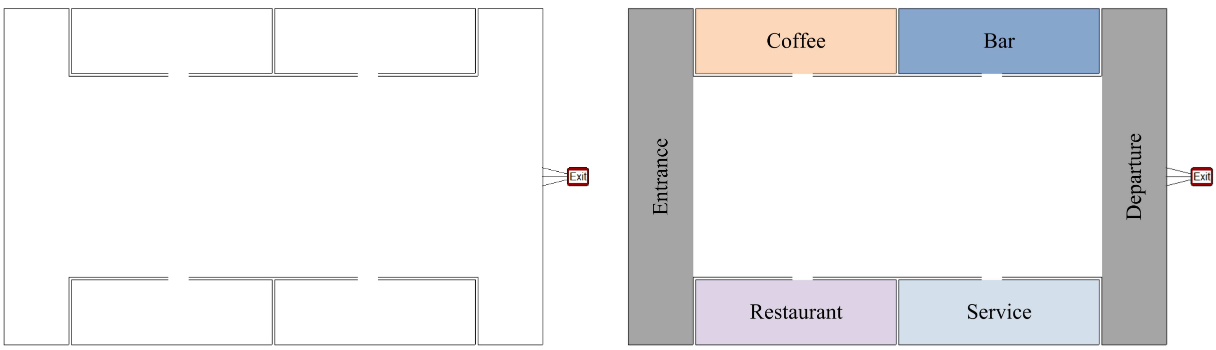
8.4. Urgency

The Urgency Verification Case aims to demonstrate the capabilities of the underlying buildingEXODUS's Urgency Model as well as the enhanced features in the CPAF's Urgency Model. In the verification case, it is not distinguished whether a demonstrated feature is originally from buildingEXODUS or from the CPAF. Instead, the emphasis is laid on demonstrating the overall impact of the extended buildingEXODUS CPAF Plug-in Urgency Model.

The Urgency Verification Case intends to demonstrate the agents' capability to be aware of their personal time limitations in planning their sojourn within a given environment. The agents are able to assess their time situation and – if necessary – adapt their plans in accordance with their personal goals.

8.4.1. Geometry

In the Urgency Verification Case a simple geometry is used to demonstrate the feature, see Figures 8.10. The geometry contains six goal locations: an entrance goal location and a departure goal location as well as four activity goal locations. The activity goal locations comprise a coffee, bar, restaurant and a service goal location. Consequently, the agents can satisfy the activity goals eat, drink and service at the four activity goal locations.



(a) The buildingEXODUS geometry. (b) The geometry with goal location type labels.

Figure 8.10.: The "Urgency" verification case geometry.

The activity goal locations' feature parameters have been set as depicted in Table 8.13. All four activity goal locations have been chosen to have the same size and price feature attribute value of 0. However, the goal locations differ in their assigned brand attribute. The bar and restaurant goal locations are assigned the same brand attribute, whereas the coffee goal location as the only goal location available for compromise tasks is assigned a different brand attribute.

Table 8.13.: The goal location feature parameters $F(l)$ of the activity goal locations in the Urgency Verification Case geometry.

Parameter	Name	Coffee	Bar	Restaurant	Service
$F_1(l)$	Price	0	0	0	0
$F_2(l)$	Brand	2	1	1	–
$F_3(l)$	Size	0	0	0	0

8.4.2. Scenarios

For the Urgency Verification Case, only the buildingEXODUS CPAF Plug-in's Trip Planning and Urgency Model features have been enabled (see Table 8.4). In all verification case scenarios, only a single agent will be sent into the environment during one simulation run. The simulated agent is assigned a complete prior knowledge of the underlying geometry. As a consequence, the agent will choose for each of their assigned activity goals those goal locations in the geometry, which closest match their personal preferences. Subsequently, they will choose a cluster-based distance-optimal route connecting the chosen goal locations.

In order to facilitate the set-up of the verification case scenario parameters, it has been set that the agent in all verification case scenarios enters the modelled environment on the same node within the entrance goal location. The agent's entrance nodal location has been chosen such that the distance from the entrance node to either the coffee or the restaurant goal location are equal. Consequently, also the distances from the entrance node to the bar and to the service goal location are equal.

The agent's personal preferences parameters in all verification case scenarios have been set such that the agent is assigned a price preference of 0, a brand preference of 1 and a size preference of 0. As a consequence, the simulated bar, restaurant and service goal locations provide a perfect attribute match. The simulated coffee goal location's brand feature attribute differs by 1 from the agent's personal brand preference. As a result, if the agent has been assigned the eat activity goal, they will initially choose the restaurant goal location and if the agent has been assigned the drink activity goal, they will choose the bar goal location. Furthermore, because of the layout of the underlying geometry, the agent will elect to first go to an eat goal location before going to either the bar goal location or the service goal location.

In summary, because of these particular verification case settings, the Urgency Model's Estimated Required Times T_v^{ERT} during the agent's initial time assessment in the beginning of the simulation are only dependent on the assigned activity goals. Therefore, the agent's Urgency behaviour in this particular verification case can be exactly determined by setting appropriate time limits.

The Urgency Verification Case comprises a total number of four verification case scenarios. In the different scenarios, the agent is assigned different sets of activity goals and different time limits, see Table 8.14 for an overview.

Table 8.14.: An overview of the Urgency Verification Case scenarios.

Scenario	Activity Goals	$\mathbf{T}_{v_d}^{\mathrm{ERT}}$	$\mathbf{T}_{v_n}^{\mathrm{ERT}}$	$\mathbf{T}_{v_f}^{\mathrm{ERT}}$	Critical Time / Available Time
Agent Parameters	eat, drink	1316.61 s	1286.90 s	1284.52 s	in [1288s, 1319s]
Compromise	eat, drink	1316.61 s	1286.90 s	1284.52 s	1286 s
Dismiss One	eat, service	1311.28 s	1284.53 s	1282.39 s	1284 s
Dismiss All	eat, service	1311.28 s	1284.53 s	1282.39 s	1000 s

The four Urgency Verification Case scenarios aim to demonstrate the agent's behaviour under different levels of perceived time pressure. As has been described in Section 4.3.1, the agents assess their time pressure situation by comparing the amount of time until their next critical time, their available time, with some estimates on the total time needed for their current plans, the estimated required times. This time assessment is undertaken at first at the agent's time of entry in the environment. After that, the agent reassesses their level of urgency after individual dynamic time intervals. The agent's available time at the first Urgency assessment at the time of their entry in the environment T_a^{entry} can be determined as follows:

$$T_a^{\mathrm{entry}} = \tau_{wait}(t_{\pi_{cr}}) - \tau^{\mathrm{entry}}$$

where $\tau_{wait}(t_{\pi_{cr}})$ denotes the agent's critical time and τ^{entry} the agent's entry time in the modelled environment. In all four Urgency Verification Case scenarios, the entry time of each agent has been set to zero $\tau^{\mathrm{entry}} \equiv 0$. As a result, the agent's available time T_a^{entry} during their first time assessment equals their assigned critical time. As a consequence, by appropriately setting the agent's assigned critical time, the different reactive behaviours to different levels of urgency can be demonstrated in the four Urgency Verification Case scenarios.

In the "Agent Parameters" scenario, the impact of an elevated urgency on the agent's behaviour and especially on the dependent agent parameters is illustrated. By varying the agent's assigned critical time – and therefore their initially available time – between the normal walk estimated required time $\mathbf{T}_{v_n}^{\mathrm{ERT}}$ and the dawdle walk estimated required time $\mathbf{T}_{v_d}^{\mathrm{ERT}}$, the dependency of the agent's walk speed, drive and patience attribute on the agent's

Urgency attribute is demonstrated. For this purpose, the agent's assigned critical time in the "Agent Parameters" scenario is varied, starting from 1288 s to 1318.6 s by constantly increasing the critical time by 3.4 s.

If the perceived time pressure is even more elevated, i.e. if the agent's initially available time is between the normal walk estimated required time $\mathbf{T}^{\text{ERT}}_{v_n}$ and the fast walk estimated required time $\mathbf{T}^{\text{ERT}}_{v_f}$, the agent has to take more drastic measures. In the Urgency Model, the agent will try to reduce their time pressure by reducing their total number of tasks. This can be achieved by either making compromises as is demonstrated in the "Compromise" scenario, or by having to dismiss some of their assigned tasks entirely as it is demonstrated in the "Dismiss One" scenario.

Finally, if the agent experiences a severe time pressure situation, the agent will elect to dismiss all dismissable elective tasks in order to at least achieve their assigned critical time task. This is the case if their initially available time is smaller than the fast walk estimated required time $\mathbf{T}^{\text{ERT}}_{v_f}$.

8.4.3. Results

The results of the Urgency Verification Case scenarios confirm the expectations on the reactive agent behaviour. Figure 8.11 illustrates the dependency of the initially determined Urgency value $U(\tau^{\text{entry}})$ on different assigned critical times $\tau_{wait}(t_{\pi_{cr}})$ in the "Agent Parameters" scenario. As can be seen, the dependency of the initial Urgency value replicates the expected dependency for positive Urgency values. For the critical time $\tau_{wait}(t_{\pi_{cr}}) = 1318.6\text{s}$, the Urgency attains a value of zero, indicating a non-urgent behavioural state.

As the agent's initially determined Urgency parameter is dependent on the agent's assigned critical time, this dependency is also reflected in the agent's walk speed, Drive and Patience attributes, see Figures 8.12. The dependent agent parameters thereby follow the assigned dependencies, see Equations (5.18).

After the agent has adapted their behaviour to the initially perceived time pressure situation, they reassess their time situation in dynamic time intervals. In addition, the agent will reassess their time situation as soon as they have completed any of their chosen tasks. Figure 8.13 shows an example time development of the Urgency parameter $U(\tau)$ with the simulation time τ for different assigned critical times $\tau_{wait}(t_{\pi_{cr}})$.

The remaining three Urgency Verification Case scenarios are intended to demonstrate appropriate agenda rescheduling behaviours for a more imminent perceived time pressure situation. The scenarios had been chosen to favour a particular adaptive reaction of the agent. These expectations have been confirmed by the outcome of the simulations.

In the "Compromise" and "Dismiss One" scenario, the agent's initially perceived time pressure caused the agent to try to reduce the total number of assigned tasks. As has been described in Section 5.6.2.2, the agent can accomplish this wish by either electing to make

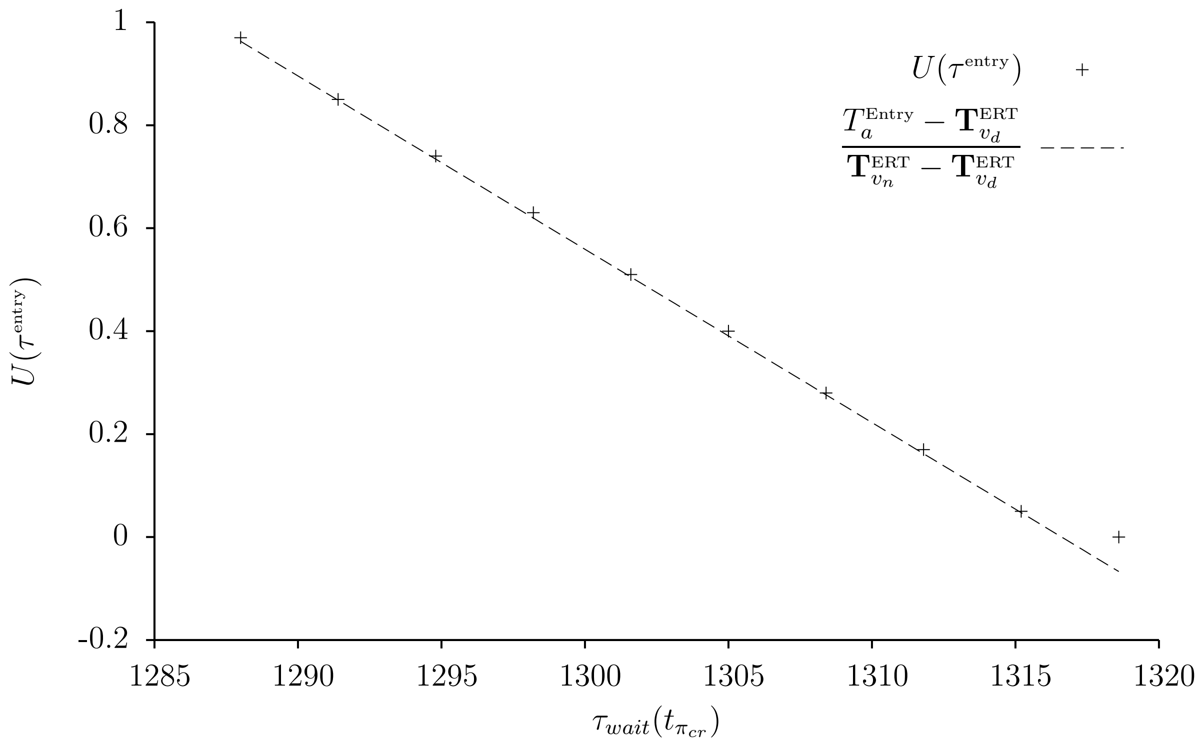
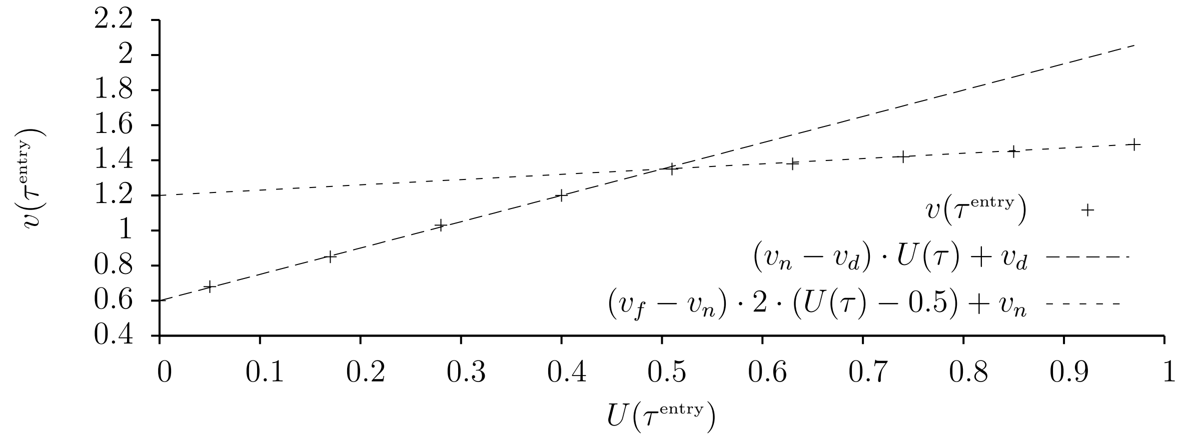
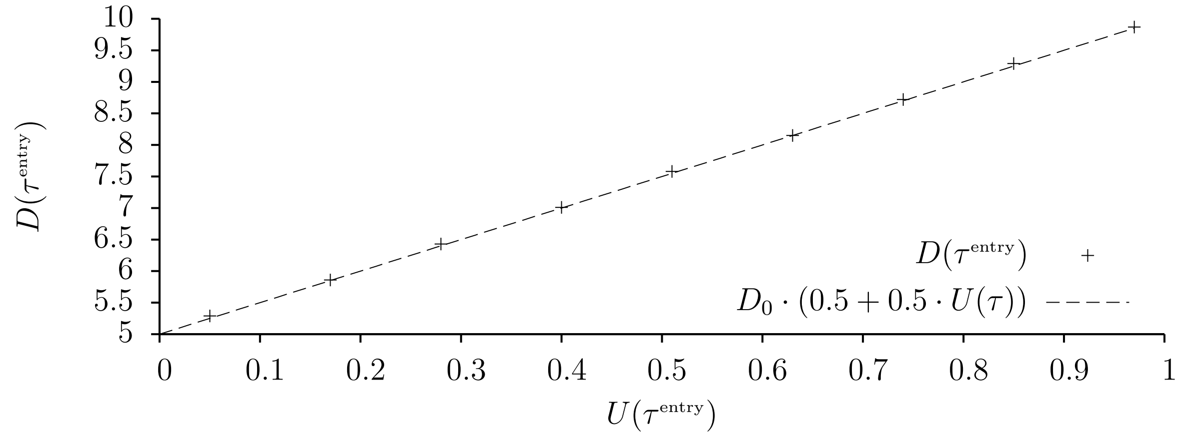


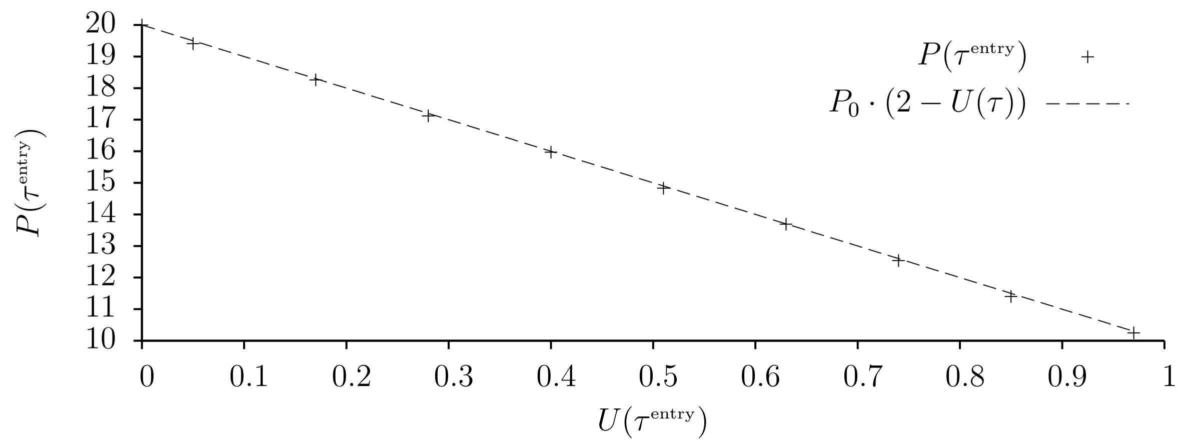
Figure 8.11.: The dependency of the Urgency parameter on the agent's assigned critical time $\tau_{wait}(t_{\pi_{cr}})$ in the "Agent Parameters" scenario. The dashed line indicates the expected Urgency dependency on the initially available time T_a^{entry}.



(a) The agent's walk speed at the time of entry $v(\tau^{\text{entry}})$. The wide dashed line thereby indicates the expected walk speed dependency for Urgency values smaller than 0.5. The short dashed line indicates the expected walk speed dependency for Urgency values greater than 0.5.



(b) The agent's Drive at the time of entry $D(\tau^{\text{entry}})$. The dashed line thereby indicates the expected Drive dependency on the Urgency parameter value.



(c) The agent's Patience at the time of entry $P(\tau^{\text{entry}})$ on the agent's initial Urgency parameter $U(\tau^{\text{entry}})$. The dashed line thereby indicates the expected Patience dependency on the Urgency parameter value.

Figure 8.12.: The dependency of the agent's walk speed, Drive and Patience attributes at the time of entry on the agent's assigned initial Urgency parameter $U(\tau^{\text{entry}})$ for different critical times in the "Agent Parameters" scenario.

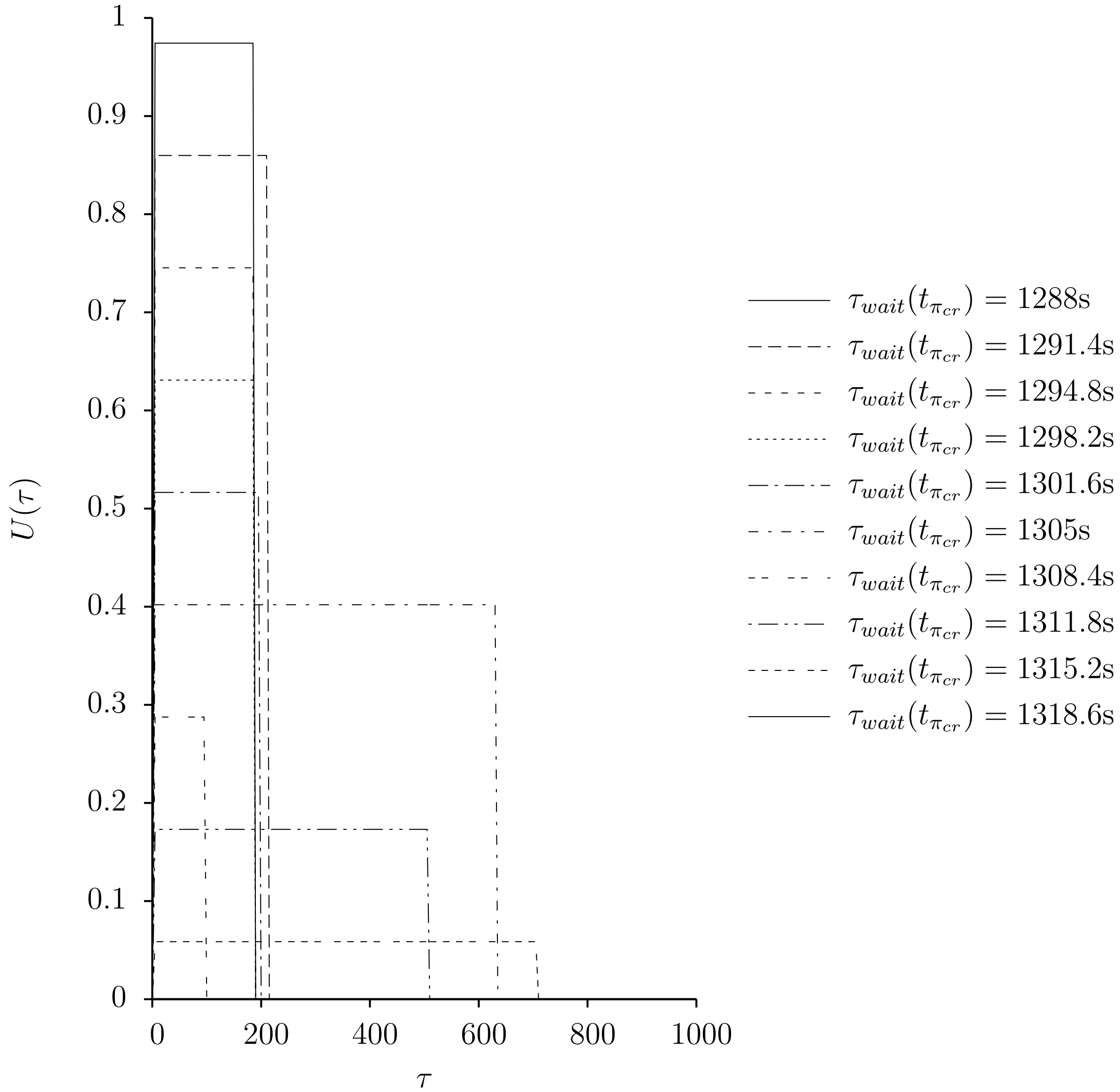
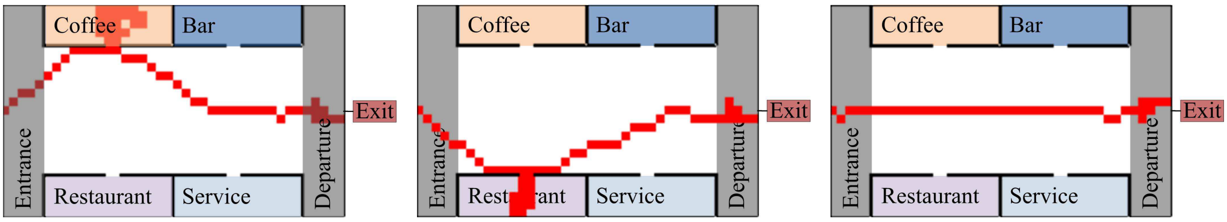


Figure 8.13.: The time development of the Urgency parameter $U(\tau)$ for different assigned critical times $\tau_{wait}(t_{\pi_{cr}})$ in the “Agent Parameters” scenario.

compromises or to relinquish one of their assigned goals.

In the “Compromise” scenario, the agent is assigned the goals to eat and to drink. Because of the settings of the available activity goal locations feature attributes and the agent’s personal preferences attributes, the agent has initially chosen to visit the restaurant and the bar goal location in order to satisfy the goal and drink respectively. However, the eat and drink goal are compromise goals (see Section 5.2.2). In addition, the underlying geometry contains a goal location, at which both compromise goals can be achieved simultaneously, the coffee goal location. However, the agent hasn’t chosen the coffee goal location initially for any of the two goals, because its goal location feature attributes don’t perfectly match their assigned personal preference attributes. When placed under a medium time pressure situation, the agent decides to rather go to the coffee goal location than to visit both the restaurant and bar goal location, thereby saving valuable time. In doing so, the agent will disregard the possibility of visiting two goal locations which pose a perfect match to their personal preferences in favour of visiting one goal location which poses a non-perfect preference match. These expectations on the agent’s behaviour are confirmed by the resulting footfall image of the “Compromise” scenario simulation, see Figure 8.14a.



(a) “Compromise” scenario. **(b)** “Dismiss One” scenario. **(c)** “Dismiss All” scenario.

Figure 8.14.: The cumulative footfall images for selected scenarios of the Urgency Verification Case.

On the other hand, in the “Dismiss One” scenario, the agent is initially assigned the goals to eat and to visit a service facility. These two goals don’t qualify for a common compromise task. When again put under medium time pressure, the agent still tries to reduce the number of planned tasks. In the case, that no compromise is possible, they need to sacrifice one or several of their assigned goals. The agent will do this in the order of the goals’ importance. The service goal is assigned a random importance in the interval $[10, 79]$, whereas the eat goal is assigned a random importance between 49 and 99 (see Chapter 5, Table 5.5). It can therefore be expected, that the agent will dismiss their service task more often than their eat task as shown in Figure 8.14b. In 10 consecutive simulation runs of the “Dismiss One” scenario, the service goal had a lower importance than the eat goal in 9 out of 10 cases. Therefore, the agent had dismissed the service task in 90% of the cases and the eat task in 10% of the cases.

Finally, in the “Dismiss All” scenario, the agent is put under extreme time pressure, which will force the agent to dismiss all of their elective tasks, see Figure 8.14c.

8.4.4. Summary

The Urgency Verification Case demonstrates the buildingEXODUS CPAF Plug-in's features of enabling the agents to exhibit contextual and adaptive behaviour in response to perceived time pressure. The verification case demonstrates the CPAF's Urgency model as one of the CPAF's reactive behaviour models to external stimuli, see Section 5.6.2. The verification case demonstrates how the CPAF agents are capable of perceiving external stimuli such as the current time and how the CPAF agents relate this information to their individual situation and plans. Based on this evaluation, the CPAF agents adapt their behaviour (walking speed, patience, drive) or their plans.

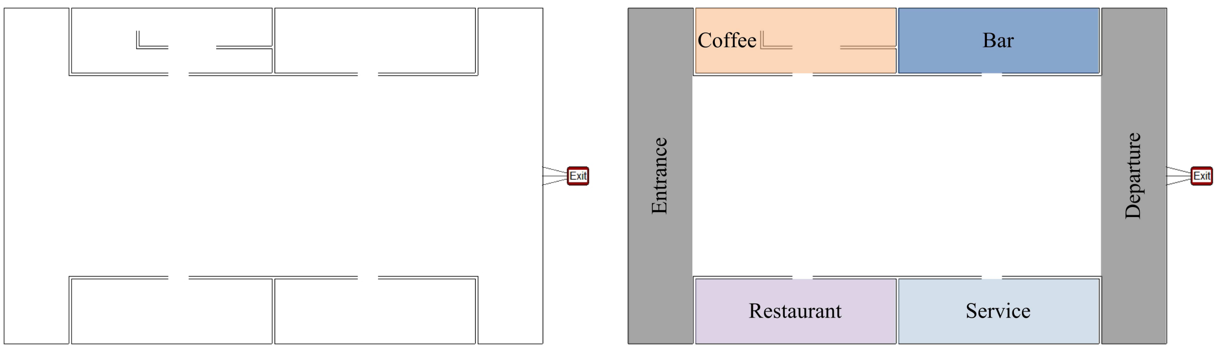
The Urgency hence addresses Research Question 4 by demonstrating how the CPAF Urgency feature simulates how pedestrians interpret and respond to external stimuli.

8.5. Perceived Crowd

The Perceived Crowd Verification Case aims to demonstrate the agents' ability to perceive and react to the external event of congestion. The agents in the CPAF are capable of continuously monitoring the surrounding congestion conditions. If the current congestion situation is perceived to have changed to a significant degree, the agent will then assess whether they need to adjust their plans in order to cope with the current situation.

8.5.1. Geometry

The geometry that is used in the Perceived Crowd Verification Case is based on the Urgency Verification Case geometry, see Figures 8.10 and 8.15.



(a) The buildingEXODUS geometry.

(b) The geometry with goal location type labels.

Figure 8.15.: The Perceived Crowd Verification Case geometry.

In addition to the goal locations already modelled in the Urgency Verification Case geometry, the Perceived Crowd Verification Case geometry also models departments. The environment's coffee goal location has been modelled as containing two departments: a department where the agents can queue up at the counter to purchase their desired products, and a seating department where the agents can elect to sit down and eat their purchase, see Figure 8.16.

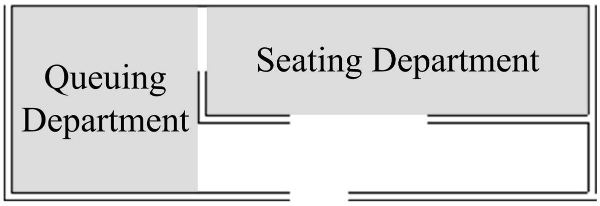


Figure 8.16.: The departments within the coffee goal location of the Perceived Crowd Verification Case geometry.

As has been described in Section 5.2.4, the queuing department is set to be obligatory in order to satisfy the desired associated goals, whereas the seating department is elective. To facilitate the analysis of the verification case's outcomes, the queuing department has been set to contain one counter. The time delay that each agent will experience at the counter once it is their turn to be served has been set to be 10s. The seating department is assigned the standard capacity of 1 agent per square metre (see Table 5.3). In this case, the coffee goal location's seating department has a size of 7 square metre.

8.5.2. Scenarios

The Perceived Crowd Verification Case makes use of the buildingEXODUS CPAF Plug-in features Trip Planning, Perceived Crowd and Urgency (see Table 8.4). In each verification case scenario, the CPAF agents are assigned the activity goals to eat, to drink and to visit a service facility. The CPAF agents are assigned a full prior knowledge of the modelled environment and a critical time, by which they need to have departed the environment. This critical time has been set such that the agents won't be put under any time pressure during the initial Urgency assessment in all scenarios of this verification case. In order to facilitate the set-up of the verification case scenario parameters, it has been set that the agents in all verification case scenarios will enter the modelled environment on the same node within the entrance goal location.

In the Perceived Crowd Verification Case, the simulation agent will experience different levels of congestion. For this purpose, some extra agents have been simulated in some verification case scenarios in the environment. These extra agents are not directed by the buildingEXODUS CPAF Plug-in, but rather have a simple agenda and will leave the environment as soon as their assigned tasks are finished. These extra agents are not capable of perceiving or reacting to any occurring congestion or time pressure, and will therefore not alter their assigned plans.

In the Perceived Crowd Verification Case, three scenarios have been designed which demonstrate the impact of the different Perceived Crowd Model parameters and the model's features, see Table 8.15. The "Threshold" scenario will demonstrate the model's sensitivity to the agent's individually assigned Perceived Crowd Threshold C^*, whereas the "Assessment Time Interval" will examine the model's dependency on the Perceived Crowd Assessment Time Interval Δ^C. The behaviour studied in the "Local Situation" scenario is independent of both the Perceived Crowd Threshold and the Perceived Crowd Assessment Time Interval. Hence, the model's default settings have been used in this demonstration scenario.

Table 8.15.: An overview of the Perceived Crowd demonstration scenarios.

Scenario	Perceived Crowd Threshold C^*	Perceived Crowd Assessment Time Interval Δ^C	Extra Agent Population
Threshold	$0.3, 0.4, 0.5, 0.6, 0.7$	5	Crowd of 30 extra agents in front of each goal location.
Assessment Time Interval	0.5	$1, 2.5, 5, 10, 20$	Crowd of 30 extra agents in front of each goal location.
Local Situation	in $[0.3, 0.6]$	15	–

In both the "Threshold" and the "Assessment Time Interval" scenarios, the agents' reactive behaviour caused by congestion on their way to their chosen tasks is studied. For this purpose, a crowd of 30 extra agents has been placed in front of each activity goal location, see Figure 8.17. The 30 extra agents are assigned the task to visit the goal location in front of which they have been positioned. The extra agents will therefore queue up in front of the respective goal location, thereby producing a certain level of congestion in front of the entrance to the goal location.

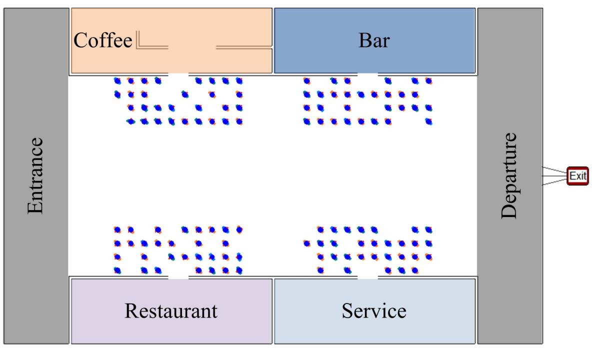


Figure 8.17.: The "Threshold" and "Assessment Time Interval" scenarios.

In both the "Threshold" and the "Assessment Time Interval" scenarios, one CPAF agent is simulated which needs to traverse the environment and seeks to satisfy their assigned activity goals. The agent is assigned a price preference of 0, a brand preference of 1 and a size preference of 0. As has been described in the Urgency Verification Case (see Section 8.4.2), the agent will therefore choose the restaurant, bar and service goal locations to satisfy their assigned activity goals to eat, drink and visit a service facility. Both the "Threshold" and "Assessment Time Interval" scenario should demonstrate, that the CPAF agent upon perceiving a level of congestion which they personally perceive to be significant will trigger an assessment of the agent's individual time planning. This Urgency assessment might or might not lead to the alteration of the agent's plans.

In the "Local Situation" scenario, the agents' reactive behaviour caused by congestion within their targeted goal location is studied. For this purpose, 10 CPAF agents are generated and sent into the environment at 20 seconds intervals. All of the agents are assigned a price preference of 0, a brand preference of 2 and a size preference of 0. As a consequence, the agents will all choose the coffee and service goal locations to satisfy their assigned activity goals to eat, drink and visit a service facility. As a result, one after the other agent will queue at the coffee goal location's queuing department and then try to enter the goal location's seating department. It is expected however, that as soon as the number of agents already within the coffee seating area exceeds the department's assigned capacity, any subsequent agent will elect to not visit the goal location's seating area, but rather take their food away.

8.5.3. Results

The "Threshold" and the "Assessment Time Interval" scenarios have been run 1000 times for each Perceived Crowd Threshold respectively Perceived Crowd Assessment Time Interval depicted in Table 8.15. Hence, for both the "Threshold" and the "Assessment Time Interval" scenario, a total number of 5000 simulation runs has been performed.

For both the "Threshold" and the "Assessment Time Interval" scenarios, it has been analysed for each simulation run, whether the CPAF agent's congestion assessment via their Perceived Crowd model had triggered an assessment of their Urgency parameter. An assessment of the agent's Urgency could have let to two possible itinerary alterations: either, the agent chose to make a compromise and visit the coffee goal location instead of visiting the restaurant and bar goal location; or, the agent could dismiss one or more of their chosen activity tasks. The proportion of the simulation runs in which the agent's Perceived Crowd Assessment triggered an Urgency assessment and in which the agent either made compromises or elected to dismiss some of their activity tasks are shown in Table 8.16 for the "Threshold" scenario and in Table 8.17 for the "Assessment Time Interval" scenario.

The results depicted in Table 8.16 respectively Table 8.17 show a great variance of the obtained simulation results, despite the large number of conducted simulation runs. This clearly demonstrates the complexity of the CPAF's Perceived Crowd model. The individual agent's behaviour during and as a result of their Perceived Crowd assessment is dependent

Table 8.16.: The average performance in the "Threshold" scenarios over a total number of 1000 simulation runs per assigned Perceived Crowd Threshold value C^*.

C^*	Proportion of 1000 simulation runs		
	Triggered Urgency Assessment	Made Compromise	Dismissed activity tasks
0.3	83.6% ± 37.05%	0.9% ± 9.45%	82.7% ± 37.84%
0.4	82.9% ± 37.67%	0.2% ± 4.47%	82.7% ± 37.84%
0.5	84.6% ± 36.11%	0.5% ± 7.06%	84.1% ± 36.59%
0.6	83.2% ± 37.41%	0.2% ± 4.47%	83.0% ± 37.58%
0.7	84.0% ± 36.68%	0.4% ± 6.32%	83.6% ± 37.05%

Table 8.17.: The average performance in the "Assessment Time Interval" scenarios over a total number of 1000 simulation runs per assigned Perceived Crowd Assessment Time Interval value Δ^{C}.

Δ^{C}	Proportion of 1000 simulation runs		
	Triggered Urgency Assessment	Made Compromise	Dismissed activity tasks
1	14.8% ± 35.53%	14.8% ± 35.53%	–
2.5	9.2% ± 28.92%	9.2% ± 28.92%	–
5	84.5% ± 36.21%	0.4% ± 6.32%	84.1% ± 36.59%
10	83.1% ± 37.49%	0.4% ± 6.32%	82.7% ± 37.84%
20	87.5% ± 33.09%	–	87.5% ± 33.09%

on both, the model's used parameters, but also on the emergent situation, e.g. the number of other agents in the agent's vicinity and the agent's distance from their current targeted goal location. The latter is a result of the probabilistic processes involved in the simulation, and can therefore be controlled only to a limited degree.

The results depicted in Table 8.16 indicate, that the value of the Perceived Crowd Threshold C^* has got no significant influence on the probability of an Urgency assessment being triggered. A linear regression analysis evaluated the dependency of the probability for an Urgency assessment $P(\text{Urgency assessment triggered})$ on the Perceived Crowd Threshold C^* to

$$P(\text{Urgency assessment triggered}) = 0.011 \cdot C^* + 0.8311$$

with an R^2 of 0.07. As a result and especially when considering the large variance in the obtained simulation results, the Perceived Crowd Threshold C^* is regarded as not being of any significant influence on the probability for an Urgency assessment. Likewise, the result of the "Assessment Time Interval" scenarios depicted in Table 8.17 don't reveal a linear relationship between the probability of an Urgency assessment being triggered and the Perceived Crowd Assessment Time Interval Δ^{C}. For the "Assessment Time Interval" scenarios, a linear regression analysis yielded a R^2 value of 0.53. In summary, these results indicate that no linear relationship between the likelihood of an Urgency assessment and either C^* or Δ^{C} exists. Any other relationship is also questionable because of the high variances in the simulation results.

It is however noteworthy, that small Perceived Crowd Assessment Time Intervals seem to favour the making of compromises. This can be explained with the nature of the Urgency Model's time assessment. An agent will compare their available time to a set of time estimates, the estimated required times. If their currently available time falls within certain estimated required time intervals, the agent either makes compromises or dismisses all of their chosen tasks. The time interval for the compromise action is relative small, since the agent's normal and fast walk speed only differ by $0.15\frac{m}{s}$, whereas the time interval associated with dismissing all activity tasks is relatively large. Therefore, if the Perceived Crowd Assessment Interval is very short, a potential Urgency assessment is triggered more often and in smaller time intervals. As a result, the likelihood for the Urgency assessment to result in compromise actions is higher.

In the "Local Situation" scenario, the CPAF agents have been expected to visit the coffee goal location in order to satisfy their eat and drink activity goals. With more and more of the agents visiting the coffee goal location, the goal location's seating area will become more and more crowded and eventually the number of agents present within the seating department will exceed the department's assigned capacity. It is therefore expected, that the agents which are generated the last might be likely to elect to not visit the seating department and rather take their purchase "for take away". Table 8.18 shows the average number of department tasks that have been completed by the agents.

Table 8.18.: The average number of completed department tasks within the coffee goal location per agent in a total of 1000 simulation runs.

Agent Number	Entry Time	Number of Completed Department Tasks
1	0s	2.00
2	20s	2.00
3	40s	2.00
4	60s	2.00
5	80s	2.00
6	100s	2.00
7	120s	2.00
8	140s	1.16 ± 0.37
9	160s	1.10 ± 0.30
10	180s	1.13 ± 0.34

As can be seen in Table 8.18, the first seven agents to enter the environment always performed both available department tasks within the coffee goal location. This confirms the expectations, since the capacity of the coffee goal location's seating department equals 1 agent per square metre and the seating department's area is 7 square metre. As could be expected, the average number of completed department tasks for the last three agents to be generated lies in the interval $[1, 2]$. The first department to be visited in the coffee goal location, the queuing department, is obligatory in order for the task to be successful and hence in order to satisfy the desired associated goal. Therefore, each of these last three to be generated agents have at least completed 1 department task. The probability for the last three to be generated agents to be able to elect to go to the seating department is greater than zero, as can be seen in Table 8.18. This is reasonable, since the time that any agent will spent within the seating department is a random variable which is uniformly distributed on a time interval dependent on the completion time attributes of the agent's desired goals and the goal location's service time attributes. In the case of the coffee goal location where each agent seeks to accomplish both their eat and drink goal, the time interval is given as $[70s, 930s]$. As soon as one agent has finished their assigned seating activity the following agents are then free to enter the seating department.

8.5.4. Summary

The Perceived Crowd Verification Case demonstrates the CPAF's features of enabling the agents to exhibit contextual and adaptive behaviour in response to perceived congestion. The verification case demonstrates the CPAF's Perceived Crowd model as one of the CPAF's reactive behaviour models to external stimuli, see Section 5.6.2. The verification case demonstrates how the CPAF agents are capable of perceiving external stimuli such as the current population density and how the CPAF agents evaluate this information with regard to their individual preferences. Based on this evaluation, the CPAF agents may decide to further evaluate their current plans, whether the perceived congestion might cause a delay.

The Perceived Crowd Verification Case hence addresses Research Question 4 by demonstrating how the CPAF Perceived Crowd feature simulates how pedestrians interpret and respond to external stimuli.

8.6. Situational Awareness

The aim of the Situational Awareness Verification Case is to demonstrate the CPAF's Unsatisfied Desired Goal Behaviour feature. With the Unsatisfied Desired Goal Behaviour Model, the agents in the CPAF are able to enquire missing structural information at for example information points in order to satisfy their assigned goals.

8.6.1. Geometry

The Situational Awareness Verification Case uses the “Route Choice” geometry that has been introduced in Section 8.2.1. The “Route Choice” geometry has been slightly enhanced such that in this verification case, a sign for each modelled information point goal location has been added to the geometry. Therefore, the agents in the Situational Awareness Verification Case are now able to perceive the modelled information points with their structural perception capability. Since no other signs have been added to the geometry, the agents are able to only perceive the information points and no other goal locations.

8.6.2. Scenario

The Situational Awareness Verification Case uses the buildingEXODUS CPAF Plug-in features Trip Planning, Structural Awareness and the Unsatisfied Desired Goal Behaviour (see Table 8.4). Because of the goal location feature parameters used in the “Route Choice” geometry, all agents in this verification case have been assigned a size preference of 0. The agents' price and brand preference are randomly assigned. No agent in this verification case is assigned any prior knowledge about the environment, but each agent is assigned the complete set of the five currently available activity goals.

Their lack of prior knowledge forces the agents to explore the environment in order to be able to satisfy all of their assigned goals. However, as has been described in Section 8.6.1, in this verification case only the information point goal locations modelled within the environment are associated with signs and are therefore perceivable by the agents. As a consequence the agents won't be able to directly explore the environment, but will rather be forced to seek the missing structural information by visiting the information point goal locations.

In this verification case, it is therefore expected that each agent initially follows a way point route because of their lack of prior knowledge and hence their incapability to make other trip plans. While following the way point route, the agents will perceive the modelled information points and add this information to their memory. At some point in time, the agents will check whether they still have got any unsatisfied agent goals and will search their memory for any goal locations, where they can accomplish these unsatisfied agent goals. It is then expected, that the agents will fail in trying to memorise any suitable goal locations, because of their lack of prior knowledge and the geometrical impossibility of perceiving the modelled activity goal locations. As a result, it is expected that the agents then turn to visit a nearby information point in order to gain the missing information.

8.6.3. Results

For the Situational Awareness Verification Case, a total number of 100 agents have been generated per simulation run. The verification case has then been run 10 times. To facilitate the discussion of the results, an area code system for the labelling of the goal locations within the "Route Choice" geometry has been introduced, see Figure 8.18. That is, the shop goal location for example in the bottom left is in the following referred to as "shop 1", whereas the shop goal location e.g. in the top middle is in the following referred to as "shop 5". The same holds for the other activity goal locations and for the way point goal locations (marked as yellow circles in Figure 8.18). The way point goal location in the centre of the geometry that is not encompassed in any area code is referred to as the "central way point".

As could be expected from the CPAF's trip planning procedure for agents with no prior knowledge of the modelled environment, all agents in each simulation run initially head towards the central way point in the centre of the underlying geometry. As a result of the triggered Unsatisfied Desired Goal Behaviour, each agent during the course of the simulation decides to visit an information point in order to retrieve missing information about the environment. Since the agents enter the environment from the left and initially head towards the centre, it is expected that more agents learn about the information points 1, 2, 5, and 6 then about the information points 3 and 4. Also, since the agents include distance considerations when their Unsatisfied Desired Goal Behaviour is triggered, it is expected that the majority of agents visit the information points 1, 2, 5 and 6. These expectations are confirmed by the results of the simulation runs, see Table 8.19.

It is however interesting to note, that the results in Table 8.19 indicate a asymmetric usage of the information points with regard to their placement along the geometry's y axis. It has been expected, that the information points 1 and 6 as well as the information points 2 and 5 respectively 3 and 4 would be visited by approximately the same proportion of the agent

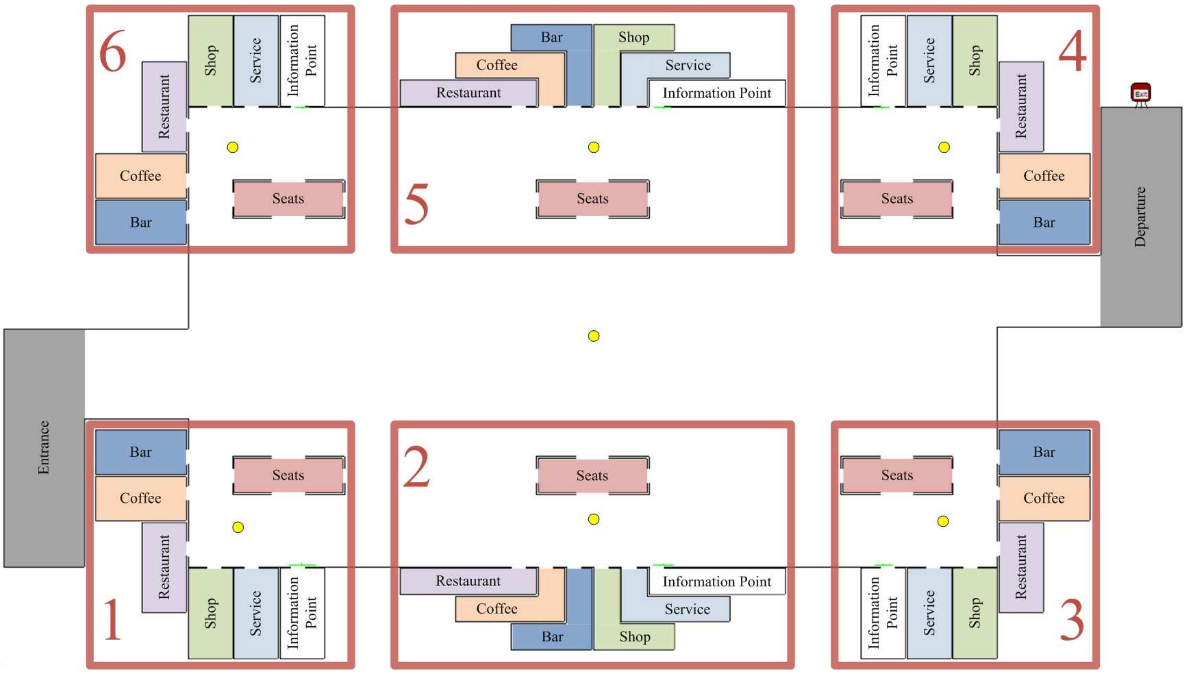


Figure 8.18.: The "Route Choice" geometry with Area Code labels.

Table 8.19.: The average number of agents that visited a certain goal location in the Situational Awareness Verification Case.

Information Point	Number of Visiting Agents out of 100
1	32.4 ± 3.66
2	2.6 ± 1.65
3	–
4	3.3 ± 2.00
5	17.2 ± 3.19
6	44.5 ± 1.27

population. Is is however apparent, that the agents did prefer the upper information points to the lower information points. These results indicate, that the "central way point" is not placed in the middle of the geometry, but is slightly shifted to the top of the geometry. As a result, since the agents aim to minimise distances, the upper information points have been preferred.

After the agents have visited the information point goal locations, they acquire the structural information necessary to satisfy their unsatisfied goal. Since the agents in the Situational Awareness Verification Case have all been assigned all five activity goals, each agent will choose a preference- and distance-optimal goal location where they can satisfy one or more of their goals. Since the goal locations modelled in the "Route Choice" geometry are all assigned the same price, brand and size attribute, the agent's goal location choice will purely be based on distance considerations.

Tables 8.20 show an overview of the average number of agents who visited a certain goal location. Table 8.20a shows the results sorted by the goal locations' type and Table 8.20b depict the results sorted by the goal locations' assigned area code.

As can be seen in Tables 8.20, the agents preferred visiting goal locations in the area codes 1, 2, 5 and 6, as has been expected. The results in Table 8.20b especially demonstrate, that those agents who visited the information points 1 and 2 predominantly visited goal locations in the area code 1 and 2. This can be seen by the fact, that e.g. the sum of the average number of agents who visited the coffee 1 and the coffee 2 goal locations approximately equals the sum of the average number of agents that chose information points 1 and 2. This observation is also confirmed for the seating, service and shop goal locations in the code areas 1 and 2. Likewise, the same observations holds for the information points 5 and 6 and the goal locations in the area code 5 and 6.

In Tables 8.20, no bar or restaurant goal location is listed, since in the Situational Awareness Verification Case no agent visited any of these goal locations. This could be expected, since each agent is assigned both the goals to eat and to drink. When enquiring information at the information point goal locations, the agent are forced to choose between goal locations where they can satisfy only one of these two goals and goal locations where they can satisfy both goals at the same time. Since in this geometry, all goal locations equally well match the agents' personal preferences, the agents will always prefer the compromise goal locations. This behaviour has been postulated in the design of the CPAF. As a result, all agents choose to satisfy their eat and drink goal at a coffee goal location instead of a bar respectively a restaurant goal location.

The discussed results of the Situational Awareness Verification Case are also confirmed by the simulations' footfall results, see Figure 8.19 for an example image.

Table 8.20.: The average number of agents that visited a certain goal location in the Situational Awareness Verification Case. No agent in this verification case visited any bar or restaurant goal location.

(a) The goal locations sorted by their goal location type.

Goal Location	Number of Visiting Agents
Information Point 1	32.4 ± 3.66
Information Point 2	2.6 ± 1.65
Information Point 3	–
Information Point 4	3.3 ± 2.00
Information Point 5	17.2 ± 3.19
Information Point 6	44.5 ± 1.27
Coffee 1	15.8 ± 3.49
Coffee 2	18.9 ± 2.38
Coffee 3	–
Coffee 4	3.2 ± 2.04
Coffee 5	40.4 ± 4.58
Coffee 6	21.7 ± 2.93
Seating Area 1	17.8 ± 2.53
Seating Area 2	18.7 ± 2.26
Seating Area 3	0.7 ± 1.25
Seating Area 4	2.4 ± 1.35
Seating Area 5	40.2 ± 4.83
Seating Area 6	20.2 ± 4.24
Service Facility 1	17.7 ± 2.67
Service Facility 2	18.9 ± 2.47
Service Facility 3	0.3 ± 0.67
Service Facility 4	1.9 ± 1.37
Service Facility 5	40.8 ± 4.61
Service Facility 6	20.4 ± 4.20
Shop 1	17.5 ± 2.27
Shop 2	19.2 ± 2.10
Shop 3	0.3 ± 0.48
Shop 4	2.1 ± 1.37
Shop 5	40.6 ± 4.55
Shop 6	20.3 ± 4.03

(b) The goal locations sorted by their assigned area code.

Goal Location	Number of Visiting Agents
Information Point 1	32.4 ± 3.66
Coffee 1	15.8 ± 3.49
Seating Area 1	17.8 ± 2.53
Service Facility 1	17.7 ± 2.67
Shop 1	17.5 ± 2.27
Information Point 2	2.6 ± 1.65
Coffee 2	18.9 ± 2.38
Seating Area 2	18.7 ± 2.26
Service Facility 2	18.9 ± 2.47
Shop 2	19.2 ± 2.10
Information Point 3	–
Coffee 3	–
Seating Area 3	0.7 ± 1.25
Service Facility 3	0.3 ± 0.67
Shop 3	0.3 ± 0.48
Information Point 4	3.3 ± 2.00
Coffee 4	3.2 ± 2.04
Seating Area 4	2.4 ± 1.35
Service Facility 4	1.9 ± 1.37
Shop 4	2.1 ± 1.37
Information Point 5	17.2 ± 3.19
Coffee 5	40.4 ± 4.58
Seating Area 5	40.2 ± 4.83
Service Facility 5	40.8 ± 4.61
Shop 5	40.6 ± 4.55
Information Point 6	44.5 ± 1.27
Coffee 6	21.7 ± 2.93
Seating Area 6	20.2 ± 4.24
Service Facility 6	20.4 ± 4.20
Shop 6	20.3 ± 4.03

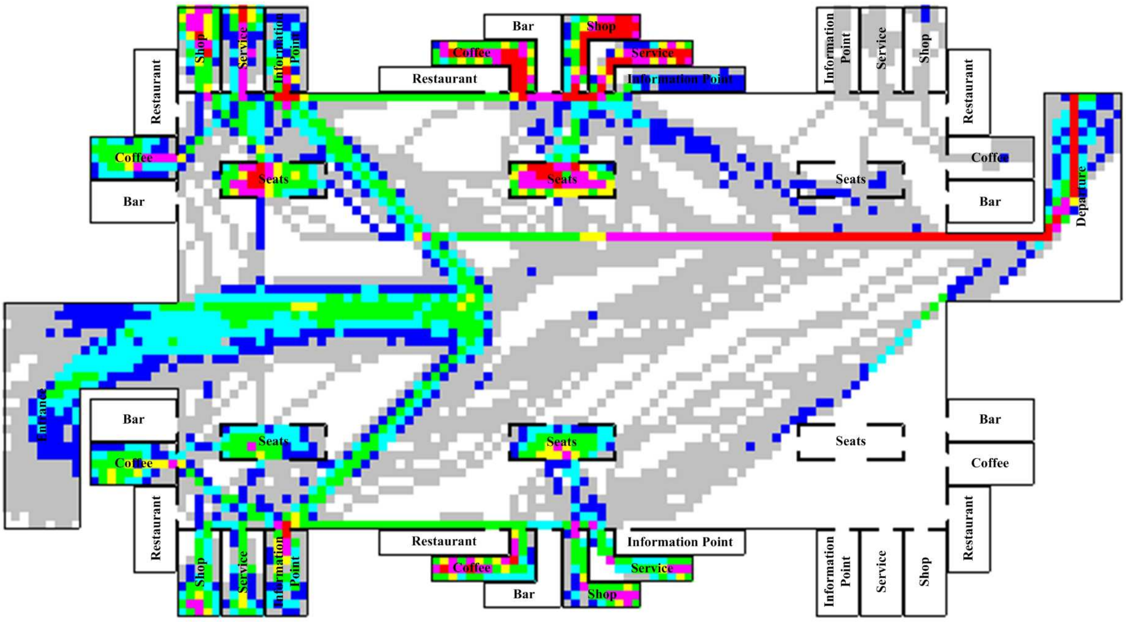


Figure 8.19.: An example footfall image of the Situational Awareness Verification Case.

8.6.4. Summary

The Situational Awareness Verification Case demonstrates the CPAF's feature of enabling the agents to enquire missing structural information. It demonstrates the CPAF's feature of enabling agents to actively seek for information if their assigned goals and their available structural knowledge necessitate.

The Situational Awareness Verification Case thereby address Research Question 4 by demonstrating how the CPAF Unsatisfied Desired Goal Behaviour feature simulates how pedestrians take actions to improve their current situation.

8.7. Motivational Action Selection: Motivations

The Motivations Verification Case aims to demonstrate the CPAF agents' capability of intrinsically creating new goals based on physiological needs. The agents are then able to make plans to satisfy these emergent goals by consulting their structural knowledge.

In the Motivation Verification Case, the "Goal Location Choice" including the signs introduced in the Structural Awareness verification case is used as the simulated environment, see Section 8.3.1.

8.7.1. Scenarios

In the Motivations Verification Case, different combinations of different features of the buildingEXODUS CPAF Plug-in will be used, see Table 8.21. Nevertheless, as could be expected, the buildingEXODUS CPAF Plug-in features to model the agents' trip planning and to model their motivations is enabled in each scenario of the Motivations Verification Case, see also Table 8.4.

Table 8.21.: An overview of the buildingEXODUS CPAF Plug-in features enabled in addition to the buildingEXODUS CPAF Plug-in's Trip Planning feature in each of the scenarios of the Motivations Verification Case.

Scenario	Additional CPAF buildingEXODUS Plug-in Features			
	Structural Perception	Short Term Memory	Meal Times	Urgency
Structural Perception	✓	–	–	–
Short Term Memory	✓	✓	–	–
Meal Times	✓	–	✓	–
Urgency	✓	–	–	✓

In each scenario of the Motivations Verification Case, all of the generated agents are assigned the activity goals to go to a service facility and to go to a shop. In addition, each agent is assigned a critical time of 3000s until which they have to have reached the environment's departure goal location. The agents are assigned no prior knowledge of the environment. Because of the layout of the "Goal Location Choice" geometry used for this verification case, each agent is assigned a size preference of 0, whereas the agents' price and brand preference are assigned randomly.

As a result of these general scenario settings, each agent in all scenarios of the Motivations Verification Case will choose a preference optimal service and shop goal location where they can satisfy their assigned agent goals. After they have finished their planned tasks, the agents will enter the departure goal location and wait their until their critical time expires.

During the course of the simulation, the agents' hunger, thirst and fatigue motivations will increase as described in Section 5.6.1. The more time elapses, the more likely it is for an agent that one or several of their motivations exceed their Lower Motivation Threshold. If a motivation is elevated, the corresponding agent goal is generated or reactivated, which causes the agent to consult their Spatial Memory Set in order to make plans to satisfy the new agent goal. These plans are then fitted in the already existing plans. If the agent is already waiting in the departure goal location when one of their motivations give rise to the activation of the corresponding agent goal, the agent will quit their current waiting task and will instead attempt the newly generated motivation task.

In the "Structural Perception" scenario, the agents will pursue their initially chosen plans to shop and visit a service facility. While doing so, the agents will perceive goal locations where motivational goals could be satisfied and they will store this information on their Spatial Memory Set for potential later use. For any potential motivational goal, goal locations within the environment exist where this goal could be satisfied. Because of the layout of the used geometry, all agents will eventually perceive all available goal locations within the geometry. It is therefore expected, that each agent will be able to satisfy any potentially arising motivational goal.

In the “Short Term Memory” scenario, the buildingEXODUS CPAF Plug-in’s Short Term Memory feature is in addition enabled. Although any agent will eventually perceive goal locations, where the motivational goals can be satisfied, the agents will now eventually forget about this acquired information. It is therefore expected, that not every agent will be able to satisfy all of their potentially arising motivational goals.

In the “Meal Times” scenario, the buildingEXODUS CPAF Plug-in’s Meal Time Model as described in Section 5.6.1.1 for the agent’s hunger motivation is enabled. The Meal Time Model is intended to simulate the effects of culturally customary meal periods: the likelihood for the agents’ hunger motivation to give rise to the goal to eat depends on the strength of the motivation and the time that the motivation becomes elevated. It is therefore expected in this scenario, that the goals to eat will mostly be generated during the assigned meal times.

In the “Urgency” scenario, the interplay between the CPAF’s internal and external stimuli representations is demonstrated. As has been described in Section 5.6, it has been set in the CPAF that emotions outrank motivations. That is, any change to the agent’s plans or goals made by the agent’s motivations can be suppressed by the agent’s emotions, especially the Urgency Model. While in the other verification case scenarios, the agents can add any number of motivational tasks even though this might lead to the violation of their assigned critical time, in this scenario the agent’s Urgency assessment can prevent the generation of tasks if the agent’s critical time might be of risk. The arising motivational goals are hence suppressed.

8.7.2. Results

Each scenario of the Motivations Verification Case has been simulated 10 times. In each simulation run, 100 agents generated and their initial motivation values were randomly assigned in the interval between zero and the Lower Motivation Threshold.

The general impact of the motivation functions in the CPAF can be best illustrated by two examples from the “Structural Perception” scenario, see Figures 8.20 and 8.21. The agent’s motivation functions increase over time. As soon as one motivation exceeds the Lower Motivation Threshold, the associated motivational goal is generated or reactivated on the agent’s Agent Goal Set. If the agent can recall a goal location, where the agent goal can be accomplished, an associated task to go to this goal location is added to the agent's itinerary. After the agent has completed a motivational task, the associated motivation function is reset to zero.

In Figure 8.20, it is illustrated that the agent first satisfied their previously assigned agent goals to shop and to visit a service facility. While visiting the service outlet, the agent's hunger motivation exceeded the Lower Motivation Threshold, thereby triggering the creation of an "eat" task after having visited the service facility. After the agent has finished their task to eat, they become tired as their fatigue motivation exceeds the Lower Motivation Threshold. Consequently, the agent decides to visit the seating goal location to rest. Subsequently, the agent heads for the departure goal location to wait there until their assigned critical time has expired. However, while the agent is waiting, their thirst motivation also exceeds the Lower Motivation Threshold, causing the agent to quit waiting and instead go to a drink goal location. The agent is then able to finish this drinking task in time and heads back to the departure goal location, which the agent leaves at their assigned critical time.

The agent whose behaviour is depicted in Figure 8.21 also at first visited a shop and a service goal location. During their stay in the chosen service facility, the agent became tired and decided to subsequently rest at the seating goal location. While the agent was resting, they became thirsty and decided to visit a drink goal location. After having completed their "drink" task, the agents walked to the departure goal location to wait. However, the agent's hunger motivation exceeded the Lower Motivation Threshold during their wait, causing the agent to immediately go to a goal location where they can eat something, although their assigned critical time is fast approaching. Consequently, the agent missed their assigned critical time while satisfying their hunger motivation. This behaviour of missing an assigned critical time while trying to get something the eat can also be seen in real-life. The pedestrian who quickly wants to last-minute grab some food might be caught in a long queue to pay for their purchase or the food preparation did take longer than they had expected.

As can also be seen in Figures 8.20 and 8.21, the agent's motivation functions are reset to zero after the associated agent goal has been satisfied by the agent completing the associated task. However, after the motivation has been reset, they start increasing again. Thereby, an agent can become hungry, thirsty or tired more than once during the course of a simulation run.

For each scenario in the Motivations Verification Case, the results of the agents' average motivational goal performance is depicted in Table 8.22. If one of the agent's motivations rise to an elevated level, the associated motivational agent goal is generated or reactivated on the agent's Agent Goal Set and the agent's itinerary is updated as described in the previous paragraph. If the agent has successfully completed a task at a goal location associated with the motivational agent goal, the goal will be marked as satisfied. If however the agent was not able to find a goal location at which they can accomplish the motivational goal, the

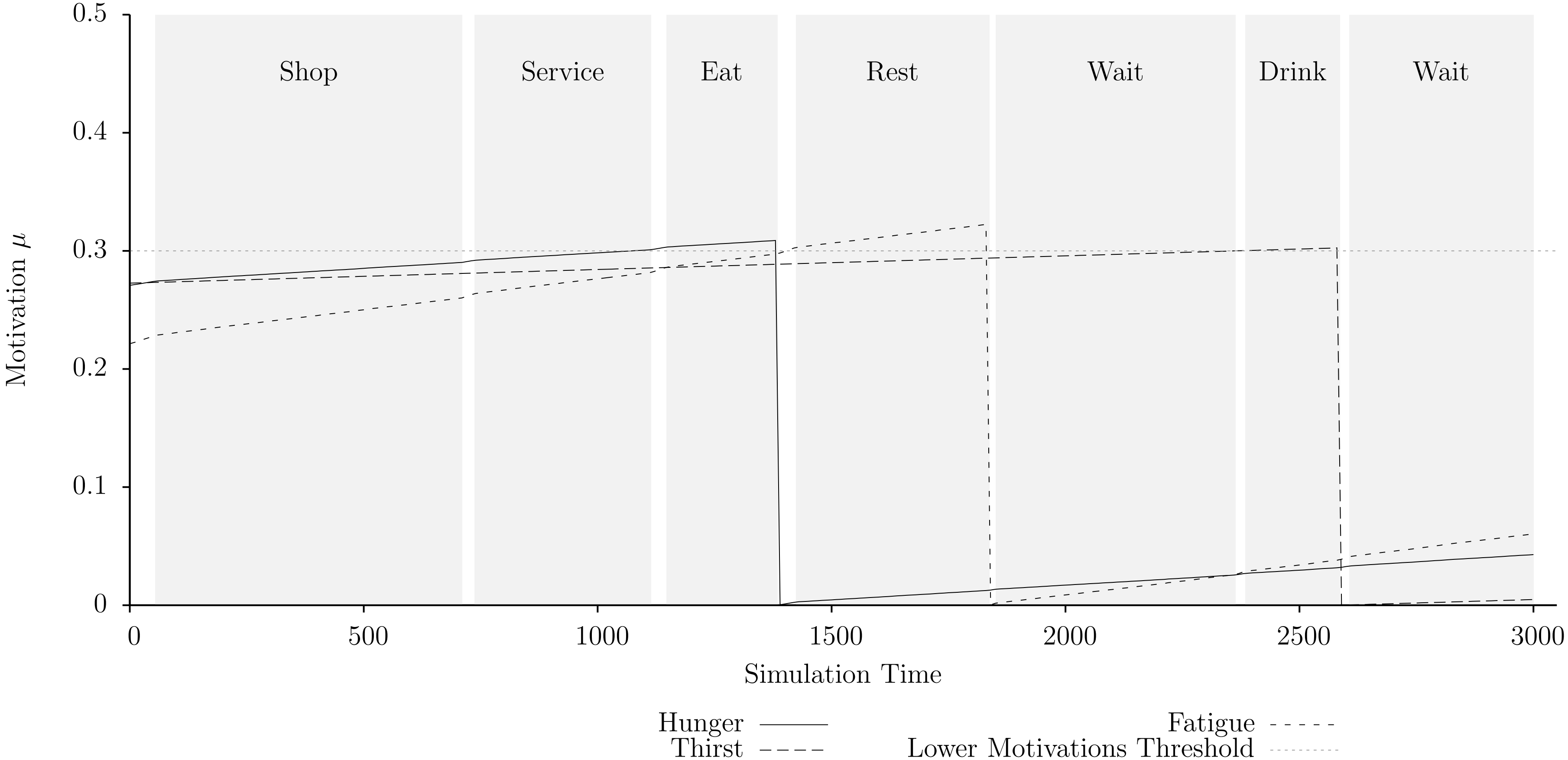


Figure 8.20.: An example for the motivational action selection capability of the CPAF in the "Structural Perception" scenario of the Motivations Verification Case. The time development of the agent's motivation functions is illustrated. The grey rectangles illustrate the time periods during which the agent performed a task to satisfy the named agent goal. In this example, the agent was able to meet their assigned critical time.

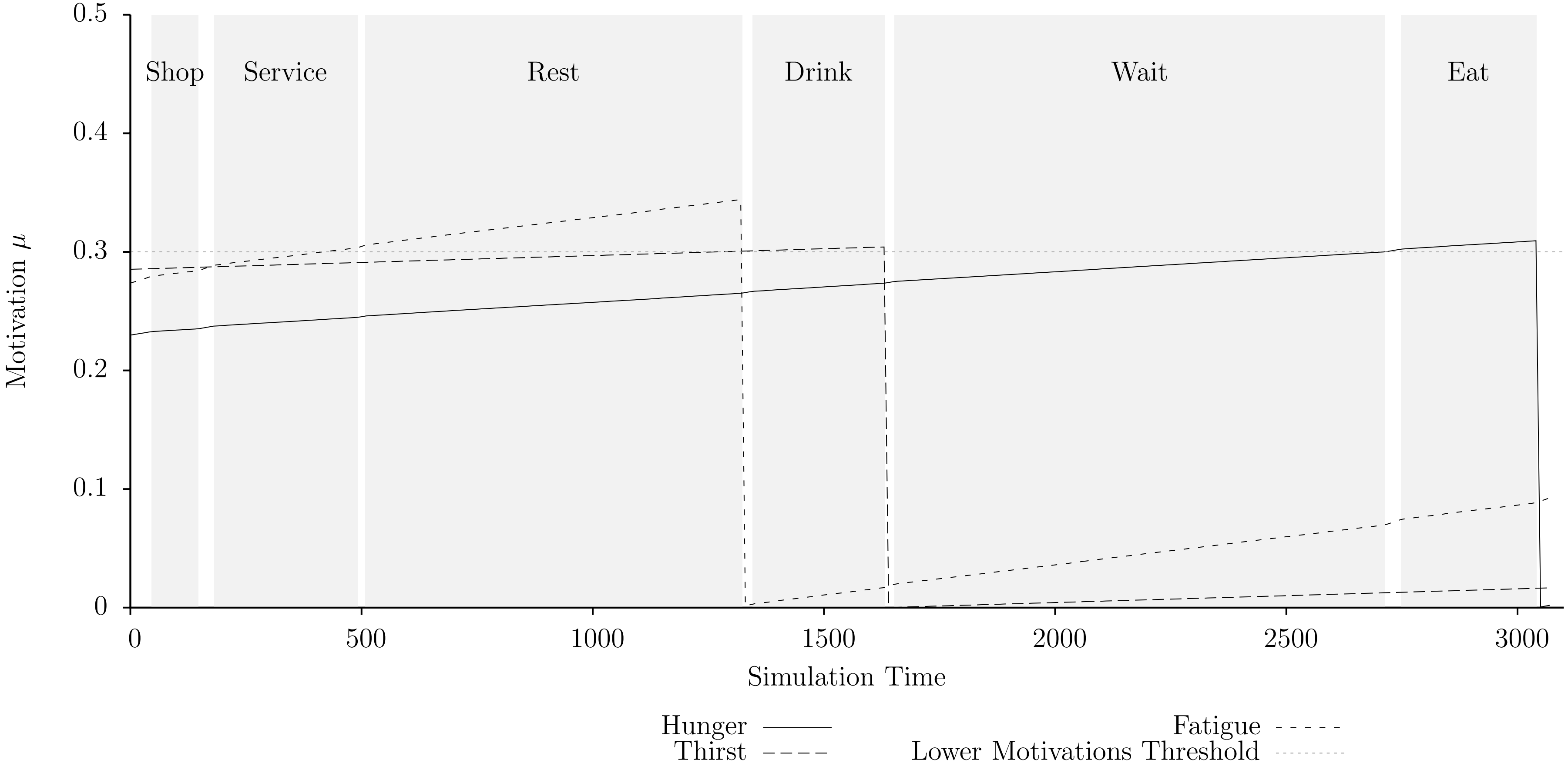


Figure 8.21.: An example for the motivational action selection capability of the CPAF in the "Structural Perception" scenario of the Motivations Verification Case. The time development of the agent's motivation functions is illustrated. The grey rectangles illustrate the time periods during which the agent performed a task to satisfy the named agent goal. In this example, the agent missed their assigned critical time.

agent goal's status stays as "unsatisfied". In addition, agent goals can also be suppressed by reacting to outer conditions and circumstances, such as customary meal time periods, if the agent is under time pressure.

Table 8.22.: The average motivational goal performance over 10 simulation instances for selected scenarios in the Motivations Verification Case.

Scenario	Goal Status	Proportion of Agent Population		
		Drink	Eat	Rest
Structural Perception	Satisfied	12.6% ± 3.17%	25.8% ± 3.82%	49.3% ± 7.14%
	Suppressed	–	–	–
	Unsatisfied	–	–	–
Short Term Memory	Satisfied	7.6% ± 3.41%	11.8% ± 4.08%	51.7% ± 3.83%
	Suppressed	–	–	–
	Unsatisfied	6.8% ± 2.10%	12.6% ± 3.41%	0.5% ± 0.71%
Meal Times	Satisfied	10.9% ± 2.60%	11.4% ± 3.10%	51.2% ± 4.57%
	Suppressed	–	11.5% ± 2.42%	–
	Unsatisfied	–	–	–
Urgency	Satisfied	11.3% ± 3.27%	17.6% ± 3.34%	34.1% ± 5.51%
	Suppressed	1.9% ± 1.20%	9.3% ± 2.45%	15.2% ± 4.05%
	Unsatisfied	–	–	–

As can be seen in Table 8.22, in all scenarios of the Motivations Verification Case, on average about a tenth of the agent population became thirsty during their sojourn in the environment and therefore generated the agent goal to drink. Likewise, about a quarter of the agent population became hungry and roughly half of the agent population became tired at some point during their sojourn in the environment. As has been expected, the agents' ability to successfully react to their intrinsic motivations, i.e. to satisfy their emergent motivational agent goals, depended on the scenario conditions.

In the "Structural Perception" scenario, each was able to satisfy all of their potentially emergent motivational agent goals. This is a result of the layout of the geometry. Each agent in the modelled geometry at some point perceives goal locations where any motivational goal can be accomplished. Since in the "Structural Perception" scenario no forgetting is simulated, each agent was therefore able to accomplish their motivational goals by choosing an appropriate goal location from their memory.

When the forgetting of goal locations over time is simulated with the buildingEXODUS CPAF Plug-in as is the case in the "Short Term Memory" scenario, the agents' motivational goal performance is less optimal. As can be seen in Table 8.22, only about half of those agents that became hungry were able to satisfy their agent goal to eat, whereas the other half of the hungry agent population were not able to remember any goal location and therefore were not able to satisfy their agent goal to eat. For the drink agent goal, also about half of the thirsty agents were able to satisfy their goals. And for the agent goal to rest, roughly 99% of those agents who became tired rested at the only available seating goal location within the geometry. The differences in the recall performance for the eat, drink and rest agent goal can be explained with the agents' unidirectional route within the environment. As can be seen in Figure 8.2b, the agents enter the environment on the left hand side and walk towards their assigned departure goal location on the right hand side. They thereby travel along the geometry from left to right, first passing by coffee and restaurant goal locations, then passing by shopping and bar goal locations and finally passing by service goal locations and the only simulated seating goal location. As a result of this unidirectional route, every agent is more likely to forget about the restaurant goal locations than about the bar and seating goal locations. This generalisation however does not apply to the coffee goal locations, because the recall probability not only depends on the perception times of the goal locations, but also on the number of goals that in general can be satisfied at the goal location, and on the number of goals that the agent wants to satisfy at the time of the recall, see Equation (5.3). Since the coffee goal locations can in general serve the two compromise goals to eat and to drink, their recall probability is higher than the recall probability of the restaurant goal locations, although all of these goal locations are perceived at the same time by the agents. Furthermore, the recall probability of a coffee goal location is higher, if the agent is trying to recall a goal location where both possible compromise agent goals rather than just one.

In the "Meal Times" scenario, the Short Term Memory functionality is disabled again for simplicity, but the agents are assigned customary meal time periods during their sojourn in the environment. In this test case scenario, the meal time periods were set to be from 150s to 450s and from 2200s to 2500s. Any non-urgent hunger motivation that arises outside these time periods is therefore likely to be suppressed. As a consequence, about 50% of those agents who became hungry did suppress their "eat" agent goal. Figure 8.22 illustrates the times at which agents have started a task in order to satisfy their motivated "eat" agent goal during the 10 simulation runs. As can be seen in Figure 8.22, the majority of those agents who did not suppress their "eat" agent goal started their "eat" tasks during or shortly after the second assigned meal time period. Only a total number of eight agents over 10 simulation runs with a total number of 100 agents did start an "eat" task outside the scope of the meal time periods. This is because they experienced a strong hunger motivation. The fact that only few agents did start an "eat" task during the first meal time period is also consistent with the model, since the hunger motivation increases over time and it is therefore more likely to become hungry at later points of time in the simulation.

Finally, in the "Urgency" scenario, the interplay between the agents' reactive behaviour to time pressure and their motivational needs is shown. As can be seen in Table 8.22, the overall agent population suppressed roughly a third of their motivational agent goals. Thereby, all of the agents were hence able to meet their assigned critical time, see Table 8.23. In the

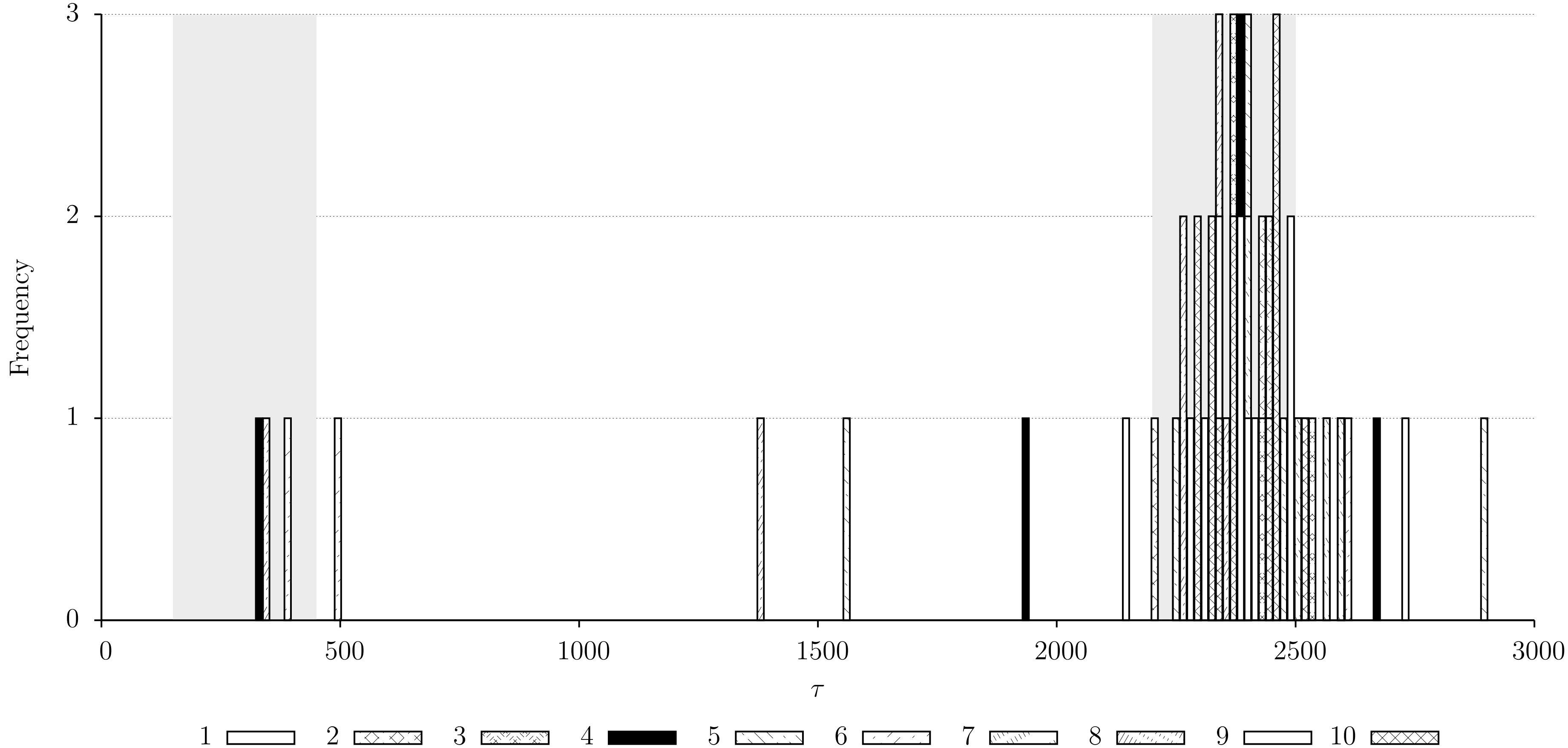


Figure 8.22.: The time distribution of the “eat” goal task start times from 10 simulation runs of the “Meal Times” scenario in the Motivations Verification Case. The light-gray rectangles illustrate the meal time periods.

other scenarios, on average about 16% of the agent population did miss their critical time, because they decided to pursue a motivational task.

Table 8.23.: The average agent population proportion over 10 simulation runs who missed their assigned critical time.

Motivations Verification Case Scenarios			
Structural Perception	Short Term Memory	Meal Times	Urgency
15.7% ± 3.64%	15.2% ± 3.59%	13.2% ± 3.39%	–

8.7.3. Summary

The Motivations Verification Case demonstrates the CPAF's feature of simulating individual internal stimuli within the agent, see Section 5.6.1. It demonstrates how the CPAF agents are capable of experiencing intrinsic motivations and how these motivations cause the agents to alter their behaviour and plans.

The Motivations Verification Case hence also addresses Research Question 4 by demonstrating how the CPAF Motivation feature simulates how observed pedestrian behaviour can be caused by internal stimuli.

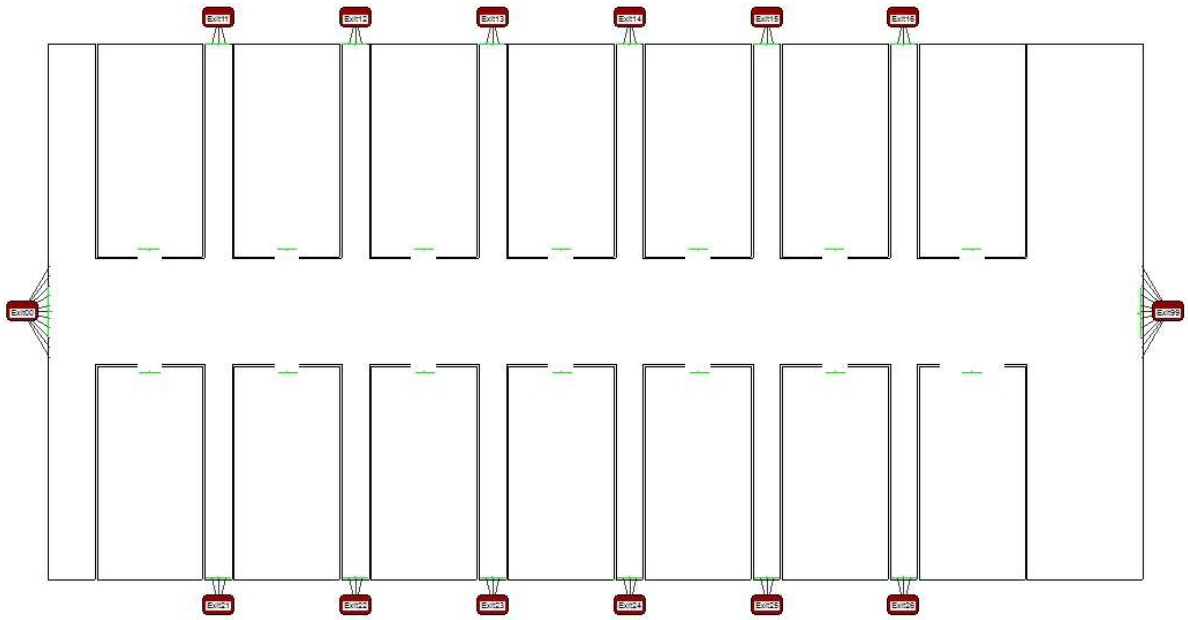
8.8. Alarm Response

In the Alarm Response Verification Case, the possibility to apply the CPAF and its intrinsic usage-cycle modelling to simulate the evacuation from a given environment is demonstrated. The evacuation is thereby not seen as an independent event, but rather the agents' experience from their prior usage of the environment is used to inform the evacuation behaviour. For this purpose, the Alarm Response Verification Case scenarios comprise the simulation of normal usage behaviour of the modelled environment and the occurrence of an alarm event at a specific point in time.

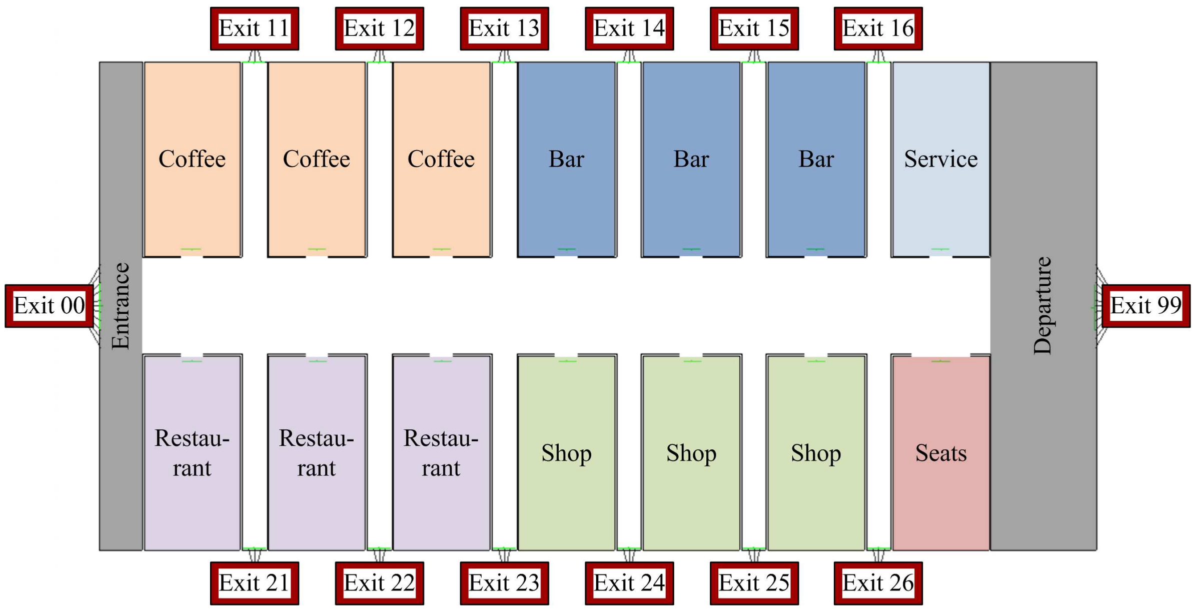
8.8.1. Geometry

The geometry that is used in the Alarm Response Verification Case is similar to the "Goal Location Choice" geometry, see Figure 8.23.

The Alarm Response Verification Case geometry comprises in total 16 goal locations: one entrance and one departure goal location; one seating and one service goal location; and three goal locations of the coffee, bar, restaurant and shop goal location type. The price and size attribute of all the goal locations are equally set to 1 for the price attribute respectively



(a) The buildingEXODUS geometry.



(b) The geometry with goal location type labels.

Figure 8.23.: The Alarm Response Verification Case geometry.

0 for the size attribute, leaving only the goal locations' brand attributes as a measure to distinguish between the goal locations.

Several exits have been modelled in the geometry in order to demonstrate the agents' exit choice behaviour. In total, 14 exits are simulated. In addition to the exit by the departure goal location, twelve side exits have been added to the geometry. Also, the entrance goal location has also been assigned an exit. With the entrance exit, the agents are then able to choose to leave the environment via their simulated way of entering the environment.

8.8.2. Scenarios

In each of the scenarios used in the Alarm Response Verification Case, a total number of 100 agents are generated. The Alarm Response Verification Case makes use of all available buildingEXODUS CPAF Plug-in features, apart from the Short Term Memory feature, see Table 8.4. By disabling the agents' short term memory, the effect of the agents' exit and route choice are easier observable. Each agent is assigned their individual set of agent goals, their Agent Goal Set, based on the standard goal distribution described in Section 8.1.2.

In all scenarios of the Alarm Response Verification Case, an alarm event is set to occur after 1000s of simulation time. As a reaction to this alarm event the agents will then start to evacuate at their individual point in time, until which they will perform their individually chosen pre-evacuation activity. The way the individual agent determines their evacuation start time and their pre-evacuation activity is dependent on the chosen response phase model.

The Alarm Response Verification Case comprises four scenarios, see Table 8.24. In the first scenario, the "Exit Choice" scenario, the agents' exit choice behaviour is demonstrated. In the remaining three scenarios, the agents' response phase behaviour is demonstrated, one scenario per currently available response phase model.

The "Exit Choice" scenario uses the buildingEXODUS CPAF Plug-in's Imposed-Time Imposed-Activities Response Phase Model. However, the scenario's focus lies on the agents' exit choice behaviour. The agents' exit choice depends strongly on their level of knowledge of the environment. By simulating the alarm response with the buildingEXODUS CPAF Plug-in, the agents have got two knowledge sources to base their exit choice upon. Some exits will be known to the agents based on their assigned level of prior knowledge of the environment. This knowledge is assigned prior to their entry in the environment, and hence at the start of the initial circulation stage. During the circulation stage, the agents can perceive additional structural information which is also used to inform the agents' exit choice. As has been described in Section 7.1, the individual agent distinguishes between these two sources of their available exit information when choosing an exit. The "Exit Choice" scenario is consequently performed with different levels of assigned prior knowledge about the environment. It is expected, that the agents' exit choice depends on the assigned level of prior knowledge.

In the second and third scenario of the Alarm Response Verification Case, the building-

Table 8.24.: An overview of the Alarm Response Verification Case scenarios. For the pre-evacuation activity distribution, it is sufficient to state either p(stand still) or p(continue), since $p(\text{stand still}) = 1 - p(\text{continue})$ in the current buildingEXODUS CPAF Plug-in.

Scenario	Prior Knowledge	Used Response Phase Model	Imposed Response Time Distribution	Pre-Evacuation Activity Distribution	Parameter Range
Exit Choice	K	IT-IA	$\mathcal{L}(4.3034, 0.08256^2)$	$p(\text{stand still}) = 0.33$	$K \in \{20\%, 40\%, 60\%, 80\%, 100\%\}$
IT-IA	100%	IT-IA	$\mathcal{L}(4.3034, 0.08256^2)$	$p(\text{stand still}) = 0.33$	–
IT-PA	100%	IT-PA	$\mathcal{L}(4.3034, 0.08256^2)$	$p(\text{continue}) = \begin{cases} 1 & \text{if } I(t_{\pi_0}) \geq \mathbf{I}^* \\ 0 & \text{else} \end{cases}$	$\mathbf{I}^* \in \{10, 30, 50, 70, 90\}$
Predicted	100%	Predicted	–	$p(\text{continue}) = \begin{cases} 1 & \text{if } I(t_{\pi_0}) \geq \mathbf{I}_1^* \\ & \quad \wedge\ r_{t_{\pi_0}} \geq \mathbf{r}_1^* \\ 1 & \text{if } I(t_{\pi_0}) \geq \mathbf{I}_2^* \\ & \quad \wedge\ r_{t_{\pi_0}} \geq \mathbf{r}_2^* \\ 0 & \text{else} \end{cases}$	$(\mathbf{I}_2^*, \mathbf{I}_1^*) \in \{(30, 60), (40, 70), (50, 80), (30, 90), (45, 75)\}$ $(\mathbf{r}_1^*, \mathbf{r}_2^*) \in \{(0.2, 0.8), (0.3, 0.7), (0.4, 0.6), (0.2, 0.6), (0.4, 0.8)\}$

EXODUS CPAF Plug-in's Imposed-Time Imposed-Activities and the Imposed-Time Predicted-Activities Response Phase Models are demonstrated. In both of these models, once the alarm event has occurred, each agent is assigned their individual evacuation start time based on a log-normal distribution. The log-normal distribution parameters are set by the user (see Appendix Chapter B). For the purpose of this verification case, the log-normal distribution parameters have been deducted from empirical data by Gwynne et al. [144]. As a result, the distribution of the individual agent's response time T_{resp} follows the log-normal distribution $\mathcal{L}(4.3034, 0.08256^2)$.

In addition to the agent's response times, a pre-evacuation activity is assigned to the agent as has been described in Sections 7.2.1 and 7.2.2. In the Imposed-Time Imposed-Activities Response Phase Model used in the second scenario of the Alarm Response Verification Case, the assignment is based on a user-stated discrete probability distribution. For the purpose of this verification case, the probability that an agent stands still and waits until their assigned response time has elapsed is set to be $p(\text{stand still}) = 0.33$. In the verification case's third scenario, the Imposed-Time Predicted-Activities Response Phase Model is used. Hereby, the agent's pre-evacuation activity is dependent on the importance of their current task at the time of the alarm event. For the purpose of this verification case scenario, the importance threshold $\mathbf{I}^*$ for the agent to decide to continue their current task varies from 10 to 90.

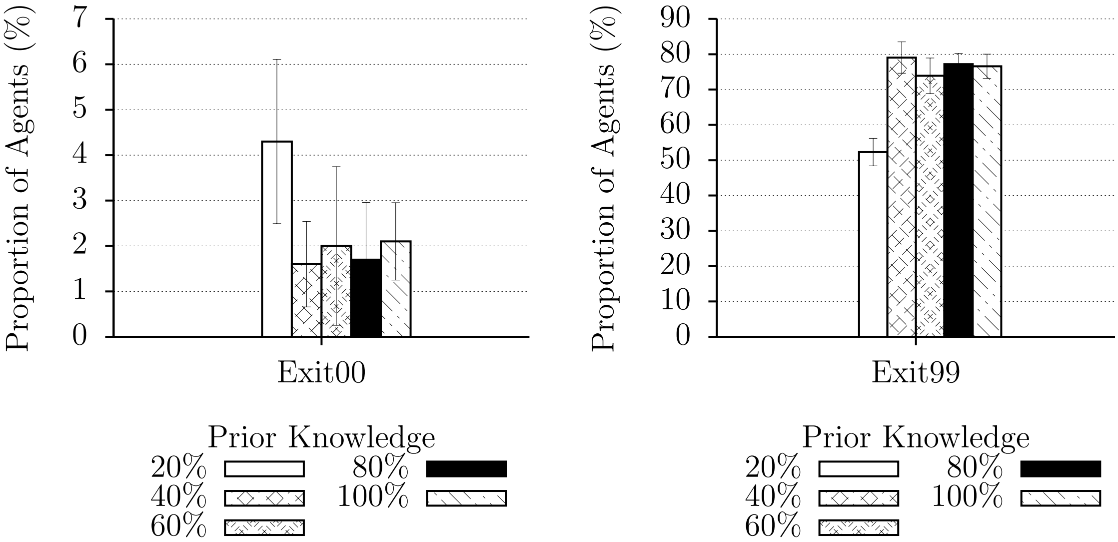
In the fourth scenario of the Alarm Response Verification Case, the agents' response time is not externally imposed from the pedestrian behaviour simulation tool. Instead, the agents' response times are dependent on their decision for a pre-evacuation activity determined by the buildingEXODUS CPAF Plug-in's Predicted Response Phase Model, see Section 7.2.3. If the individual agent decides to continue pursuing their current task, they will start evacuating after they have finished this task. Otherwise, they will start to evacuate immediately after the alarm event. The response phase model's importance threshold parameters $\mathbf{I}_1^*$ and $\mathbf{I}_2^*$ respectively the completion time ratio thresholds $\mathbf{r}_1^*$ and $\mathbf{r}_2^*$ are varied as depicted in Table 8.24.

8.8.3. Results

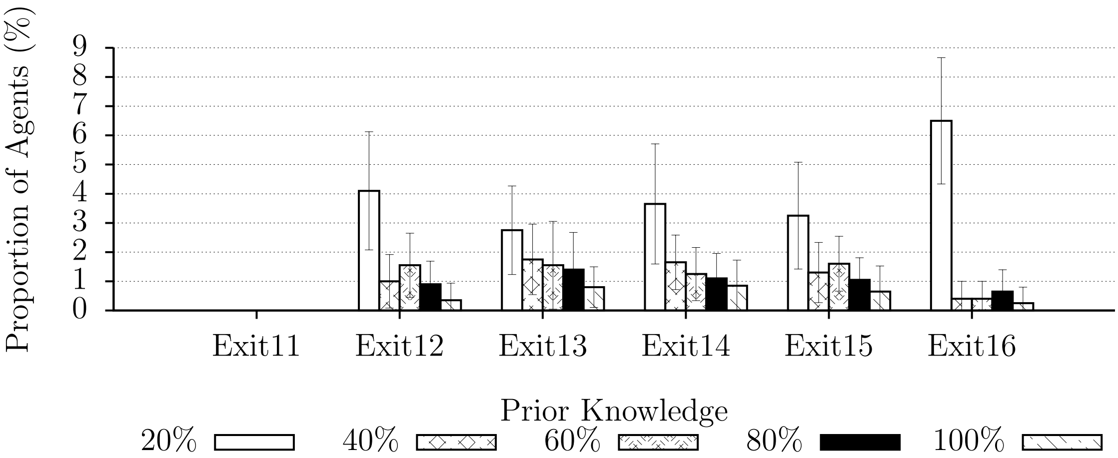
For each scenario of the Alarm Response Verification Case, 100 agents are generated per simulation run. Each scenario has been run 20 times per studied parameter combination.

The "Exit Choice" scenario is intended to study the impact of the agent's initially assigned level of prior knowledge on their exit choice in the simulated event of an alarm. For this purpose, the agents' exit usage is compared for each level of assigned prior knowledge and connections between the exit usage and the agents' locations within the environment at the time of the alarm event are investigated. Figures 8.24 illustrate the exit usage per assigned prior knowledge level of all the 16 exits simulated in the environment.

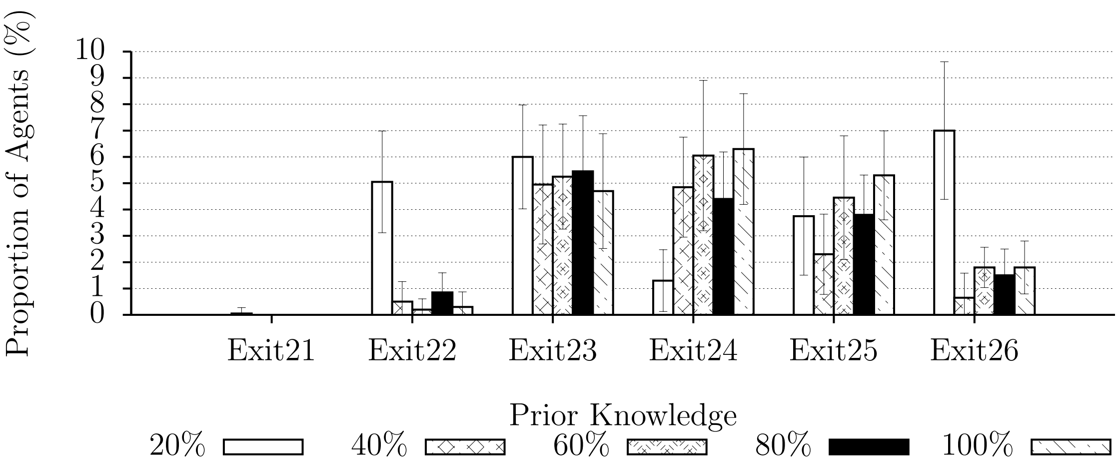
As can be seen in Figures 8.24, in all prior knowledge level cases the majority of the



(a) The entrance and departure exits.



(b) The top side exits.



(c) The bottom side exits.

Figure 8.24.: The average exit usage in the “Exit Choice” scenario of the Alarm Response Verification Case, depending on the assigned level of prior structural knowledge.

agents chose the exit connected to the departure goal location (Exit99). However, the actual average proportion of the agent population using this exit increased with increasing assigned prior knowledge. The increase of the usage of Exit 99 is distinct from 20% of assigned prior knowledge to 40% prior knowledge, but no further significant change in the usage of Exit 99 is detected if the assigned prior knowledge is further increased to 40%, 60%, 80% and finally 100%. The initial increase in the usage of the departure exit is mirrored in the decreasing usage of the entrance and top side exits with increasing prior knowledge, with the same momentum of changes observable for lower levels of assigned prior knowledge and no distinct changes for higher levels of prior knowledge. In the special case of the left most side exits, Exit 11 and Exit 21, no agent in any prior knowledge case chose either of these two exits. For the remaining bottom side exits, no distinct tendency of the exits' usage per assigned prior knowledge level can be observed.

The fact, that most agents chose to exit via the departure goal location exit can be explained by studying the agents' local distribution at the time of the alarm event and the distance range of the modelled exits. Figure 8.25 shows the distance maps of the exits 16, 25 and 99.

(a) Exit 99. **(b)** Exit 16. **(c)** Exit 25.

Figure 8.25.: The distance map of selected exits in the Alarm Response Verification Case. The nodes highlighted in the images indicate those nodal locations, for which the depicted exit is the closest exit in the geometry.

As can be seen in Figure 8.25, because of the location of Exit 99, its distance range contains not only the departure goal location, but also the service and the seating goal location. That implies, that the Exit 99 is the closest exit for all agents present in the mentioned goal locations at the time of the alarm event. Consequently, all agents within these goal locations that know about the Exit 99 through either prior knowledge or through perception will choose this exit to evacuate. For Exit 16 on the other hand, the distance range is much smaller. Only for those agents present in the left hand side of the right most bar goal location and who are familiar with Exit 16 will choose this exit in the event of an alarm. Finally, Exit 25 as an example for another side exit will be chosen by those agents to whom the exit is familiar and who are present in the highlighted areas of the two right most shop goal locations.

Based on these distance considerations, the agents' emergent exit choice behaviour can be related to their initially assigned level of prior knowledge and their location within the geometry at the time of the alarm event. Figure 8.26 shows the average number of agents being present in a certain goal location type at the time of the alarm event. As can be seen in Figure 8.26, in all cases of the "Exit Choice" scenario, the average proportion of the agent population present within a certain goal location type is independent of the assigned prior knowledge level as had to be expected. In each cases of the "Exit choice scenario, roughly about 55% of the agent population was waiting at the environment's departure goal location at the time of the alarm event. About 15% of the agent population was present in the seating goal location, about 3% were present in the service goal location and roughly 12% were present in one of the shop goal locations at the time of the alarm event. On average about 9% of the agent population was not within any modelled goal location at the time of the alarm event, but was rather travelling between the goal locations in the corridor of the geometry.

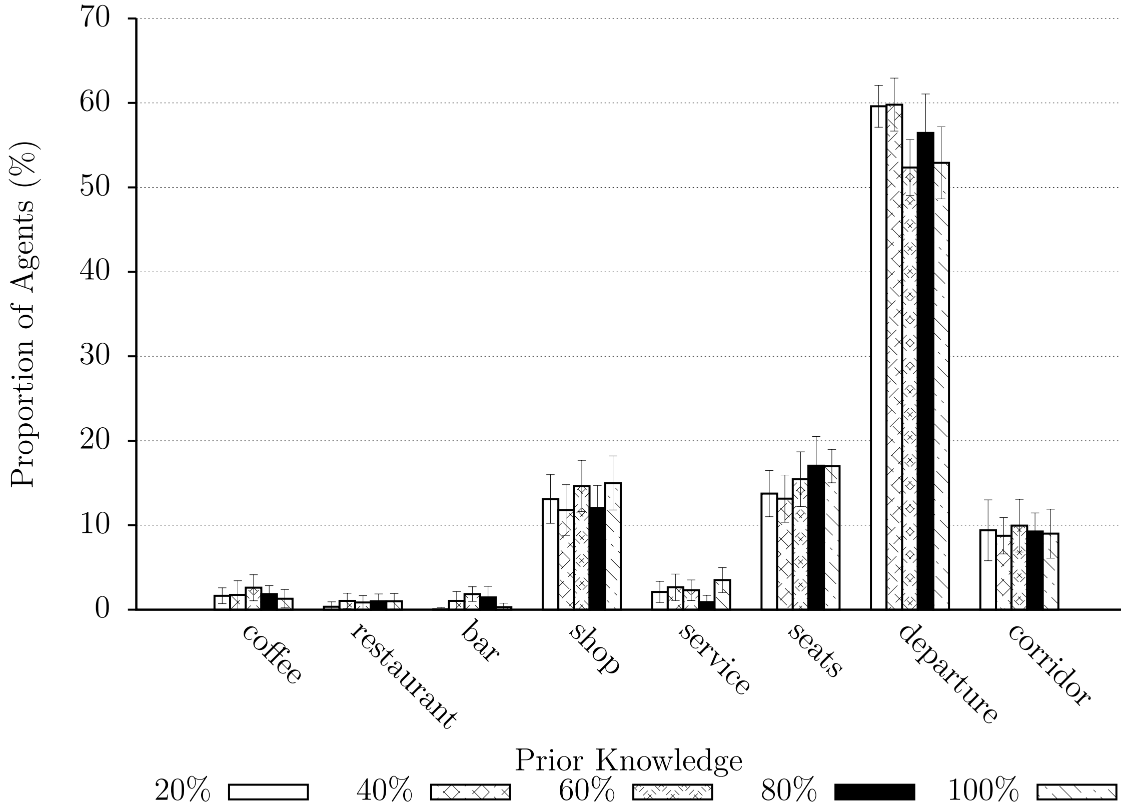


Figure 8.26.: The average proportion of the agent population being in a goal location of the specified type at the time of the alarm event. The results are averaged over 20 simulation runs per assigned level of prior structural knowledge in the "Exit Choice" scenario of the Alarm Response Verification Case.

In summary, the increase in the usage of the departure goal location exit (Exit 99) is not caused by changes in the local distribution of the agents at the time of the alarm event with increasing level of prior knowledge. Instead, the increased usage is a result of more agents who are in the distance range of Exit 99 being aware of this exit. The plateau of the exit usage of Exit 99 on the other hand is down to the total number of agents within its distance range. As can be seen in Figure 8.26, the proportion of the agent population present in the departure, service and seating goal location at the time of the alarm event is about 73%. Given, that some agents that were in the environment's corridor also chose to exit via Exit 99, this results in the usage plateau of about 75% of Exit 99.

The higher usage of the bottom side exits compared to the top side exits as observed in Figure 8.24 can also be explained by the local distribution of the agent population illustrated in Figure 8.26. As can be seen, about 12% of the agent population were present within one of the three available shop goal locations and about 2% were present within a restaurant goal location. All of these six goal locations are situated at the bottom of the geometry. The coffee and bar goal locations on the other hand which are situated at the top of the geometry have only been used by 3% respectively 2% of the agent population at the time of the alarm event. This local distribution leads to a higher usage of the bottom side exits.

The level of assigned prior knowledge also has a distinct influence on the proportion of the agent population, that reconsidered their exit choice during the evacuation. Table 8.25. illustrates the proportion of the agent population which finally exited by a different exit than they had chosen during their alarm response phase. These exit reconsiderations are a result of the agents perceiving exits that are closer than the one they initially had chosen.

Table 8.25.: The average proportion of the agent population in the "Exit Choice" scenario of the Alarm Response Verification Case to change their initially chosen exit because of structural perception.

Prior Knowledge				
20%	40%	60%	80%	100%
16.7% ± 3.59%	0.8% ± 0.65%	0.8% ± 0.76%	0.3% ± 0.43%	–

The results of the remaining three scenarios of the Alarm Response Verification Case demonstrate the three available response phase models in the buildingEXODUS CPAF Plug-in. Each response phase model is characterised by the way in which the length of the agents' response phase, their response time T_{resp}, and the activities that the agent performs during their response to the alarm event, the pre-evacuation activities, are assigned to the agent.

The second and third scenario demonstrate the Imposed-Time Imposed-Activities and the Imposed-Time Predicted-Activities Response Phase Models respectively. In both of these models, the agents' response times are assigned according to a log-normal distribution provided by the model user. In the third scenario which demonstrates the Predicted

Response Phase Model, the agents' response times are emergent outcomes of their chosen pre-evacuation activities. The agents will simply start to evacuate once their chosen pre-evacuation activity is completed. In the Predicted Response Phase Model, the agents choose their pre-evacuation activity based on the importance of the task they were trying to achieve at the time of the alarm event and the duration that the agent has already spent performing the task. In the same manner, in the Imposed-Time Predicted-Activities Response Phase Model used in the third verification case scenario, the agent chooses a pre-evacuation activity based on the importance of their current task. They will perform the chosen pre-evacuation activity until their previously assigned response time is elapsed. Finally, in the second scenario using the Imposed-Time Imposed-Activities Response Phase Model, the agents' pre-evacuation activities are assigned based on a user-given probability distribution. Again, they will perform the chosen pre-evacuation activity until their previously assigned response time is elapsed.

In the following, the results of the second, third and fourth scenario of the Alarm Response Verification Case regarding the agent population's response times and their pre-evacuation activities are discussed.

For the "IT-IA" scenario, Table 8.26 depicts the average proportion of the agent population that has been assigned one of the two currently modelled pre-evacuation activities. The assignment of the pre-evacuation activities is based on the probability distribution stated in Table 8.24. Consequently, it is expected that roughly a third of the agent population in the "IT-IA" scenario are assigned to stand still at the currently occupied location until their response time has elapsed. The remaining two thirds of the agent population should simply carry on with their current plans. The results in Table 8.26 confirm the correct assignment of the pre-evacuation activity.

Table 8.26.: The average agent proportion per pre-evacuation activity in the "IT-IA" scenario the Alarm Response Verification Case.

Pre-Evacuation Activity	
Carry On	Stand Still
66.6% ± 3.82%	33.5% ± 3.82%

For the "IT-PA" scenario, Table 8.27 likewise lists the average agent population proportions following any of the two available pre-evacuation activities. In this scenario, the agent's pre-evacuation activity choice depends on the importance of their currently ongoing task and the importance threshold $\mathbf{I}^*$ used as a model parameter. Accordingly, Table 8.27 lists the agents' pre-evacuation activity performance for different possible importance thresholds $\mathbf{I}^*$.

As can be seen in Table 8.27 and as has been expected, the proportion of the agent population choosing to carry on with their currently ongoing task at the time of the alarm event decreases with increasing importance threshold $\mathbf{I}^*$. If the importance threshold equals 10,

Table 8.27.: The average agent proportion per pre-evacuation activity for the different importance thresholds $\mathbf{I}^*$ in the "IT-PA" scenario the Alarm Response Verification Case.

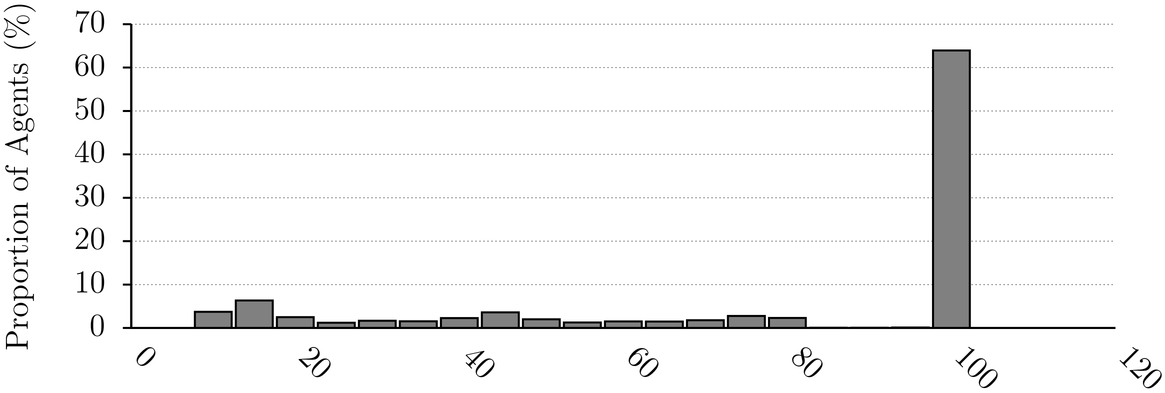
$\mathbf{I}^*$	Pre-Evacuation Activity	
	Carry On	Stand Still
10	100.0%	–
30	86.2% ± 1.71%	13.9% ± 1.71%
50	78.5% ± 2.02%	21.5% ± 2.02%
70	68.7% ± 5.80%	31.3% ± 5.80%
90	66.6% ± 3.00%	33.4% ± 3.00%

every agent decides to carry on. This behaviour is expected, since 10 is the minimal possible importance a task in the buildingEXODUS CPAF Plug-in can attain. If the importance threshold is set to 90, still roughly two thirds of the agents decide to carry on with their task since the task's importance is greater than the importance threshold. This large proportion could also be expected since according to Figure 8.26, roughly about 55% of the agent population is already waiting at the departure goal location and therefore following their goal to depart the environment. This goal is a compulsory goal and its importance has therefore been set to be 100. The distribution of the importance values of the tasks that the agents are currently pursuing at the time of the alarm event is illustrated in Figures 8.27. Figure 8.27a thereby depicts the complete distribution of the alarm response task's importance values, whereas Figure 8.27b illustrates the distribution of the alarm response task importance values that are less than the maximum value of 100.

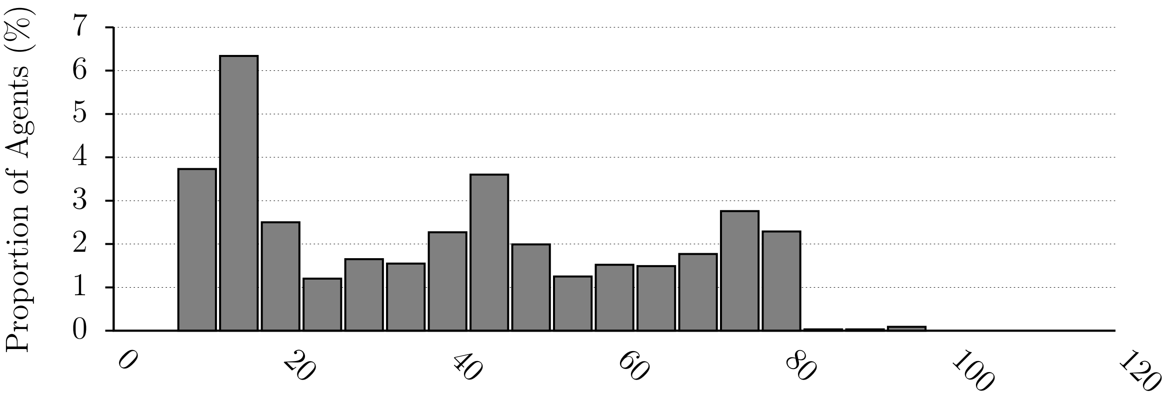
In the the "IT-IA" respectively the "IT-PA" verification case scenario, the agents are assigned a response time T_{resp}. After their response time has elapsed, i.e. at the simulation time $\tau^{\text{Alarm}} + T_{resp}$, the agents in these two scenarios will initiate their evacuation, independent of their chosen pre-evacuation activity. A histogram of the resulting response time distribution for the "IT-IA" and a randomly chosen example case of the "IT-IA" scenario are illustrated in Figure 8.28a.

As can be seen in Figure 8.28a, the resulting response time distribution replicates the assigned log-normal distribution. Figure 8.28b illustrates the resulting exit times. The log-normal tendency can also be observed in the resulting exit times. However, the exit time distribution doesn't fully replicate a log-normal distribution. This is due to the fact, that the agents did have to travel varying distances to their chosen exit.

Finally, for the "Predicted" scenario, Table 8.28 depicts the average proportion of the agent population that chose one of the two currently available pre-evacuation activities in the Predicted Response Phase Model. Contrarily to the Imposed Response Phase Model, the agents in the Predicted Response Phase Model can decide to either carry on with their

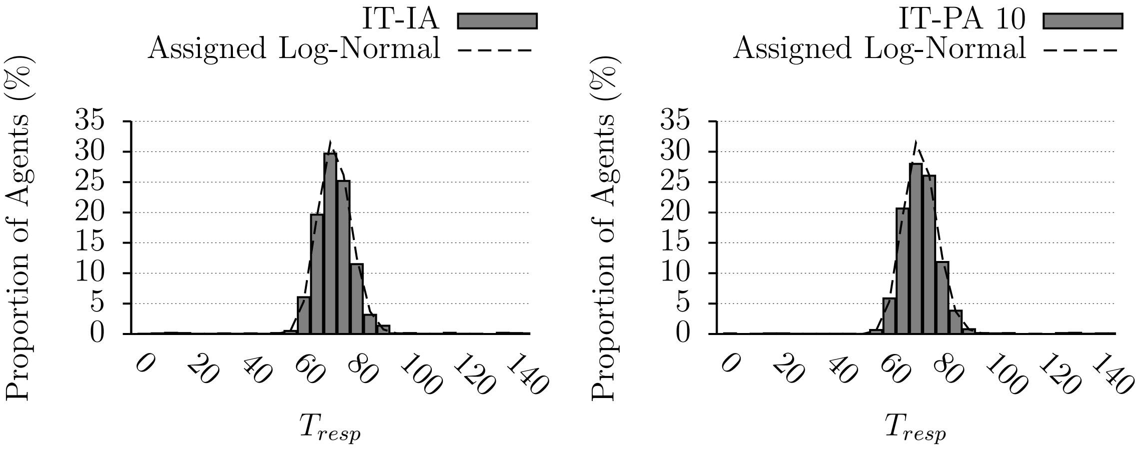


(a) The complete importance distribution.

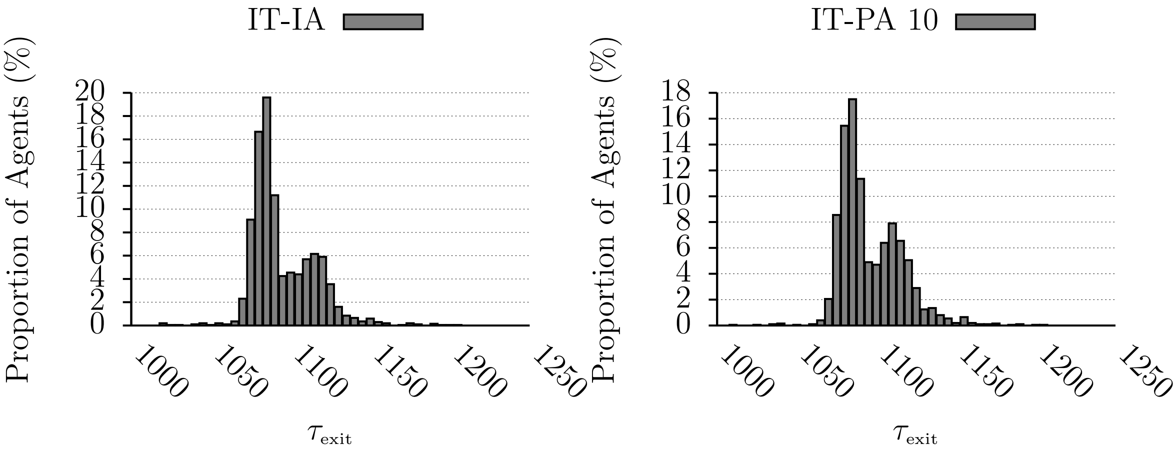


(b) The distribution of importance values smaller than 100.

Figure 8.27.: The distribution of the alarm response task's importance value in the "IT-PA" scenario of the Alarm Response Verification Case.



(a) The distribution of the response times in the "IT-IA" and an example case of the "IT-PA" scenario.



(b) The distribution of the exit times in the "IT-IA" and an example case of the "IT-PA" scenario.

Figure 8.28.: The response time distributions in the "IT-IA" scenario and one example "IT-PA" scenario case of the Alarm Response Verification Case.

currently planned activities or to immediately initiate their evacuation. The agent population's response phase behaviour is shown for different assigned model parameters. Although the parameters are varied to a significant degree, the general model outcome proves to be insensitive to the changes in the model parameters. In each of the studied scenario cases, roughly 70% of the agent population chose to carry on with their current activities rather than to stand still.

Table 8.28.: The average agent proportion per pre-evacuation activity for the different importance thresholds pairs $(\mathbf{I}_2^*, \mathbf{I}_1^*)$ and completion time ratio threshold pairs $(\mathbf{r}_1^*, \mathbf{r}_2^*)$ in the "Predicted" scenario of the Alarm Response Verification Case.

Case No.	$(\mathbf{I}_2^*, \mathbf{I}_1^*)$	$(\mathbf{r}_1^*, \mathbf{r}_2^*)$	Pre-Evacuation Activity	
			Carry On	Immediate Evacuation
1	$(30, 60)$	$(0.3, 0.7)$	72.0% ± 3.74%	28.0% ± 3.74%
2	$(40, 70)$	$(0.3, 0.7)$	72.1% ± 3.19%	28.0% ± 3.19%
3	$(50, 80)$	$(0.3, 0.7)$	65.3% ± 2.87%	34.7% ± 2.87%
4	$(30, 90)$	$(0.3, 0.7)$	69.3% ± 3.67%	30.8% ± 3.67%
5	$(45, 75)$	$(0.3, 0.7)$	66.8% ± 2.84%	33.2% ± 2.84%
6	$(40, 70)$	$(0.2, 0.8)$	71.6% ± 3.71%	28.5% ± 3.71%
7	$(40, 70)$	$(0.3, 0.7)$	69.2% ± 2.57%	30.8% ± 2.57%
8	$(40, 70)$	$(0.4, 0.6)$	71.1% ± 3.02%	29.0% ± 3.02%
9	$(40, 70)$	$(0.2, 0.6)$	70.3% ± 2.27%	29.7% ± 2.27%
10	$(40, 70)$	$(0.4, 0.8)$	67.9% ± 2.98%	32.2% ± 2.98%

The results depicted in Table 8.28 illustrate the pre-evacuation activity choice of the entire agent population. However, the agent's alarm response behaviour in the buildingEXODUS CPAF Plug-in's Predicted Response Phase Model follows two distinct subroutines, depending on the type of the agent's current task at the time of the alarm event. The buildingEXODUS CPAF Plug-in's Predicted Response Phase Model distinguishes between those agents which pursued a critical time task at the time of the alarm event and those agents that did not pursue a critical time task. It is therefore necessary to study the verification case results for each of these two groups separately.

Those agents that were pursuing a critical time task at the time of the alarm event will always choose the "carry-on" pre-evacuation activity, as has been described in Section 7.2.3. These agents are then assigned a response time based on a log-normal distribution. As for the Imposed Response Phase Models, the agents will hence initiate their evacuation as soon as their response time has elapsed. The shape of the underlying log-normal distribution thereby depends on the remaining amount of time that the agent should wait at the designated location, see Equation (7.1). The resulting response times for those agents that were pursuing a critical time task at the time of the alarm event are depicted in Figure 8.29. As can be clearly seen in Figure 8.29, the resulting response times replicate the assigned response time distribution.

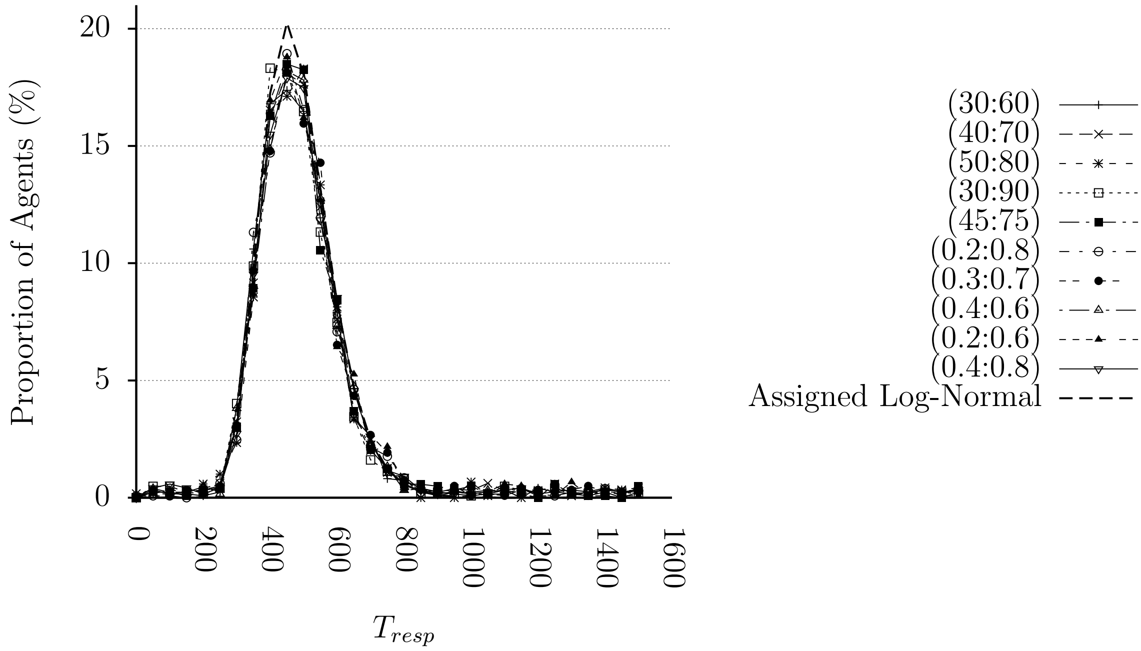


Figure 8.29.: The response time distribution for the agents pursuing a critical time task at the time of the alarm event in the "Predicted" scenario of the Alarm Response Verification Case.

For those agents that were not pursuing a critical time task at the time of the alarm event, their response times are a result of their pre-evacuation activity choice. Table 8.29 lists the proportion of those agents that did not pursue a critical time task at the time of the alarm event which chose one of the two available pre-evacuation activities.

Contrarily to the overall observed pre-evacuation activity choice behaviour depicted in Table 8.28 and as expected, the results in Table 8.29 show a dependency on the model's parameters. The first three results depict the agents' choice dependency on the importance thresholds by constant importance threshold range. The agent proportion which choose to carry on with their current activities thereby decreases when both importance thresholds are increasing. This is reasonable, since the the agents' current task's importance values in the "Predicted" scenario should resemble the importance distribution depicted in Figure 8.27, and therefore the majority of the agents' tasks have a small or medium importance value. Also as expected, fewer agents are carrying on with their current activities if the range of the importance threshold interval is reduced as illustrated by the fourth and fifth case result.

When varying not the importance thresholds but the completion time ratio thresholds, a contrary trend can be observed in some situations. In the first scenarios where the completion time ratio thresholds interval length is decreased, no distinct dependency of the agents' pre-evacuation activity choice can be observed. However, fixing the completion time ratio interval

Table 8.29.: The average agent proportion per pre-evacuation activity for the different importance thresholds pairs $(\mathbf{I}_2^*, \mathbf{I}_1^*)$ and completion time ratio threshold pairs $(\mathbf{r}_1^*, \mathbf{r}_2^*)$ in the "Predicted" scenario of the Alarm Response Verification Case. Considered are only those agents, that did not pursue a critical time task at the time of the alarm event.

Case No.	$(\mathbf{I}_2^*, \mathbf{I}_1^*)$	$(\mathbf{r}_1^*, \mathbf{r}_2^*)$	Pre-Evacuation Activity	
			Carry On	Immediate Evacuation
1	$(30, 60)$	$(0.3, 0.7)$	$27.7\% \pm 4.94\%$	$72.3\% \pm 4.94\%$
2	$(40, 70)$	$(0.3, 0.7)$	$20.1\% \pm 7.09\%$	$79.9\% \pm 7.09\%$
3	$(50, 80)$	$(0.3, 0.7)$	$14.3\% \pm 4.60\%$	$85.7\% \pm 4.60\%$
4	$(30, 90)$	$(0.3, 0.7)$	$18.7\% \pm 6.06\%$	$81.3\% \pm 6.06\%$
5	$(45, 75)$	$(0.3, 0.7)$	$14.6\% \pm 3.82\%$	$85.4\% \pm 3.82\%$
6	$(40, 70)$	$(0.2, 0.8)$	$18.9\% \pm 5.52\%$	$81.1\% \pm 5.52\%$
7	$(40, 70)$	$(0.3, 0.7)$	$23.2\% \pm 6.06\%$	$76.8\% \pm 6.06\%$
8	$(40, 70)$	$(0.4, 0.6)$	$18.8\% \pm 6.60\%$	$81.2\% \pm 6.60\%$
9	$(40, 70)$	$(0.2, 0.6)$	$25.4\% \pm 8.21\%$	$74.6\% \pm 8.21\%$
10	$(40, 70)$	$(0.4, 0.8)$	$18.9\% \pm 5.81\%$	$81.1\% \pm 5.81\%$

length but instead shifting the interval from lower values to upper values does have an effect on the agents' choice behaviour. The agents are more likely to carry on with their current activity if their completion time threshold is smaller rather than if their completion time ratio threshold is larger for a fixed interval length.

If the agents chose the "Immediate Evacuation" pre-evacuation activity, their response time is naturally zero. If they chose to carry on with their activities, the agents will have initiated their evacuation at the time that they have finished their activities. Figure 8.30 illustrates the resulting response time distributions for the different model parameters in the "Predicted" verification case scenario.

As can in general be seen in Figure 8.30, at least 50% of the emergent response times lie between 20s and 210s for all scenario cases. However, outliers as high as about 480s are observed.

In the first five scenario cases, the completion time ratio threshold parameters are fixed to 0.3 respectively 0.7. As can be seen on the left hand side of Figure 8.30, the response time distributions for fixed length importance threshold intervals but shifting the interval to higher values has a distinct effect on the response time distribution, see case numbers 1, 2 and 3. With higher importance threshold values, the response time distribution shifts to lower response time values and is less positively skewed. On the other hand, if as in case numbers 4 and 5 the importance threshold interval length is increased, the positive skewness of the resulting response time distribution increases.

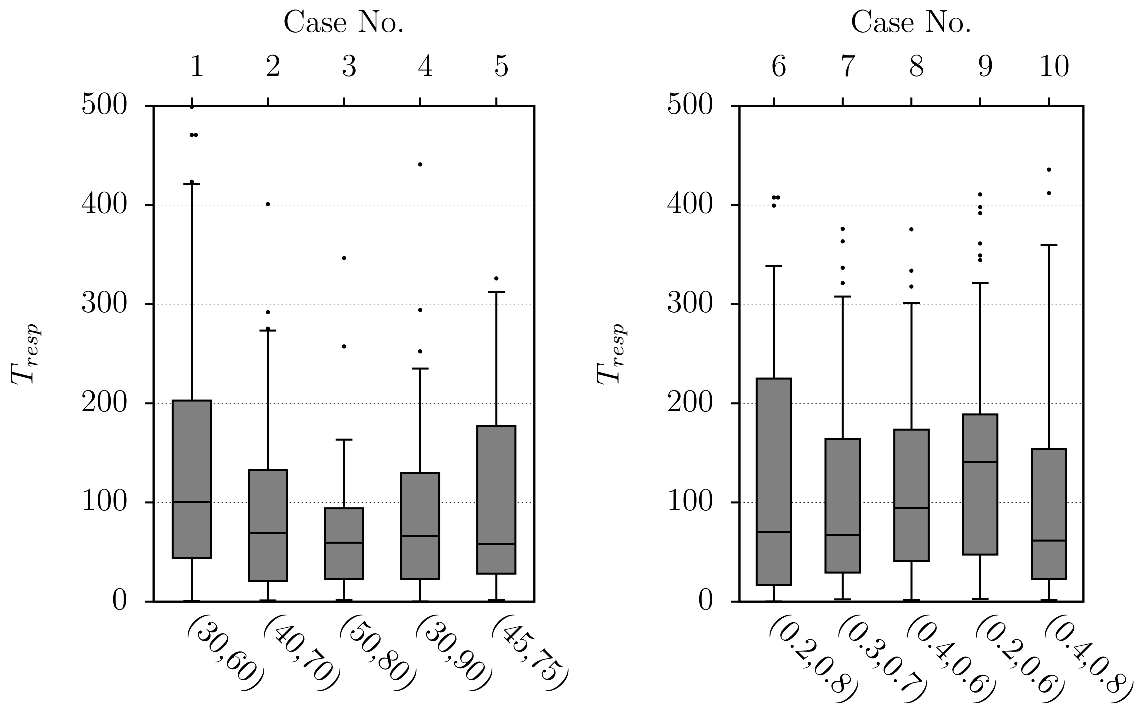


Figure 8.30.: Box-and-whisker graphs of the response time distribution for the agents which didn't pursue a critical time task at the time of the alarm event and chose to carry on with their current activities in the "Predicted" scenario of the Alarm Response Verification Case.

In the last five scenario cases, the importance threshold parameters are fixed to 40 respectively 70. In the cases 6 to 8, the lower completion time ratio threshold is increased from 0.2 to 0.4 and simultaneously the upper completion time ratio threshold is decreased from 0.8 to 0.6, thereby narrowing the completion time ratio interval whilst maintaining a constant middle point of the interval. As can be seen on the right hand side of Figure 8.30, a significant tendency for the resulting emergent response time distributions for these three cases can be observed. The interquartile ranges of the response time distribution narrows for narrower completion time ratio threshold intervals. These results are a direct consequence of the fact that in these cases the completion time ratio threshold interval length is decreasing, thereby equalising the remaining time that the agent spends pursuing a task after having decided to carry on with their current activities.

In the scenario cases 9 and 10, the lower completion time ratio threshold is increased from 0.2 to 0.4 whilst simultaneously increasing the upper completion time ratio threshold from 0.6 to 0.8. The completion time ratio threshold interval length is therefore preserved. As can be seen in Figure 8.30, the emergent response time distributions of these two scenario cases vary significantly. The shifting of the completion time ratio threshold interval results in shift of the resulting response time distribution's interquartile range to lower values. The length of the interquartile range is however preserved. This is reasonable, since if an agent in case 9 chooses to carry on with their current activities, they will have between 40% and 80% of the task's duration remaining to complete after the alarm event, resulting in large response time values. On the other hand, if an agent in case 10 chooses to carry on with their current activities, they will have between 20% and 60% of the task's duration remaining to complete after the alarm event, resulting in smaller response time values compared to case 9. It is also interesting to note, that the shape of the response time distribution varies from a negatively skewed distribution in case 9 to a positively skewed distribution in case 10.

8.8.4. Summary

The Alarm Response Verification Case demonstrates the buildingEXODUS CPAF Plug-in's feature of simulating pedestrian alarm response behaviour which builds upon the pedestrians' prior usage of the environment. It demonstrates how the agents simulated by the buildingEXODUS CPAF Plug-in choose their initially targeted exit in the case of a simulated alarm event. The Alarm Response Verification Case also demonstrates the buildingEXODUS CPAF Plug-in's three different response phase models by studying the impact of different response phase model parameters on the emergent outcomes of the evacuation simulation.

The Alarm Response Verification Case therefore addresses Research Question 6 by demonstrating how the buildingEXODUS CPAF Plug-in Alarm Response feature simulates how pedestrians make informed decisions in the event of an alarm based on their previous experience and their current individual plans.

8.9. Summary

In this chapter, the capabilities of the Cognitive Pedestrian Agent Framework (CPAF) have been demonstrated in functional verification cases simulated with the buildingEXODUS CPAF Plug-in. This chapter therefore addresses Research Objectives 4 and 5.

The individual components and features of the CPAF have been demonstrated and verified in concise verification cases for the buildingEXODUS CPAF Plug-in. It has been verified that the features of the proposed CPAF agent model serve as a reasonable approach to produce consistent and comprehensible pedestrian agent behaviour in a pedestrian circulation and evacuation scenario. The functional verification cases further demonstrate the impact of the various model parameters of the buildingEXODUS CPAF Plug-in and the results of any parameter variations have been discussed and interpreted.

Chapter 9:

Model Demonstration: Long-Distance Traffic Facility Verification Case

In this chapter the Cognitive Pedestrian Agent Framework (CPAF) and its capability to simulate the entire pedestrian usage cycle of a given complex multi-purpose environment is demonstrated. After having demonstrated the individual features of the CPAF in Chapter 8, this chapter aims to demonstrate the interplay of the different features. In this comprehensive verification case, the buildingEXODUS CPAF Plug-in is therefore applied in the simulation of a real-world scenario: the simulation of pedestrian behaviour in a railway station terminal.

In detail, the Long-Distance Traffic Facility Verification Case should illustrate:

- How the CPAF enables agents to purposefully make use of a given environment. This implicates that the special nature of the environment as being a long-distance train station terminal should reflect in the behaviour of the agents.
- How the CPAF enables agents to make individual decisions based on their individual level of knowledge and their individual preferences.
- How the CPAF enables agents to be situationally aware and show contextual behaviour.

9.1. Motivation

Long-distance traffic facilities usually comprise not only the essential transport facilities, but also several outlets which cater for various needs, including retail outlets, catering outlets, information booths and service outlets. The pedestrians within a long-distance traffic facility might visit these outlets during their sojourn in the facility, prior to departing on their designated mode of transport.

The behaviour of the pedestrians is in addition governed by the implemented procedural scheme, the *transport schedule*. The transport schedule imposes various constraints on the individual pedestrian: a departure time and a compulsory procedure, which must be accomplished in a certain order. The compulsory procedure varies according to which type of a long-distance traffic facility is being modelled. For a railway station terminal, the procedure is fairly minimalist: the pedestrian needs to acquire a ticket prior to boarding the train. For an airport terminal, the procedure involves acquiring a ticket, checking-in, dropping the baggage, passing security controls and controls at their designated departure gate prior to boarding their designated plane.

Another characteristic of long-distance traffic facilities is the influence of passengers arriving at the facility, the *transport passengers*. Transport passengers arrive in a usually large group in a short period of time on the corresponding mode of transport. They subsequently leave the facility via any available exit. By contrast, those pedestrians that arrive at the long-distance traffic facility at an entrance location and leave the facility by their assigned mode of transport are in the following referred to as the *foot passengers*.

Transport passengers increase the population density locally for a short period of time and cause counterflow at bottlenecks such as stairs and escalators. In general, whether transport passengers have got a significant impact on the behaviour of the departing foot passengers or not, is dependent on the procedural scheme deployed and therefore on the type of the long-distance traffic facility studied. For example in an airport terminal, the influence of the arriving transport passengers on the departing foot passengers is minimal to non existent, because of the largely separate route guiding systems. On the other hand for a railway station terminal, the behaviour of the transport passengers has a high impact on the departing foot passengers by causing counterflow and congestion, since the arrival and departure routes are largely the same.

In order to be able to model long-distance traffic facilities, the Cognitive Pedestrian Agent Framework Scenario Specification Generator (see Appendix Chapter B) has been equipped with the possibility to generate a transport schedule and assign both foot and transport passengers to a mode of transport. This information is then read in by buildingEXODUS and the buildingEXODUS CPAF Plug-in via the produced Scenario Specification File.

9.2. Railway Station Geometry

The procedural processes involved in a railway station terminal need also be reflected in the environment model. Therefore, goals which represent these procedural processes have been added in addition to the buildingEXODUS CPAF Plug-in's Global Goal Set, see Table 5.5. These *procedural goals* for the specific simulation of a railway terminal environment are listed in Table 9.1.

As has been mentioned before, the procedural processes in a railway station terminal are sparse compared to those procedural processes implemented in for example an airport terminal. In the railway station terminal modelled for this verification case, the foot passengers can acquire a ticket in the station environment. If an agent decides to purchase a ticket, they will queue at a designated goal location in order to accomplish this procedural goal. The

Table 9.1.: Additional procedural goals necessary to model pedestrian behaviour in long-distance traffic facilities.

Name	Goal Category	Goal Action	Relative Importance Range	Completion Time Range [s]
"ticket"	Procedural	queue	$[100, 100]$	n/a
"departure wait"	Procedural	wait	$[100, 100]$	n/a
"departure zone"	Procedural	wait	$[100, 100]$	n/a

"departure wait" and "departure zone" procedural goals reflect the need to be at a certain goal location at a certain time. In a railway station environment, the "departure wait" goal represents the need to be at the designated platform by the time that the assigned train is due to arrive at the platform. The "departure zone" goal then represents the need to have boarded the assigned train prior to the train's departure from the platform.

A railway station geometry has been designed and modelled in buildingEXODUS, see Figure 9.1. The geometry comprises two floors and thirteen platforms as well as a variety of retail and catering outlets which can be visited by the agents to accomplish elective tasks prior to boarding their assigned train.

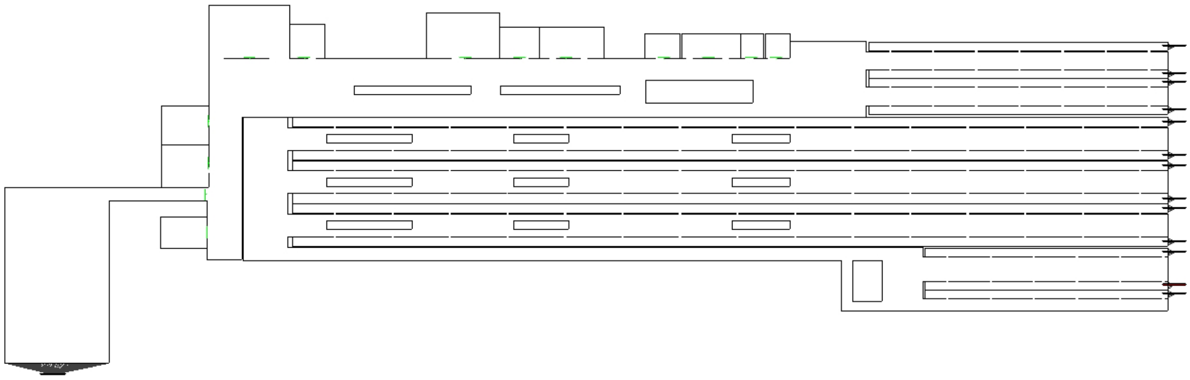
The modelled environment comprises five entrance goal locations, four of which are located on the ground floor and one is located on the upper floor. All the platforms and train tracks are located on the upper floor.

The station environment has been designed such that the train connections serving the modelled environment can be grouped in two categories. The first category comprises suburban or short-distance train services, whereas the second category comprise long-distance train connections. For the underlying environment model, this design decision is of consequence for the length of the modelled platforms. Since commonly suburban or local trains consist of a fewer number of carriages than long-distance train connections, the platforms for local train services are shorter than the platforms for the long-distance train services.

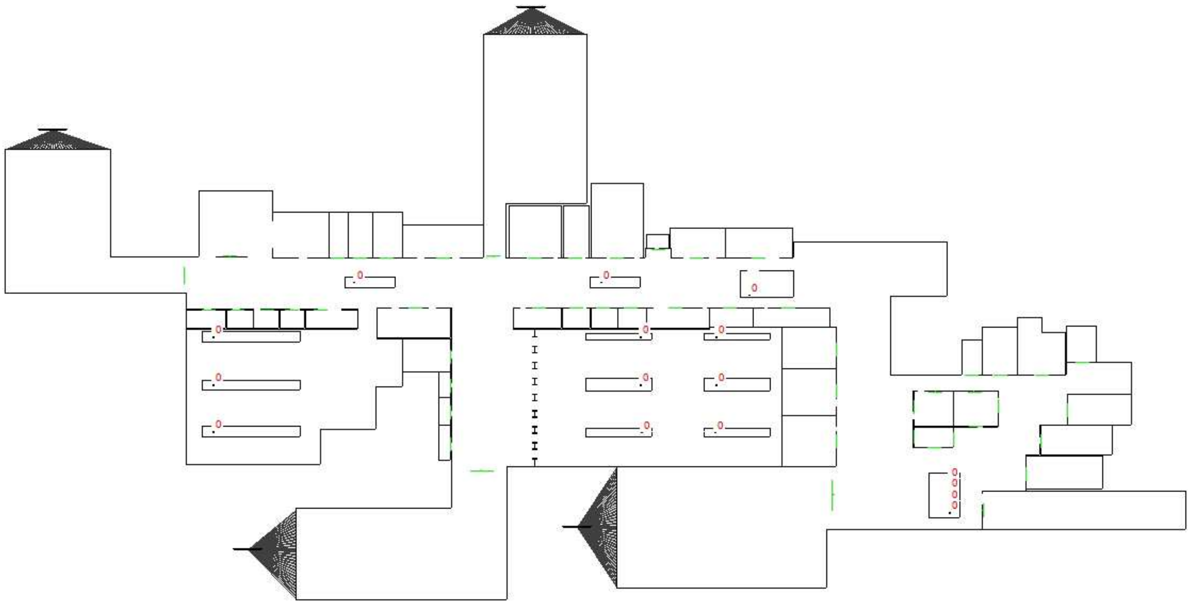
The modelled station geometry comprises a number of different facilities as well as catering or retail outlets represented by goal locations. Table 9.2 lists the number of modelled goal locations per available goal location type.

Those goal locations representing coffee shops, restaurants, food-on-the-go outlets and shopping facilities have been randomly assigned a price and a brand goal location attribute. In addition, the modelled service facilities have been assigned a random price attribute. The goal locations' size attributes are a result of the geometry's design. Of those goal locations which are represented by compartment zones in buildingEXODUS, 29 goal locations are of the size attribute 0, 25 goal locations are of the size attribute 1 and 30 goal locations are of the size attribute 2.

Each goal location has been identified with a sign to allow for being perceived by the



(a) Upper floor of the buildingEXODUS station geometry.



(b) Ground floor of the buildingEXODUS station geometry.

Figure 9.1.: The buildingEXODUS station geometry of the Long-Distance Traffic Facility Verification Case.

Table 9.2.: An overview of the number of modelled goal locations in the railway station geometry and the associated goals per goal location type.

Goal Location Type	Associated Goal(s)	Number of modelled Goal Locations
Coffee Shop	"eat", "drink"	7
Restaurant	"eat"	5
Food-on-the-Go Outlet	"eat", "drink"	13
Seating Area	"rest"	1
Shop	"shop"	16
Service Facility	"service"	6
Information Point	"information"	3
Way Point	"way point"	10
Ticket Office	"ticket"	3
Platform	"departure wait"	13
Train Zone	"departure zone"	13

modelled agents. The way point goal locations which can be used for navigation by the agents have been placed along the corridors on both the ground and upper floor, as well as on corridor junctions.

Some of the goal locations within the modelled station environment have been designed to contain departments. For the purpose of this verification case, all shopping goal locations with a size attribute of 2 are assigned a selection and a queuing department. In addition, all food-on-the-go goal locations have been assigned a queuing department and a seating department. Goal locations which represent ticket offices contain queuing departments.

9.3. Scenarios

Each scenario within the Long-Distance Traffic Facility Verification Case involves the generation of foot passenger agents and transport passenger agents, as has been described in Section 9.1. This is achieved by the means of the Cognitive Pedestrian Agent Framework Scenario Specification Generator, see Appendix Chapter B.

For the purpose of this verification case, two verification case scenarios have been designed. The first scenario, the "Circulation" scenario, simulates the normal usage behaviour in the modelled environment. The second scenario, the "Evacuation" scenario, uses the identical settings as the "Circulation" scenario, but involves an alarm event and therefore the transition from normal to evacuation behaviour.

9.3.1. Agent Set-Up

The initialisation and the behaviour of the foot passenger agents follows the CPAF's usage-cycle modelling described in Chapter 6. With the Cognitive Pedestrian Agent Framework Scenario Specification Generator, each foot passenger agent is assigned one of the five entrance goal locations and in addition a train by which the foot passenger agent will leave the environment. The assignment of the train includes the assignment of the platform goal location where the foot passenger agent's train will depart from. As has been described in Section 6.2, foot passenger agents are assigned their individual level of prior spatial knowledge of the modelled environment and a set of individual agent goals which they will want to achieve during their sojourn in the station environment. In this verification case, the assignment of prior spatial knowledge is based on the probability distribution depicted in Table 9.3. The goal assignment is based on the probability distribution depicted in Table 9.4.

Table 9.3.: The prior knowledge group probability distribution used in the Long-Distance Traffic Facility Verification Case.

Prior Knowledge Probability Distribution (X% Prior Knowledge)				
0%	20%	50%	70%	100%
20%	15%	20%	15%	30%

Table 9.4.: The probability for a goal from the Global Goal Set (see Table 5.5) or the set of procedural goals in a railway station environment (see Table 9.1) to be assigned to a foot passenger agent during the simulation initialisation stage. This goal assignment probability distribution is used for both the "Circulation" and the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case.

Goal	Goal Category	Assignment Probability
"eat"	Activity	50%
"drink"	Activity	33%
"rest"	Activity	10%
"shop"	Activity	67%
"service"	Activity	20%
"ticket"	Procedural Goal	20%
"departure wait"	Procedural Goal	100%
"departure zone"	Procedural Goal	100%

Based on their individual level of prior knowledge about the environment, foot passengers agents will have planned an initial route in the environment, see Section 6.3. As has been described in Section 6.4, they will pursue their individual itinerary, thereby perceiving their environment and potentially adapting their plans based on the emergent environment conditions, until their assigned train is scheduled. In order to catch their assigned train, the foot passenger agents will aim to enter their assigned platform goal location by the train's arrival time. The foot passenger agents will then try to enter the train by the time of the train's scheduled departure.

On the other hand, those agents representing transport passengers will arrive at the station geometry by their assigned train at the train's arrival time. They will then try to get off the train before the train leaves the station again. Subsequently, the transport passenger agents will head directly towards any of the five modelled entrance goal locations where the transport passenger agents will leave the geometry. Consequently, the transport passengers agents are not assigned any agent goals other than to exit the environment.

9.3.2. Train Station Scenario Design

Both scenarios are intended to represent the weekday morning period from 7am to 11am in the modelled environment. The scenario therefore replicates the morning rush hour from 7am to 9am and the quieter post rush hour time from 9am to 11am. This scenario design is reflected by the assigned train schedule and the number of transport passenger agents per train, see Table 9.5. In both the "Circulation" and the "Evacuation" scenario, a total number of 10,000 foot passenger agents are simulated. The number of simulated foot passenger agents has thereby been chosen such that the given station geometry is used to capacity.

Table 9.5.: The specifications used to generate the train schedule for both the "Circulation" and the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case.

Services	Platforms	Maximum Seating Capacity	Simulated Time Period	Average Number of Trains per Platform	Train Passenger Usage Rate [1]
Local	1-4	150	7am-9am	8	100% – 120%
			9am-11am	6	30% – 60%
Local	11-13	150	7am-9am	3	100% – 120%
			9am-11am	4	30% – 60%
Long-Distance	5-10	350	7am-11am	0.67	60% – 100%

[1] in % of the maximum seating capacity

For the local train services, it is distinguished between the rush hour period of 7am-9am and the late morning period of 9am-11am for the specifications of the train schedule. During the rush hour period, more local service trains arrive at and depart from the modelled station than during the post rush hour period. In addition, the local service trains are occupied with a larger number of passengers during the rush hour period. On the other hand, the long-distance services are assumed to run the same schedule throughout the entire day. Therefore, the long-distance train schedule specifications are the same for the entire modelled period from 7am to 11am. As can be seen from Table 9.5, the total expected number of train passengers for a simulation of the given train schedule specifications is 10,315. Consequently the number of generated train passenger agents matches the number of simulated foot passenger agents.

The simulated time period from 7am to 11am includes the customary breakfast period. Consequently, a meal time period is included in the simulation. The meal time period has been set to last from 7.30am to 9.30am. During this time period, the foot passenger agents are more likely to frequent goal locations where they can eat.

9.3.3. Alarm Event Scenario Design

In the case of the "Evacuation" verification case scenario, an alarm event is triggered at the simulated time of 9.15am. In this Long-Distance Traffic Facility Verification Case, the Predicted Response Phase Model of the buildingEXODUS CPAF Plug-in is used, since this response phase model makes full use of the information available through the CPAF. For a discussion and comparison of the three currently available response phase models in the buildingEXODUS CPAF Plug-in see Section 8.8.

For the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case, the parameters of the used Predicted Response Phase Model have been chosen such that the probability for an agent to continue with their current plans after the alarm event has occurred, $p(\text{continue})$ is given by

$$p(\text{continue}) = \begin{cases} 1 & \text{if } I(t_{\pi_0}) \geq 60 \ \wedge \ r_{t_{\pi_0}} \geq 0.33 \\ 1 & \text{if } I(t_{\pi_0}) \geq 30 \ \wedge \ r_{t_{\pi_0}} \geq 0.5 \\ 0 & \text{else} \end{cases}$$

As has been previously specified, t_{π_0} denotes the agent's currently ongoing task. The probability for the agent to initiate their evacuation immediately after the sounding of the alarm event is hence given by $1 - p(\text{continue})$.

9.3.4. Scenario Specification Summary

Table 9.6 summarises which specifications have been used in the Long-Distance Traffic Facility Verification Case to inform the buildingEXODUS CPAF Plug-in.

Table 9.6.: An overview of the environment and scenario specifications used in the Long-Distance Traffic Facility Verification Case.

Specification Type	Used Specification
Purpose of the Environment	Train Station Procedural Goals, see Table 9.1
	Train Schedule, see Table 9.5
	Meal Times: Breakfast Period from 1800s to 9000s
Facilities in the Environment	Global Goal Set, see Table 5.5
	Feature Parameters, see Table 5.2: uniformly distributed
Agent Parameter Distributions	Prior Knowledge, see Table 9.3
	Goal Assignment, see Table 9.4
	Personal Preferences, see Table 5.6: uniformly distributed
	Perceived Crowd Threshold: uniformly distributed in the interval $[0.3, 0.6]$
Alarm Event Specifications	Predicted Response Phase Model
	Alarm Time of 8000s

9.4. Results

Both the "Circulation" and the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case have been run five times, each time simulating a total number of 10,000 foot passenger agents.

As has been stated in the introduction to this chapter, the results of the Long-Distance Traffic Facility Verification Case should fulfill certain expectations on the impact of the used CPAF on the overall simulation. These expectations are demonstrated by using the results of the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case. The results of the "Evacuation" scenario are used to demonstrate the fulfilment of the expectations detailed in the chapter's introduction regarding the example alarm response behaviour realised in the buildingEXODUS CPAF Plug-in.

9.4.1. Purposeful Environment Usage: Adherence to Procedural Processes

As has been stated in this chapter's introduction, the Long-Distance Traffic Facility Verification Case should demonstrate that the CPAFs allows for the simulation of purposeful pedestrian behaviour in the given train station environment. The main purpose of the studied environment is that foot passenger agents should aim to accomplish their assigned procedural goals. In the case of the simulated train station terminal environment, all foot passenger agents should aim to accomplish their goal to board their assigned train on time.

This implicates that the foot passenger agents should also aim to reach their assigned platform on time. In addition, those foot passenger agents which have been assigned to require to purchase a train ticket should aim to accomplish this goal. Table 9.7 shows the proportion of the agent population that have been assigned the procedural goal in question and their performance in trying to accomplish this procedural goal.

Table 9.7.: The foot passengers' average procedural goal performance in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case over five simulation runs.

Procedural Goal	Agent Population	Goal Performance		
		Satisfied	Suppressed	Unsatisfied
"ticket"	20.3% ± 0.16%	19.9% ± 0.17%	0.1% ± 0.04%	0.3% ± 0.04%
"departure wait"	100%	95.3% ± 0.32%	–	4.7% ± 0.32%
"departure zone"	100%	98.6% ± 0.12%	–	1.3% ± 0.12%

In accordance with the verification case's chosen agent goal distribution settings (see Table 9.4), Table 9.7 demonstrates that every agent has been assigned the "departure wait" respectively the "departure zone" goal, and about a fifth of the agent population has been assigned the "ticket" procedural goals. As has been expected, the agents in the "Circulation" scenario did aim to accomplish these compulsory procedural goal. On average 98% of the agent population that had been assigned the procedural goal to get a ticket were able to satisfy this goal. The remaining 2% of the agent population who had been assigned to get a ticket attempted to board their assigned train without the required ticket. In very few cases, the agents had elected to suppress their "ticket" goal because of emergent time pressure. The agents thereby evaluated the need to get to their train on time higher than the need to purchase a ticket.

In the case of this verification case, the "departure wait" procedural goal is interpreted to reach the assigned platform well in time before the assigned train's departure. As can be seen in Table 9.7, on average about 95.3% of the agent population reached their platform well in time, whereas on average about 4.7% did not meet the goal to be at the platform a sufficient time before the train's departure. But as can be seen by the performance results of the "departure zone" procedural goal, on average about 98.6% of the agent population nevertheless made their assigned train on time, meaning that about 3% of the agent population had to hurry to get to their train. However, on average 1.3% of the agent population did miss their assigned train.

The observed procedural goal performance is due to the ability of the CPAF agents to act according to procedural processes. In the case of this demonstration scenario, the agents are able to evaluate their situation in context of their individual critical time task to get to the train on time. The agents regularly assess their individual time situation using the CPAF's

Urgency model, see Section 5.6.2.2. After having assessed their time situation, the agent then draws conclusions for their behaviour by evaluating their current plans.

The agent might adjust their behaviour in order to accomplish their task to board their train on time. The agent can decide to either behave "more urgently" or even to dismiss some tasks from their current agenda. The agent's level of urgency can be demonstrated by the *Urgency Ratio (UR)*:

$$\mathrm{UR} = 100\% \cdot \frac{\text{total amount of time where } U(\tau) > 0}{\text{total time spent in environment}}$$

In the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case, on average about 57% of the agent population did have a positive Urgency Ratio. Therefore, over half of the agent population did behave urgently for some period of time during their sojourn in the station environment, meaning they did walk faster, were less patient and more insistent in following their way. Table 9.8 depicts the global statistics of the agents' Urgency Ratio in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

Table 9.8.: The global statistics of the agents' Urgency Ratio (UR) in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

Average	Minimum	Q_1	Median	Q_3	Maximum
9.6% ± 17.14%	0.0%	0.0%	4.0% ± 0.06%	9.5% ± 0.27%	100.0% ± 0.00%

As can be seen from the statistics in Table 9.8, the Urgency Ratio distribution is strongly negatively skewed. On average 75% of the agent population did spent less than 9.5% of their time in an urgent state, whereas the average maximum Urgency Ratio value is as high as 100%.

9.4.2. Purposeful Environment Usage: Activity Goals

An elevated urgency is not the only way in which agents can react to a time pressure situation when trying to accomplish their procedural goals. The agents can also decide to dismiss tasks from their agenda as a result of their time situation evaluation. For this evaluation, the agent needs to be able to distinguish between tasks on their current agenda in terms of their current importance to the individual agent. In the CPAF, each task on the agent's agenda or rather the corresponding agent goal can be of an individual importance to the agent, see Section 5.3.2. In the goal representation used for this thesis and this verification case, the procedural goals are all of the highest importance value of 100 to any agent. In addition, the goal to visit an information point is also uniformly set to the lowest possible importance value of 10 for each agent. The personal importance value of the remaining five activity agent goals can attain any value in the importance range of the associated goal, see Section 5.3.2 and Table 5.5. Figure 9.2 shows the personal importance distribution for the five activity agent goal at the end of the simulation.

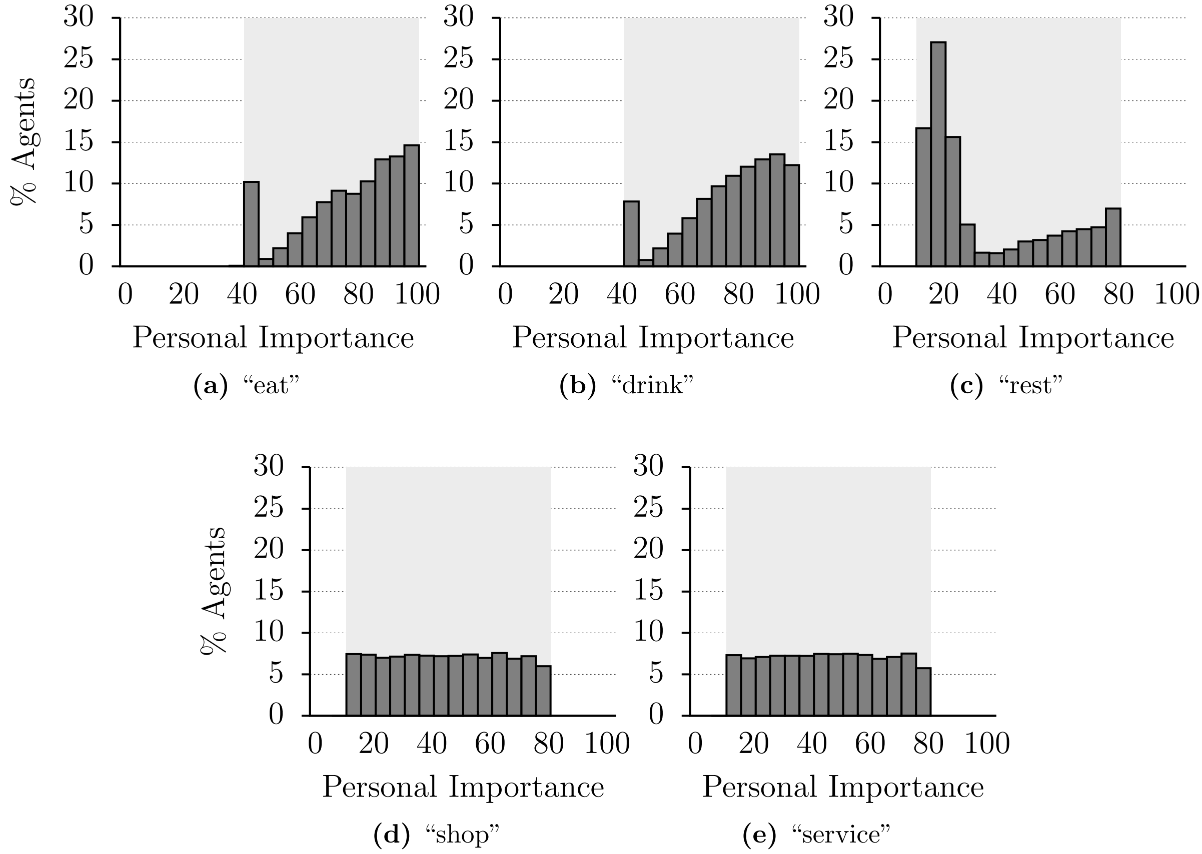


Figure 9.2.: The distribution of the personal importance of the activity agent goals at the end of the simulation in the “Circulation” scenario of the Long-Distance Traffic Facility Verification Case. The grey shaded area indicates the importance range $[\mathbf{I}_{low}(\widehat{g}), \mathbf{I}_{up}(\widehat{g})]$ of the associated goal $\widehat{g} \in$ GGS.

The results depicted in Figure 9.2 demonstrate the difference between those activity goals that are related to the agents' internal stimuli, their “hunger”, “thirst” and “fatigue” motivations (see Section 5.6.1), and the “shop” and “service” activity goals. The latter show a uniform personal importance distribution. This has been expected, since when the agent is assigned one of these two activity goals, the personal importance is once determined by a uniform distribution for the given importance range. Thereafter, the personal importance value remains unchanged during the course of the simulation. Contrarily, the personal importance value of the three activity agent goals “eat”, “drink” and “rest” is directly related to the behaviour of the corresponding motivation function and therefore changes during the course of the simulation, see Equation (5.7). As a consequence, the tasks on an agent's agenda are of varying importance to the agent at any given time during the course of the simulation.

Dependent on their tasks' importance, the agent may decide to rather dismiss a non-compulsory task in favour of getting to their train on time. In the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case, each agent did dismiss on average 1.0 ± 1.40 tasks from their total number of 5.4 ± 2.51 non-compulsory tasks because of a high time pressure situation. In other words, each agent did dismiss on average 19% of their planned elective tasks during the course of the simulation in order to meet their assigned procedural goals.

This dismissal behaviour can also be analysed dependent on the amount of time that the agent initially had at their disposal until the departure of their assigned train. For this purpose, the agent population has been grouped according to the amount of their initially available time until their train' scheduled departure. Three Initially Available Time (IAT) Groups have been defined, "Early", "Medium" and "Late". For the IAT Group Definition, the range between the minimum and maximum Initially Available Time, $T_{\text{IA}}^{\text{range}} := T_{\text{IA}}^{\text{max}} - T_{\text{IA}}^{\text{min}}$, of the foot passenger population over all five simulation runs have been determined. A foot passenger agent is then assigned to the IAT Groups, according to their Initially Available Time T_{IA}:

$$\begin{array}{rcccccl} \frac{2}{3} \cdot T_{\text{IA}}^{\text{range}} + T_{\text{TA}}^{\text{min}} & \leq & T_{\text{IA}} & \leq & T_{\text{IA}}^{\text{max}} & \Longrightarrow & \text{"Early" IAT Group} \\ \frac{1}{3} \cdot T_{\text{IA}}^{\text{range}} + T_{\text{TA}}^{\text{min}} & \leq & T_{\text{IA}} & \leq & \frac{2}{3} \cdot T_{\text{IA}}^{\text{range}} + T_{\text{TA}}^{\text{min}} & \Longrightarrow & \text{"Medium" IAT Group} \\ T_{\text{IA}}^{\text{min}} & \leq & T_{\text{IA}} & \leq & \frac{1}{3} \cdot T_{\text{IA}}^{\text{range}} + T_{\text{TA}}^{\text{min}} & \Longrightarrow & \text{"Late" IAT Group} \end{array} \tag{9.1}$$

Table 9.9 lists the agents' task performance results dependent on their IAT Group.

Table 9.9.: The agents' average urgency and task performance dependent on their Initially Available Time (IAT) Group in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

IAT Group	% Agent Population	UR	Number of elective Tasks planned	Number of elective Tasks dimissed because of Urgency
"Early"	58.8% ± 7.58%	6.5% ± 0.21%	5.6 ± 0.03	0.7 ± 0.01
"Medium"	25.5% ± 7.31%	10.8% ± 0.31%	5.3 ± 0.06	1.2 ± 0.03
"Late"	16.7% ± 6.86%	20.1% ± 0.67%	4.9 ± 0.07	2.1 ± 0.03

The results depicted in Table 9.9 confirm the expectations that the later an agent enters the station environment before their scheduled train departure, the more severe measures they need to undertake in order to make it to their train on time. Both the agents' average Urgency Ratio as well as the proportion of elective tasks that are dismissed as a result of the Urgency assessment increase with decreasing initially available time.

The agents' Urgency behaviour is also reflected in their elective goal performance, see Table 9.10.

Table 9.10.: The foot passengers' average elective agent goal performance in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

Elective Goal	Proportion of Agent Population	Proportion of Agents who attempted Elective Goal		
		Satisfied	Suppressed	Unsatisfied
"eat"	55.7% ± 0.61%	31.5% ± 0.57%	68.5% ± 0.88%	0.0% ± 0.01%
"drink"	36.2% ± 0.74%	72.5% ± 0.66%	27.5% ± 0.66%	0.0% ± 0.01%
"rest"	30.0% ± 0.27%	51.4% ± 0.70%	47.1% ± 0.70%	1.5% ± 0.14%
"shop"	66.9% ± 0.38%	70.0% ± 0.40%	30.0% ± 0.39%	0.0% ± 0.01%
"service"	19.9% ± 0.49%	66.3% ± 0.75%	33.5% ± 0.72%	0.2% ± 0.07%
"information"	11.0% ± 0.25%	79.4% ± 0.87%	16.9% ± 0.78%	3.7% ± 0.40%

The results in Table 9.10 show, that almost every elective agent goal that has been assigned to the foot passengers has either been satisfied or suppressed. The fact that almost no elective agent goal remained unsatisfied implicates, that the reason for any foot passenger not to be able to satisfy any of their assigned elective activity goals is not an ignorance of suitable goal locations, but rather the outcomes of decision making processes. The reason for an agent goal to get suppressed is almost exclusively a time pressure situation found during the agent's Urgency assessment. The only exception being the "eat" goal, which can also be suppressed because of customary meal time periods, see Section 5.6.1.1.

The higher ratio of agents with an unsatisfied "rest" and "information" elective goals is explained by the number of available goal locations for these goals. As depicted in Table 9.2, the studied train station geometry contains only one seating area and three information points. This reduces the probability of an agent knowing any of these facilities. Although there are more information points in the geometry than seating areas, the proportion of agents who were not able to satisfy their "information" agent goal is higher than the proportion of agents who were not able to satisfy their "rest" agent goal. This is also reasonable, since the "information" agent goal is an emergent agent goal which is only assigned if the agent still has unsatisfied agent goals and if they don't know any goal locations where they can satisfy these unsatisfied agent goals. Therefore, the probability for an agent getting assigned the "information" agent goal is higher if they have fewer spatial knowledge about the environment. Conclusively, an agent with an "information" agent goal is more likely not to know an information point goal location. Another reason for the high un-satisfaction ratio is the low importance of the "information" goal. As can be seen in Table 5.1, the "information" agent goal will always attain the lowest agent goal importance for each agent. Therefore, if an agent is on the way to an information point goal location and passes by a suitable goal location where they can satisfy any of their currently unsatisfied agent goals, the agent will in any case decide to rather satisfy this agent goal than to satisfy their "information" agent goal.

It is interesting to notice, that even so the worst un-satisfaction ratio is observed for the "information" elective goal, also the best satisfaction performance can be observed for this elective goal. This is reasonable, since the "information" agent goal is only evoked when the agent has satisfied all elective agent goals, for which they know goal locations where to satisfy them. Conclusively, if the agent is assigned the "information" agent goal, they will either head directly towards a known information point goal location, or they will seek an information point goal location by exploring the geometry.

The next best goal performance can be observed for the "drink", "shop" and "service" goals. Between two thirds and three quarter of those foot passenger agents who intended to seek something to drink, to shop or a service facility during the course of the simulation were also able to satisfy these needs. Only between a quarter and a third of these foot passengers had to suppress their intended "drink", "shop" or "service" agent goal in favour of reaching their train on time. It is reasonable that of these three elective goals the "drink" goal has the best goal performance, since it has the highest importance range (see Table 5.1) and of these three goals the most goal locations where it can be satisfied in this geometry, see Table 9.2. The "shop" goal can be satisfied at a comparable number of goal locations, but it has a lower importance range, making it more likely to be suppressed when the agent is in a time pressure situation. The "service" goal has the same lower importance range as the "shop" goal, but it can be satisfied at six goal locations in the geometry, which is a third of the number of goal locations where the "drink" and the "shop" goal can be accomplished.

Of those foot passengers who had the need to rest, only about half of them were able to satisfy this need, the other half had to suppress it. As described above, this goal performance is a result of only one goal location being available in the geometry where the "rest" agent goal can be satisfied. Also, the "rest" goal has a low importance range, as has the "shop" and "service" goal location. This leads to any agent being more likely to satisfy any other unsatisfied agent goal rather than their "rest" agent goal.

The worst average goal performance is observed for the "eat" agent goal. Only about a third of those foot passenger agents that did become hungry during the course of the simulation were able to satisfy their need, the remaining two thirds did have to suppress it. This behaviour is not as obvious, since "eat" goal has the highest importance range and the highest number of goal locations in the geometry where it can be satisfied. The reason for the high suppression rate must therefore be the effect of the customary meal time periods. This hypothesis is confirmed by the detailed results of the "eat" goal performance as depicted in see Table 9.11.

As can be seen in Table 9.11, only a fifth of the foot passengers who intended to eat during the course of the simulation did suppress their agent goal because of Urgency consideration.

Table 9.11.: The foot passengers' "eat" goal performance in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case. Thereby only those foot passengers are considered which intended to eat.

Agent Goal	"eat"
Satisfied	31.5% ± 0.57%
Suppressed by Urgency	20.7% ± 0.38%
Suppressed by Meal Times	47.9% ± 0.50%
Unsatisfied	0.0% ± 0.01%

Compared to the suppression rate of the other elective goals depicted in Table 9.10, this is the best suppression performance of all elective goals. This behaviour could have been expected, because of the high importance range of the "eat" goal and the numerous available goal locations. As can be seen in Table 9.11, the bad overall goal performance of the "eat" goal is clearly the result of the agents respecting the customary meal time periods.

In addition to the overall elective goal performance, it is interesting to study how the elective goals were assigned to the individual foot passenger agent. Most of the goals chosen for this thesis are assigned to the agent at the start of the simulation based on the given probability distributions. Only those goals, that are linked to motivational functions (see Section 5.6.1) can be assigned to the individual agent during the course of the simulation. In the case of this thesis, the motivational goals comprise the "eat", "drink" and "rest" goals, which are linked to the individual agent's "hunger", "thirst" and "fatigue" motivations. Table 9.12 depicts the proportions of the foot passenger agents who intended a motivational goal, distinguished by the agent goal's source.

Table 9.12.: The proportion of the foot passengers per motivational goal in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case. It is distinguished between whether the motivational goal has been initially assigned to the foot passenger or whether it did emerge during the course of the simulation.

Agent Goal	Goal Source	
	assigned	emerged
"eat"	89.6% ± 0.33%	10.4% ± 0.33%
"drink"	92.0% ± 0.73%	8.0% ± 0.73%
"rest"	33.9% ± 0.72%	66.1% ± 0.72%

As can be seen in Table 9.12, the majority of the foot passenger agents who intended to eat or drink during the course of the simulation have been assigned this goal during their initialisation phase. This assignment is done based on the provided probability distribution, see Table 9.4. On the other hand, for about two thirds of those foot passenger agents who intended to rest during the course of the simulation did the “rest” goal emerge during the course of the simulation. This behaviour can be explained by the shape of the motivational functions, see Equations (5.11). The slope of the “fatigue” motivation function is twice the slope of the “hunger” motivation function and twelve times the slope of the “thirst” motivation function. It is therefore reasonable, that the proportion of the foot passenger agent population who intended to rest and whose “rest” goal did emerge during the course of the simulation is eight times as high as the corresponding foot passenger agent population for the “drink” goal. However, although the “hunger” and “fatigue” motivation functions have a comparable slope, the proportion of agents whose “eat” goal did emerge during the course of the simulation is much smaller than the corresponding proportion of the agent population for the “rest” goal. This effect can be explained by the assigned goal probability distribution, see Table 9.4. Whereas only 10% of the entire foot passenger agent population is initially assigned the goal to rest, already half of the entire foot passenger agent population is assigned the goal to eat during their simulation initialisation phase.

9.4.3. Experience and Knowledge

Agents can only satisfy their assigned agent goals if they are aware of goal locations which are associated with their agent goals. In the “Circulation” scenario of the Long-Distance Traffic Facility Verification Case, a foot passenger agent knew on average 74.8% ± 22.74% of the total number of 62 goal locations. In the CPAF, there are three possible sources for an agent’s spatial knowledge: experience, structural perception and information enquiry.

Experience or prior spatial knowledge is assigned to each agent during the simulation initialisation phase based on a probability distribution, see Section 6.2.1. For the Long-Distance Traffic Facility Verification Case, the probability distribution stated in Table 9.3 has been used. In addition to their assigned prior spatial knowledge, the CPAF allows for he agents to learn new structural information by perception, see Section 5.5. Furthermore, the agents can enquire spatial information at special goal locations in the environment, the information points, with the CPAF’s Unsatisfied Desired Goal Behaviour feature (Section 6.4.2). The CPAF distinguishes between these different sources of spatial knowledge in terms of the knowledge’s memory persistence (Section 5.3.2): prior spatial knowledge is always available to the agent, whereas spatial knowledge obtained by either structural perception or information enquiry is subject to the agent’s short term memory.

Table 9.13 depicts the average proportion of the goal locations which are known to each agent within the five different Prior Knowledge Groups. In addition, Table 9.13 shows the the proportion of known goal locations by their knowledge source.

As could have been expected, the results in Table 9.13 demonstrate that the proportion of goal locations which are known to an agent in the respective Prior Knowledge Group increases with increasing level of prior spatial knowledge.

Table 9.13.: The average proportion of known goal locations (GLs) for each foot passenger agent and the proportion of known goal location (GLs) per knowledge source by Prior Knowledge (PK) Group in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

PK Group	Known GLs (%)	Proportion known GLs per Knowledge Source		
		Prior Knowledge	Spatial Perception	Information Enquiry
0% PK	43.0% ± 11.05%	6.5%	36.0% ± 10.65%	0.6% ± 2.64%
20% PK	57.5% ± 12.02%	28.9% ± 5.04%	28.1% ± 11.37%	0.5% ± 1.73%
50% PK	74.1% ± 8.48%	56.2% ± 6.04%	17.6% ± 7.90%	0.1% ± 0.55%
70% PK	84.6% ± 6.02%	73.8% ± 5.48%	10.7% ± 5.49%	0.1% ± 0.34%
100% PK	100%	100%	–	–

The results for the proportion of goal locations that are known to the average foot passenger agent by prior knowledge in each Prior Knowledge Group in Table 9.13 seem to be showing an inconsistency between the obtained simulation results and the assignment of the amount of prior spatial knowledge. However, the obtained results are correct. The fact that e.g. the average foot passenger agent with no initially assigned prior knowledge knows 6.5% of all available goal locations from prior knowledge can be explained by the design of the CPAF. A CPAF agent knows by default the goal location where they entered the environment and the exit that is attached to this entrance goal location. This behaviour model is reasonable, and it is also reasonable to assume that the agent will not forget where they entered the environment. For these reasons, their entrance goal location and their entrance exit are stored in the agent's Spatial Memory Set as being from prior knowledge. Furthermore, the simulation of a long-distance traffic facility with the buildingEXODUS CPAF Plug-in has been realised such that each agent will know about their assigned "departure wait" and "departure zone" goal location by prior spatial knowledge. As a consequence, each foot passenger agent knows four additional goal locations by prior spatial knowledge, disregarding their assigned Prior Knowledge Group. These four additional goal locations result in the 6.5% of all goal locations, by which the results for the proportion of goal locations that are known to the average foot passenger agent by prior knowledge in Table 9.13 differ from the amount of prior knowledge that they did get assigned based on their assigned Prior Knowledge Group.

The results depicted in Table 9.13 show further that the proportion of goal locations that are known to the agents by information enquiries using the CPAF's Unsatisfied Desired Goal Behaviour feature decreases with increasing prior knowledge. These results are reasonable, since the more a foot passenger agent initially knows about the environment, the fewer they will have to seek information. It is also noteworthy, that the average foot passenger agent did not have to enquire additional spatial information too often, since the average proportion of the goal locations that had to be enquired is only at maximum 0.6%. This implicates, that even those foot passenger agents who weren't assigned any prior spatial knowledge about the environment were able to acquire most of their needed spatial information by exploring the environment. Although, the relatively high standard deviations for the Prior Knowledge Groups with zero prior knowledge and 20% prior knowledge indicate, that there were foot passenger agents who did have to enquire many goal locations.

The proportion of goal locations that are known to the average foot passenger agent by spatial perception is also decreasing with increasing prior spatial knowledge. These results are a direct consequence of the agents' prior knowledge group: if a goal location is perceived, it is only added to the agent's Spatial Memory Set if it isn't already known to the agent. Therefore, if an agent perceives a goal location that the agent already knew from their assigned prior spatial knowledge, the source of the goal location's memory in the agent's Spatial Memory Set will still be their prior knowledge. In this context it is however interesting to study, how many goal locations were perceived by the average foot passenger agent in every Prior Knowledge Group, see Table 9.14.

Table 9.14.: The average proportion of goal locations that were perceived per foot passenger agent by Prior Knowledge Group in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

Prior Knowledge Group	Proportion perceived Goal Locations
0% Prior Knowledge	49.7% ± 14.80%
20% Prior Knowledge	48.0% ± 19.21%
50% Prior Knowledge	48.2% ± 19.23%
70% Prior Knowledge	48.6% ± 19.56%
100% Prior Knowledge	48.8% ± 19.70%

The results in Table 9.14 clearly implicate, that no significant dependency of the number of perceived goal locations from the agent's Prior Knowledge Group exists. However, the fact that the number of perceived goal locations is highest for those foot passenger agents with no initially assigned prior spatial knowledge is reasonable. These foot passenger agents need to explore the environment in order to find goal locations suitable to satisfy their goals.

The agents in the CPAF choose their goal locations where they want to satisfy their assigned agent goals according to the goal locations' features and their corresponding personal preferences, see Sections 6.1.1 and 6.4.1. The agents thereby aim to minimise the deviation of the goal location's feature parameters (5.2.3) from their individual personal preferences (5.3.1). It is therefore reasonable to assume, that the more goal locations are known to the foot passenger agent, the better are their choices of goal locations.

The quality of the agents' goal location choice can be measured by several means. For the purpose of this thesis, the L_1 norm, also known as Taxicab or Manhattan norm, has been used:

$$\delta_P(l) := \sum_{i=1}^{3} |F_i(l) - P_i|$$

For the purpose of this dissertation the goal locations' feature parameters as well as the agents' personal preference attributes can attain the following values (see Tables 5.2 and 5.6):

$$P_i, F_i(l) \in \{0, 1, 2\} \quad \forall\, i \in \{1, 2, 3\}$$

Therefore, the maximum and minimum possible values for the goodness of an agent's goal location choice are

$$\min_{l,P} \delta_P(l) = 0 \qquad\qquad \max_{l,P} \delta_P(l) = 6$$

Based on these considerations, seven Feature-Preference Deviation Groups have been defined, according to the seven possible values for the quality of a goal location choice $\delta_P(l)$.

In the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case, each goal location that had been chosen by an agent for satisfying one or multiple of their assigned agent goals is hence evaluated according to the above norm and the Feature-Preference Deviation Groups. Hereby only those goal locations were considered, where the corresponding task on the agent's Agent Task List has been completed. For each agent, the number of goal locations in each Feature-Preference Deviation Group has been determined. Table 9.15 shows the average proportion of goal locations within the different Feature-Preference Deviation Groups relative to the total amount of chosen goal locations per foot passenger agent.

Table 9.15.: The average proportion of goal locations in each Feature-Preference Deviation Group per foot passenger agent.

Goal Location Proportion per Feature-Preference Deviation Group ($\delta_P(l)$)						
0	1	2	3	4	5	6
30.0% ± 36.81%	39.7% ± 38.80%	20.8% ± 32.83%	6.6% ± 12.93%	2.5% ± 12.93%	0.4% ± 5.23%	0.0% ± 1.33%

As depicted in Table 9.15, 70% of the goal locations chosen by the average foot passenger agent were either a perfect match to their individual preferences (i.e. $\delta_P(l) = 0$), or one of the goal locations feature parameters differed from one of the agent's personal preference attributes by one (i.e. $\delta_P(l) = 1$). Goal locations which had a deviation of 3 or worse only make up less than 10% of the average agent's total number of chosen goal locations. These results clearly indicate, that the Cognitive Pedestrian Agent Framework agents did aim to find goal locations that matched their personal preferences as good as possible. However, the high standard deviations especially for the Feature-Preference Deviation Groups with $0 \leq \delta_P(l) \leq 4$ clearly indicate, that choosing optimal goal locations was not possible for every agent. However, the more goal locations are known to the foot passenger agents, the more optimal goal locations should have been found by the agent. The results depicted in Table 9.16 confirm this hypothesis.

Table 9.16.: The average proportion of goal locations in each Feature-Preference Deviation Group per agent per Prior Knowledge (PK) Group.

PK Group	Goal Location Proportion per Feature-Preference Deviation Group ($\delta_P(l)$)						
	0	1	2	3	4	5	6
0% PK	13.9% ± 26.17%	26.0% ± 34.21%	29.8% ± 35.98%	19.2% ± 32.43%	9.3% ± 24.12%	1.8% ± 10.92%	0.2% ± 2.82%
20% PK	22.1% ± 31.69%	41.2% ± 37.57%	25.9% ± 34.37%	8.7% ± 23.31%	1.9% ± 10.75%	0.1% ± 1.99%	0.0% ± 0.29%
50% PK	31.0% ± 36.97%	44.2% ± 39.45%	20.5% ± 32.88%	3.7% ± 15.56%	0.6% ± 5.86%	0.0% ± 0.31%	–
70% PK	35.4% ± 38.66%	45.0% ± 39.68%	17.1% ± 31.15%	2.2% ± 11.51%	0.3% ± 4.28%	0.0% ± 0.59%	–
100% PK	42.8% ± 39.49%	43.5% ± 39.38%	13.3% ± 27.85%	0.4% ± 4.83%	0.0% ± 0.71%	0.0% ± 0.08%	–

9.4.4. Situational Awareness and Contextual Behaviour

One of the reasons why agents can choose near optimal goal locations is their ability to perceive and evaluate their structural surroundings and relate this information to their individual goals and preferences. Based on this information, the agents can decide to change their Agent Task List by changing one of their planned goal locations in favour of a recently perceived goal location, see Section 6.4.1. Likewise, the agents can also perceive and evaluate their current situation and react accordingly, if necessary. They can perceive their surrounding level of congestion as well as the congestion in front of their next target, see Section 5.6.2.1. As a consequence, the agents might feel required to reassess their current time pressure situation and might find that they need to dismiss one or several tasks from their task list. Table 9.17 gives an overview how many tasks the average foot passenger agent did change as a result of their structural or situational awareness.

By far the most common task adaptation undertaken by the average foot passenger agent is that they had changed a task's goal location in favour of a recently perceived goal location, because the perceived goal location provided a better match to the agent's personal preferences. Each agent did change on average 0.22 of their tasks because of this structural assessment. As could be expected, the agent is far less likely to change a task's goal location because they could satisfy multiple goals at the recently perceived goal location, instead of visiting several other goal locations. The average foot passenger agent only adapted on

Table 9.17.: The average number of task changes per foot passenger for selected alteration causes and alteration effects in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case.

Alteration Cause	Alteration Effect	Number of Task Changes
Structural Perception	Changed Goal Location	0.22 ± 0.49
Structural Perception	Compromise Goal Location	0.01 ± 0.11
Urgency triggered by Perceived Crowd Assessment	Dismissed Task	0.00 ± 0.02
Local Situation Assessment	Dismissed Task	0.01 ± 0.20

average 0.01 tasks for this reason. This is reasonable, because the probability for an agent being in such a situation in the "Circulation" scenario of the Long-Distance Traffic Facility Verification Case is very small. The agent would need to currently intend both the "eat" and the "drink" agent goal, they would need to have perceived a goal location where both goals can be accomplished and they would need to have a task planned for one of these two goals at a goal location which provides a worse feature-preference match than the recently perceived goal location.

The results depicted in Table 9.17 show, that the other two adaptations based on the agent's situational awareness occurred similarly infrequently. The average foot passenger agent dismissed almost no task because of a time pressure assessment that had been triggered by perceived congestion. This result indicates, that the population density within the environment only seldom reached a level at which the foot passenger agents were led to dismiss tasks because of their time situation. Also, the average foot passenger agent dismissed only 0.01 tasks because of the population density in front or within their currently targeted goal location. This result also indicates, that the population density within the goal locations only seldom exceeded the critical threshold (see Section 5.6.2.1).

9.4.5. Alarm Response Behaviour

As has been described in Chapter 1 and Chapter 7, one of the motivations to develop the Cognitive Pedestrian Agent Framework (CPAF) has been to facilitate the simulation of evacuation scenarios in the situation of sparse empirical data. This can for example be the case, when the building to be studied is still in the construction phase. In such a scenario, reasonable assumptions need to be made in order to inform an evacuation simulation. The CPAF aims to inform an evacuation scenario based on the occupants' simulated prior building usage, their acquired knowledge about the environment and their individual goals. The "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case demonstrates the example alarm response behaviour that has been realised in the buildingEXODUS CPAF Plug-in. The resulting exit usage and response time distribution are discussed in this section.

As has been stated in Section 9.3.3, the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case has been set up such that initially a circulation simulation is started and at a certain point in time an alarm event is simulated. With this setup, the buildingEXODUS CPAF Plug-in enables the agents to first make use of the environment under normal conditions, thereby acquiring knowledge about the environment and following their individual plans and goals. At the time of the alarm event, the agents will therefore be able to react according to their knowledge and plans.

As has also been stated in Section 9.3.3, the buildingEXODUS CPAF Plug-in's Predicted Response Phase Model has been used to simulate the agents' alarm response behaviour in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case. As has been discussed in Sections 7.2.3 and 8.8, the agents' response and evacuation time as well as their chosen exits will hence be the result of the individual agents' assessment of their current situation and their spatial knowledge. The “Evacuation” scenario of the Long-Distance Traffic Facility has been studied for the fixed set of alarm response model parameters depicted in Section 9.3.3. For a discussion of the impact of different model parameters on the simulation outcomes, please refer to Section 8.8.

In order to assess the results of the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case, a reference evacuation simulation has been run with building-EXODUS. The reference simulation has been set up such that the initial spatial distribution of the agents did match the average distribution of the agents at the time of the alarm event in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case. In the reference simulation, the agents did choose their exit based on the shortest distance heuristic. Their response time has been set to follow a log-normal distribution. For the response time distribution, the default response time distribution of buildingEXODUS has been used. Since no data of response times for this railway station environment is available, the usage of the buildingEXODUS's default settings are reasonable. The reference simulation has been run 10 times, each time randomising the location of the agents within the respective goal locations.

In the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case, the agents' alarm response locations are the result of the agents' goals and their environment usage during the preceding circulation stage. Table 9.18 lists the proportion of the foot passenger agent population that have been present in a goal location of the depicted type at the time of the simulated alarm event in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case.

As can be seen in Table 9.18, the vast majority of foot passengers agents present in the environment at the time of the alarm event were either in the corridor en route to their next planned task or already waiting at their designated platform goal location. About 3% of the foot passenger agent population were about to enter the environment via one of the modelled outside zones. Based on their locations within the environment at the time of

Table 9.18.: The proportion of the foot passengers agent population that were located within a goal location of the depicted type at the time of the simulated alarm event in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case.

Goal Location Type	Proportion Agent Population
Coffee Shop	2.7% ± 0.29%
Restaurant	1.2% ± 0.30%
Food-on-the-Go Outlet	4.0% ± 0.42%
Seating Area	6.1% ± 0.54%
Shop	13.8% ± 2.23%
Service Facility	1.6% ± 0.23%
Information Point	0.6% ± 0.16%
Ticket Office	1.1% ± 0.40%
Platform	43.6% ± 1.41%
Train Zone	1.2% ± 0.14%
Outside Zone	3.5% ± 0.46%
Corridor	20.6% ± 1.29%

the alarm event, the foot passenger agents in the “Evacuation” scenario chose their initially targeted exit and their pre-evacuation activities.

At the time of the alarm event in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case, the agents chose one of their known exits as their initial target exit according to the algorithm described in Section 7.1. If the agent perceives another exit on their way to their initial target exit, the agent may decide to change their target exit to the recently perceived one based on their Structural Awareness model (Section 6.4.1). Table 9.19 lists the final exit usage rates in the “Evacuation” scenario. For a reference on the exit labels see Figure 9.3.

Table 9.19.: The average exit usage in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case.

Exit 1	Exit 2	Exit 3	Exit 4	Exit 5
7.4% ± 0.46%	9.6% ± 0.92%	54.3% ± 1.59%	5.9% ± 0.60%	22.7% ± 0.60%

The results in Table 9.19 show, that the Exit 3 was chosen as final exit by over half of the foot passenger agent population. This result is reasonable, since Exit 3 is the most central of all available exits in the simulated railway station terminal environment (see Figure 9.3). Similarly, the high usage rate of about a quarter of the foot passenger agent population for Exit 5 is also reasonable, since Exit 5 is the closest exit to the platforms 11 to 13, as well as is also the nearest exit for all foot passenger agents who were present in the lower right part

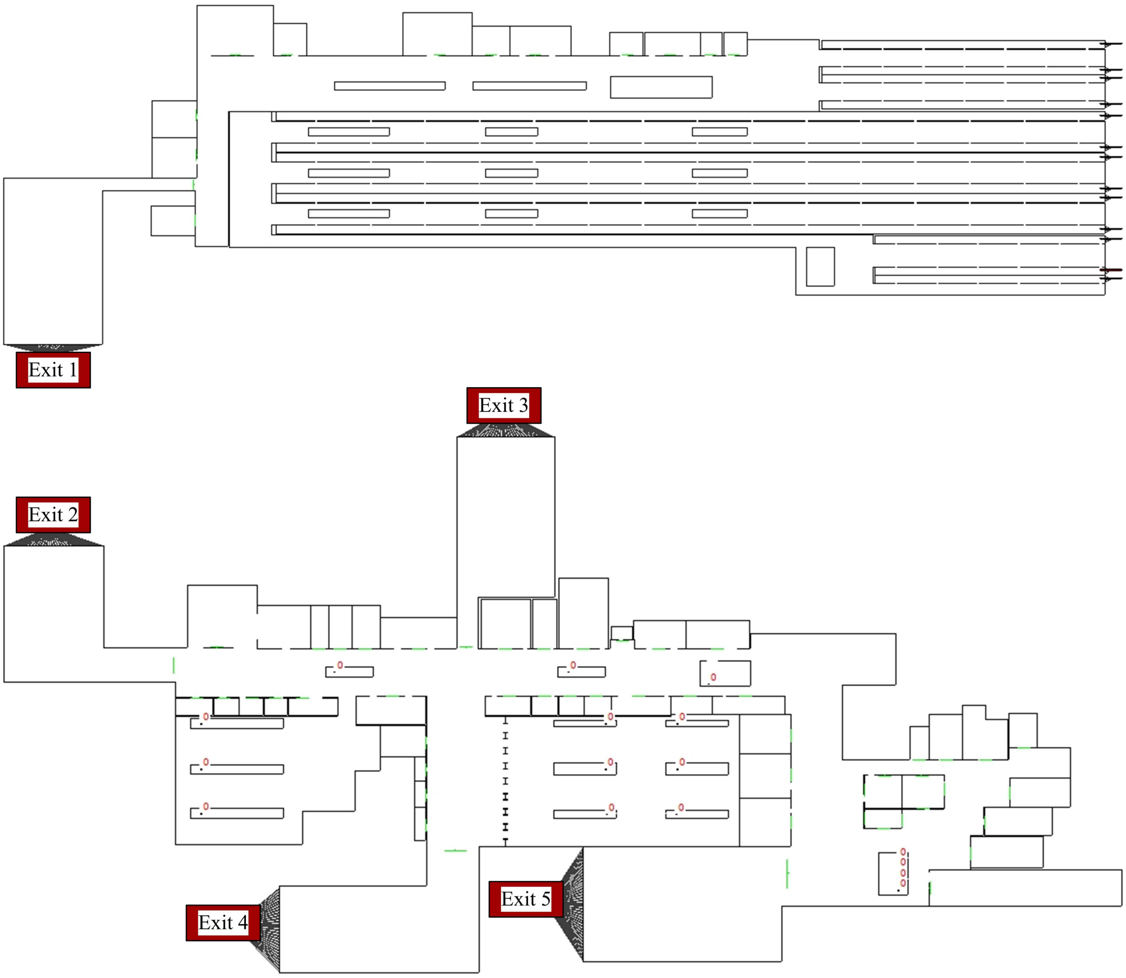


Figure 9.3.: The buildingEXODUS station geometry of the Long-Distance Traffic Facility Verification Case with exit labels.

of the geometry at the time of the alarm event. The preference for Exit 3 and Exit 5 for the agents' exit choice is confirmed by the results of the reference simulation, see Table 9.20.

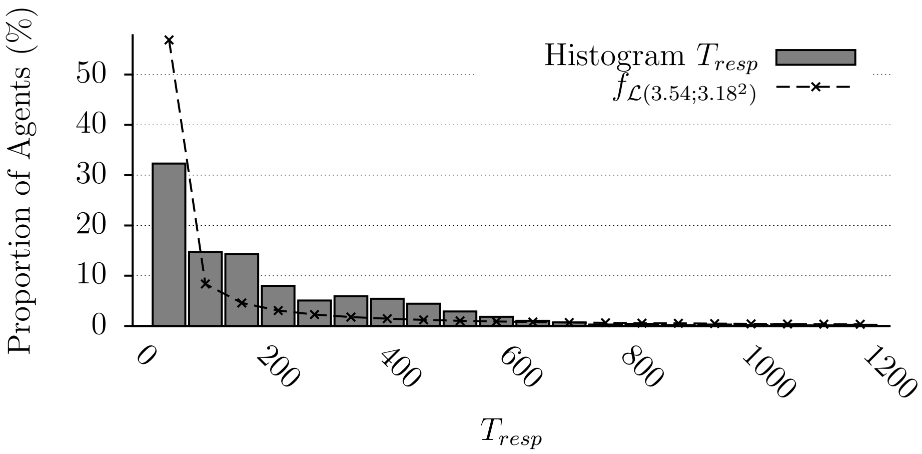
Table 9.20.: The average exit usage in the reference simulations of the Long-Distance Traffic Facility Verification Case. Outside exits have been chosen on the minimum distance principal.

Exit 1	Exit 2	Exit 3	Exit 4	Exit 5
6.0% ± 0.43%	7.1% ± 0.48%	59.6% ± 0.68%	3.9% ± 0.32%	23.4% ± 0.49%

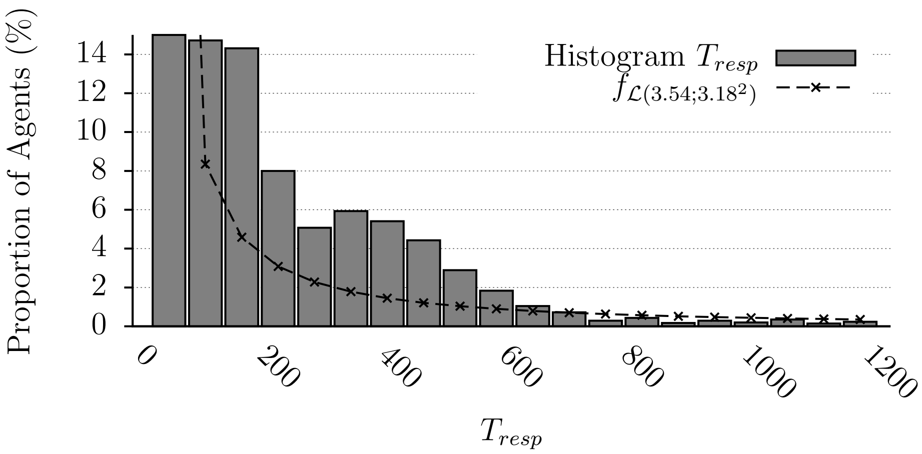
It is interesting to note, that the results of the "Evacuation" scenario realised with the buildingEXODUS CPAF Plug-in, which used the CPAF's generic decision heuristic (Table 9.19), closely match the results depicted in Table 9.20 when the agents chose their exits based on the minimal distance heuristic. It can therefore be assumed, that the exit choice algorithm of the buildingEXODUS CPAF Plug-in in most cases did find the foot passenger agents' nearest exits. This is also confirmed by determining the proportion of foot passenger agents who did change their initially chosen exit because of their structural awareness. Only 0.005% ± 0.0037% of the foot passenger agents present in the environment at the time of the alarm event did change their initially chosen exit because they came across a more suitable exit.

After having chosen their initially targeted exit, the foot passengers in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case decided on their pre-evacuation activities based on their current situation. The choice of a pre-evacuation activity directly impacts the foot passenger agents' response time: In the Predicted Response Phase Model, the agents initiate their evacuation as soon as they have completed their chosen pre-evacuation activity, see Section 7.2.3. The response time distribution of the foot passenger agent population, see Figures 9.4, is hence also an emergent result of the agents' decision making with respect to their individual situation.

As can be seen in Figures 9.4, the emergent response time distribution for all foot passengers who were present in the environment at the time of the simulated alarm event is a unimodal distribution with a main peak for response times between zero and 60 seconds. Since current research suggests that a log-normal distribution is an appropriate distribution to approximate the occupants' response time T_{resp} [155], a log-normal curve has been fitted to the emergent response time distribution in Figures 9.4. The parameters of the log-normal curve have been estimated from the response time data. As can be seen in Figures 9.4, the emergent response time distribution does follow the trend of the estimated log-normal distribution. However, the estimated log-normal distribution overestimates the proportion of foot passenger agents with a response time of less than 60s and underestimates the proportions of foot passengers agents for response times between 60s and 600s. A χ^2 goodness of fit tests consequently confirms, that the emergent response time distribution depicted in Figures 9.4 is not distributed according to the estimated log-normal distribution, even though



(a) The response time distribution.



(b) The response time distribution scaled to fit the histogram columns for response times greater than 60s.

Figure 9.4.: The response time distribution in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case. The bin size for the histogram of the foot passenger agents' response times has been chosen to be 60s.

the general trend is qualitatively replicated.

As has been discussed in Section 7.2.3 and also in Section 8.8, the foot passenger agents' response time distribution of the Long-Distance Traffic Facility Verification Case in Figures 9.4 is the superposition of two different response time assignment methods. One method for those foot passenger agents which were pursuing a critical time task at the time of the alarm event, and one for those foot passenger agents who were not.

If a foot passenger agent is pursuing a critical time task when the alarm event occurs, the agent will always decide to carry on with their current task. They are then assigned a response time based on the parameters of their critical time task, see Equation (7.1). In the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case, this would apply to all foot passenger agents who were waiting at the time of the simulated alarm event either at their designated platform goal location or in their designated train goal location for the train's departure. Figure 9.5 shows the resulting response time distribution for those foot passenger agents who were pursuing a critical time task at the time of the simulated alarm event.

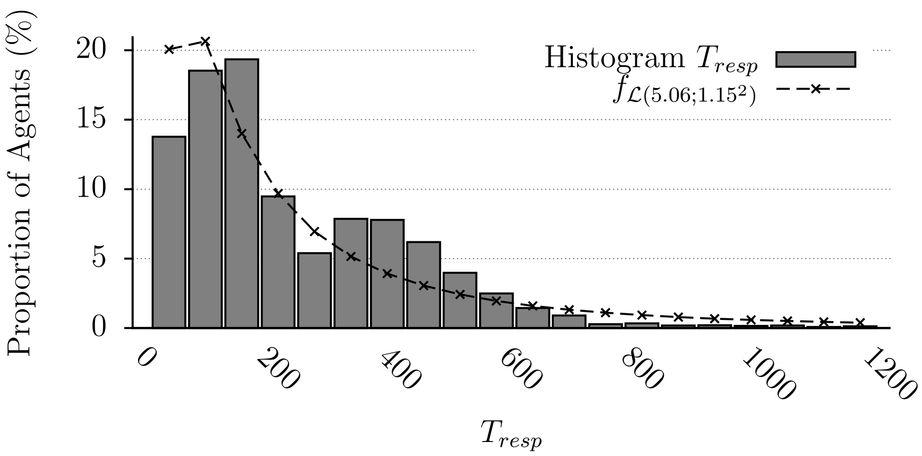


Figure 9.5.: The response time distribution in the “Evacuation” scenario of the Long-Distance Traffic Facility Verification Case for those foot passenger agents who pursued a critical time task at the time of the simulated alarm event. The bin size for the histogram of the foot passenger agents' response times has been chosen to be 60s.

As has been described in Section 7.2.3, the log-normal distribution according to which a response time is assigned to a foot passenger agent who is pursuing a critical time task depends the task's critical time. In the case of the Long-Distance Traffic facility, this critical time is the agent's designated train departure time. At the time of the simulated alarm event, the foot passenger agents who were pursuing a critical time task were waiting for one of 82 train departures. The resulting response time distribution for those foot passenger agents who were pursuing a critical time task at the time of the simulated alarm event depicted in Figure 9.5 is hence the cumulative result of a superposition of 82 log-normal response time distributions. The histogram of the resulting cumulative response time distribution shows one main peak at about 150s and one minor peak at about 300s. As can be seen in Figure 9.5, the depicted histogram of the agents' response times doesn't follow the estimated log-normal distribution. This has also been confirmed by a χ^2 goodness of fit test.

As has been stated in Section 8.8, the most interesting alarm response behaviour is exhibited by those foot passenger agents in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case, who were not pursuing a critical time task at the time of the simulated alarm event. As has been described in Table 7.1 in Section 7.2.1, this group of foot passenger agents could choose between the options to carry on with their current plans, to rush their plans or to terminate respectively abort their current plans. Table 9.21 shows the proportion of foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event per chosen pre-evacuation activity.

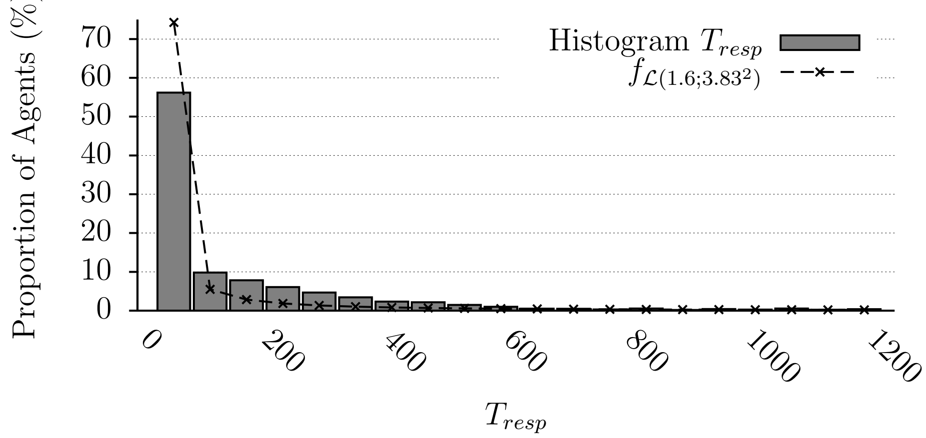
Table 9.21.: The proportion of those foot passengers agents who did not pursue a critical time task at the time of the simulated alarm event per pre-evacuation activity in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case.

Task Situation	Pre-Evacuation Activity	Proportion Foot Passenger Agents
Heading to next Task	"carry-on but rush"	17.2% ± 1.74%
	"abort"	12.9% ± 1.38%
Pursuing a Task	"carry-on as planned"	37.5% ± 1.39%
	"terminate"	31.4% ± 1.51%
All Tasks Finished	–	1.0% ± 0.51%

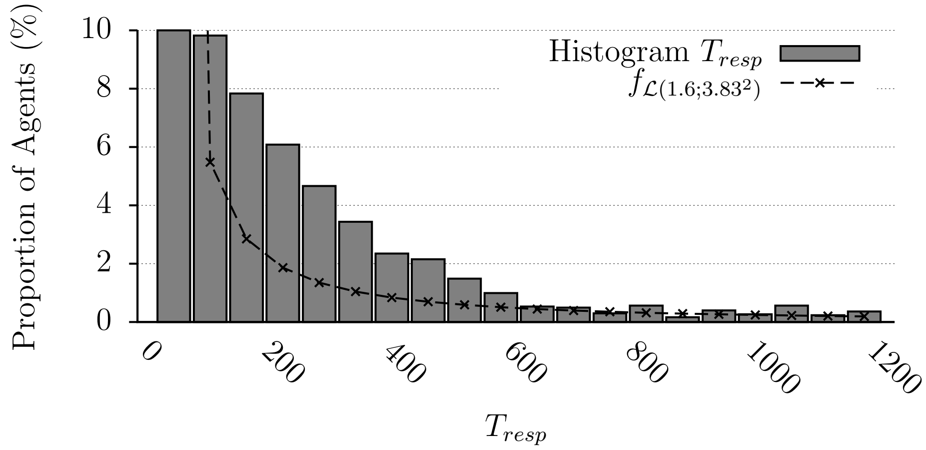
The results in Table 9.21 show, that about 30% of those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event were en route towards their next planned task when the simulated alarm event occurred. Of this foot passenger agent group, more than half chose to attempt their next planned task in a hurry, whereas the others chose not to attempt their next planned task and to initiate their evacuation immediately. A similar relation holds true for those foot passengers agents who were pursuing a task other than a critical time task at the time of the simulated alarm event: about 55% of this foot passenger agent group decided to carry on as planned with their current task, whereas about 45% of this foot passenger agent group decided to immediately terminate their current task.

Finally, about 1% of those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event had finished all their planned tasks, but were still in the environment. This situation occurred for example if a foot passenger agent was caught in congestion and had hence to dismiss their critical time tasks to go to their assigned platform respectively their assigned train. This group of foot passenger agents hence also initiated their evacuation immediately.

When the foot passengers agents decided to initiate their evacuation immediately, their response time was consequently zero. If they however decided to carry on with their planned activities, the foot passenger agents' response time was then dependent on the amount of time that the individual agents had left to complete their tasks. Figures 9.6 show the resulting response time distributions for those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event.



(a) The response time distribution.



(b) The response time distribution scaled to fit the histogram columns for response times greater than 60s.

Figure 9.6.: The response time distribution in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case for those foot passenger agents who didn't pursue a critical time task at the time of the simulated alarm event. The bin size for the histogram of the foot passenger agents' response times has been chosen to be 60s.

Figure 9.6a shows the response time distribution for all foot passengers who were not pursuing a critical time task at the time of the simulated alarm event. Figure 9.6a shows that about 55% of those foot passengers who were not pursuing a critical time task at the time of the simulated alarm event had a response time of less than 60s. This result is confirmed by the results depicted in Table 9.21, since about 45% of the foot passenger agents who were not pursuing a critical time task at the time of the alarm event did elect to initiate their evacuation immediately, their response time hence being zero.

From the emergent response times of those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event, parameters for a suspected log-normal distribution have been estimated, which is also depicted in Figures 9.6. As can be seen in Figure 9.6a respectively in the scaled Figure 9.6b, the response times of this foot passenger agent group clearly follows the trend of the estimated log-normal distribution. However, the empirical response time distribution for small response times is smaller than the estimated log-normal distribution, whereas it is larger for those histogram bars for response times greater than 60s. The estimated log-normal distribution hence overestimates the proportion of foot passengers agents having small response times and underestimates the proportion of foot passenger agents for larger response times. A χ^2 goodness of fit test also confirms, that the empirical response time distribution for those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event is not distributed according to the estimated log-normal distribution. Nevertheless, the estimated log-normal distribution well represents the qualitative nature of the empirical response time distribution for this foot passenger agent group.

The emergent response time distributions can be further analysed by selected descriptive statistics, see Table 9.22.

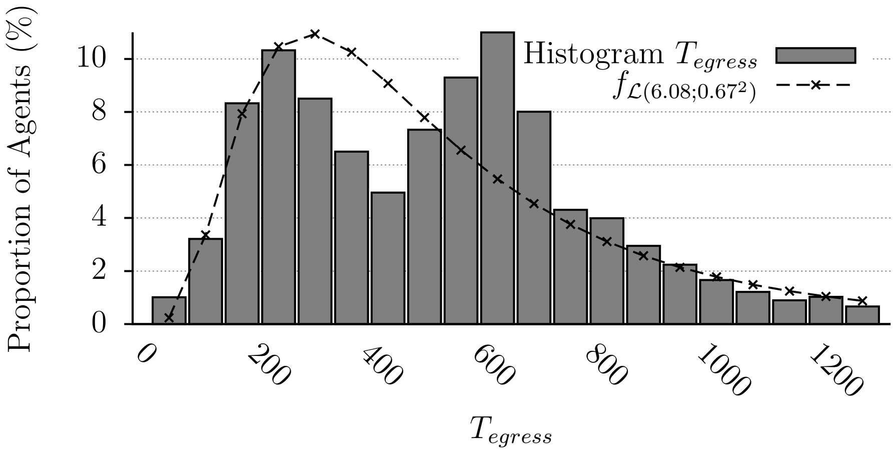
Table 9.22.: The statistics of the foot passenger agents' response time in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case.

Agent Group	Average	Min	Q_1	Median	Q_3	Max
All	203.6	0.0	17.7	130.5	306.4	2206.5
Critical Time	251.0	0.0	104.8	171.9	364.9	2206.5
Not Critical Time	142.7	0.0	0.0	25.0	193.8	1791.9

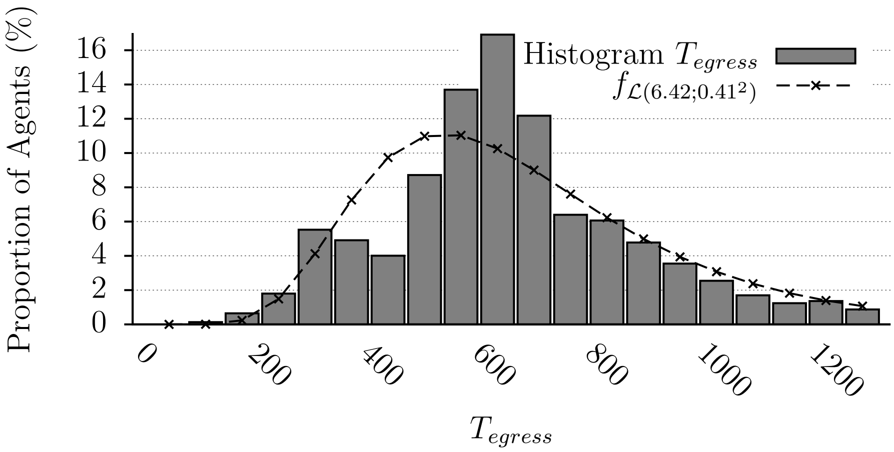
As can be seen in Table 9.22, the average emergent response time was 203.6s with the maximum emergent response time being as high as 2206.5s. It is not surprising, that the median response time of those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event is as low as 25s, given that 45% of the foot passengers in this foot passenger agent group had a response time of zero.

Aside from the occupants' response time distribution, it is also interesting to study the occupants' emergent egress times, see Figures 9.7.

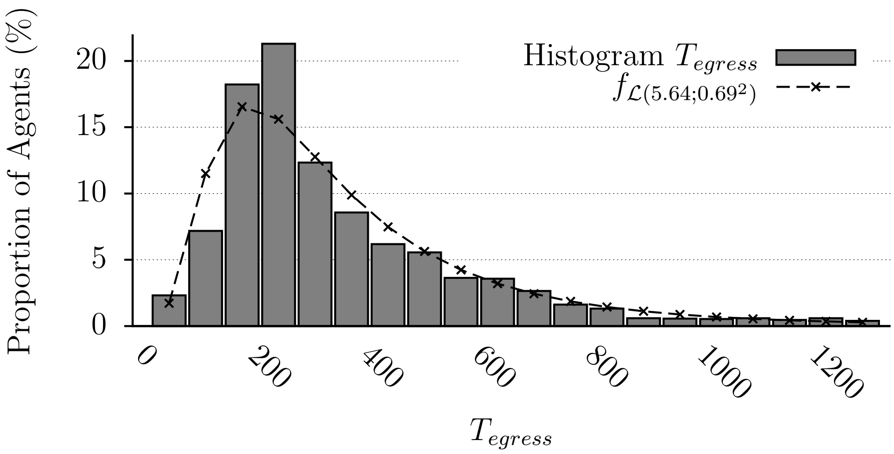
Figure 9.7a shows the emergent egress time distribution for all foot passenger agents who were present in the environment at the time of the simulated alarm event. The histogram indicates a bimodal distribution of the foot passenger agents' egress times. This is plausible because of the two different response time assignment methods in the buildingEXODUS



(a) The egress time distribution for all foot passenger agents.



(b) The egress time distribution for those foot passenger agents who pursued a critical time task at the time of the simulated alarm event.



(c) The egress time distribution for those foot passenger agents who did not pursue a critical time task at the time of the simulated alarm event.

Figure 9.7.: The egress time distribution in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case. The bin size for the histogram of the foot passenger agents' egress times has been chosen to be 65s.

CPAF Plug-in's Predicted Response Phase Model, depending on whether the agent is pursuing a critical time task at the time of the simulated alarm event or not. This hypothesis is confirmed by studying the egress time distributions of those foot passenger agents who were respectively were not pursuing a critical time task at the time of the simulated alarm event, see Figures 9.7b respectively 9.7c.

In the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case, on average 56.3% ± 1.47% of the foot passenger agent population present in the simulated environment at the time of the simulated alarm event were pursuing a critical time task at the time of the alarm event. Consequently, the egress time histograms Figure 9.7b and Figure 9.7c each account for approximately half of the foot passenger agent population present at the time of the simulated alarm event.

The emergent egress time distribution for those foot passenger agents who were pursuing a critical time task at the time of the simulated alarm event depicted in Figure 9.7b show a non-unimodal distribution of egress times. The first distinct peak is observed for an egress time of about 300s, whereas the dominant peak is observed for an egress time of about 600s. The emergent egress time distribution for those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event depicted in Figure 9.7c shows a unimodal and positively skewed empirical distribution with a peak at about 230s. The egress times for this foot passenger agent group are the result of the response time respectively pre-evacuation activity assignment heuristic described in Algorithm 7.1.

As for the foot passenger agents' response time distributions, log-normal curve parameters have been estimated from the observed foot passenger agents' egress times. As can be seen in Figures 9.7, a log-normal distribution has been estimated for the egress time distribution of all foot passenger agents as well as for the egress time distributions of those foot passenger agents who were respectively were not pursuing a critical time task at the time of the alarm event. Figure 9.7a shows, that the observed egress time distribution does not follow the estimated log-normal distribution. This has clearly been expected because of the bimodal shape of the egress time distribution. However, it is interesting to notice that the egress time distribution for small and for large egress times does follow the trend of the estimated log-normal distribution. Similar observations hold true for the egress time distribution of those foot passenger agents who were pursuing a critical time task at the time of the simulated alarm event and the corresponding estimated log-normal distribution depicted in Figure 9.7b.

Figure 9.7c shows a qualitative good correspondence between the observed egress time distribution and the estimated log-normal distribution for those foot passenger agents who were not pursuing a critical time task at the time of the simulated alarm event. This could have been expected, since the response time distribution for this foot passenger agent group depicted in Figures 9.6 also showed a qualitative good correspondence between the empirical results and the estimated log-normal distribution. However, a χ^2 goodness of fit test again confirmed, that the observed egress time distribution is not distributed according to the estimated log-normal distribution.

To further analyse the observed results for the foot passenger agents' egress time distributions, selected descriptive statistics have been determined, see Table 9.23.

Table 9.23.: The statistics of the foot passenger agents' egress time in the "Evacuation" scenario of the Long-Distance Traffic Facility Verification Case.

Agent Group	Average	Min	Q_1	Median	Q_3	Max
All	532.9	7.9	275.9	518.9	681.0	2696.1
Critical Time	669.2	79.0	514.8	625.6	780.6	2696.1
Not Critical Time	357.4	7.9	187.3	263.7	442.8	1942.4

The results depicted in Table 9.23 confirm the non-uniform distribution of the egress times for the different studied foot passenger agent groups. However, it is interesting to notice that albeit the different shape of the egress time distributions, the inter-quartile range for the foot passenger agent groups of those foot passengers who were pursuing a critical time task at the time of the simulated alarm event and those foot passengers who were not pursuing a critical time task at the time of the simulated alarm event are comparable. The inter-quartile range of the emergent egress time distribution for the first foot passenger agent group amounts to 265.8s whereas the inter-quartile range for the latter foot passenger agent group amounts to 255.5s. This indicates that the spread of the egress time distributions for the two foot passenger agent groups is comparable.

9.5. Summary

In this chapter, the capabilities of the Cognitive Pedestrian Agent Framework (CPAF) have been demonstrated in a comprehensive verification case. The simulation of the verification case has been conducted using the buildingEXODUS CPAF Plug-in. This chapter therefore addresses Research Objectives 4 and 5.

In the Long-Distance Traffic Facility Verification Case, a railway station terminal as an example of a complex multi-purpose environment has been simulated. In the verification case, the entire usage-cycle of a station is simulated both under emergency and non-emergency conditions. It has been demonstrated that the individual features of the CPAF, which are based on different human behaviour theories and observations, do collaborate to produce reasonable cumulative pedestrian circulation behaviour. Further, the results of the Long-Distance Traffic Facility Verification Case demonstrate that the CPAF could be applied to realistically simulate pedestrian alarm response behaviour. The buildingEXODUS CPAF Plug-in's Alarm Response Model did indeed reproduce common theories in the field of evacuation modelling in this railway station terminal verification case.

Chapter 10:

Conclusions and Future Work

In this chapter, the proposed Cognitive Pedestrian Agent Framework (CPAF) is briefly summarised. It is discussed why the CPAF has been developed in the way proposed in this thesis. Subsequently in Section 10.2, it is outlined how and to what extent the proposed CPAF addresses the research questions identified in Section 1.2.4. Finally, a list of suggestions for future work regarding this thesis' topic are compiled in Section 10.4.

In this thesis, an approach to model advanced cognitive and purpose-related human behaviour in the field of pedestrian behaviour simulation research has been proposed. The proposed Cognitive Pedestrian Agent Framework (CPAF) has been developed on the basis of a literature review of current pedestrian behaviour simulation models, suitable virtual reality simulation tools and original human behaviour research. Theories from the research disciplines of artificial intelligence, psychology, decision theory and human behaviour science have been assessed and combined in this thesis' agent framework in order to propose a holistic approach for modelling goal-driven, cognitive individual pedestrian behaviour.

The CPAF itself is intended to be generically applicable in any pedestrian behaviour simulation model which provides the base functionalities required by the CPAF. In addition, an implementation of the CPAF has been integrated in the existing pedestrian behaviour simulation tool buildingEXODUS in order to demonstrate the proposed approach in various verification cases (see Chapters 8 and 9). buildingEXODUS facilitates the integration of additional features by providing a plug-in interface. Therefore, the CPAF implementation could be realised as a plug-in to the current buildingEXODUS version [14]. With the support of the buildingEXODUS team of the Fire Safety Engineering Group, it was possible to extend the already available plug-in interface and tailor the extensions to what has been required to realise the buildingEXODUS CPAF Plug-in. The buildingEXODUS CPAF Plug-in could make use of the environment and agent structure already available in buildingEXODUS, instead of developing these pedestrian behaviour simulation fundamentals from scratch. buildingEXODUS already provides advanced features which could be used to realise the CPAF features, such as for example compartment zones (see Section 4.1.1), agent itineraries (see Section 4.1.2.1) and an exit signage model (see Section 4.5.1).

10.1. An Overview of the Cognitive Pedestrian Agent Framework

The CPAF proposes an approach to model individual pedestrian behaviour, specifically in complex multi-purpose environments. This pedestrian behaviour model should be realised by a holistic individual agent model. Because of this requirement, the CPAF has been designed to have the structure of a cognitive architecture (see Section 3.1). As has been shown in the literature review on pedestrian behaviour simulation tools in Chapter 2, the CPAF is the first approach for modelling pedestrian behaviour that utilises the concepts of cognitive architectures. This concept has so far only been used in virtual reality pedestrian simulation models.

The CPAF comprises several components to account for the pedestrians' goals, their knowledge, the perception of the environment and their decision making. The components of the CPAF have been designed with the specific requirement to simulate human and pedestrian behaviour as accurately as possible.

The CPAF comprises a sophisticated decision making component which is based on well-proven theories in the human behavioural and cognitive sciences. It however is not based on only one human decision making approach but combines two well proven human decision making approaches in one decision making model. Particularly, the CPAF's decision making model has been tailored to replicate findings of human behaviour wayplanning studies, see Section 6.1.2.2. The CPAF is the first known approach to include this empirical wayplanning theory in a pedestrian behaviour simulation model.

The CPAF comprises a memory model which is an adaptation of the ACT-R's memory model (see Section 3.2.2) to the specific use case of modelling pedestrian behaviour in complex multi-purpose environments (see Section 5.3.2). The ACT-R's memory model is also based on empirical findings in the psychological sciences. The CPAF's memory model is the first approach in explicitly modelling short-term memory in a pedestrian behaviour simulation tool.

The CPAF is capable of simulating complex multi-purpose environments by introducing the notion of purpose both in the environment (Section 5.2) and agent model (Section 5.3). Based on this purpose representation, the agents in the CPAF are capable of perceiving and evaluating their environment, to relate these finding to their individual plans and thereby exhibit adaptive behaviours (Sections 5.6 and 6.4).

Another main motivation to develop the CPAF has been to couple pedestrian circulation and pedestrian evacuation modelling more closely. This requirement for pedestrian behaviour simulation models has been mentioned by expert researchers (see Section 2.3). In particular, Gwynne and Kuligowski [9] have proposed the so called ICE concept. The potential benefit of the CPAF for modelling the alarm response phase has been presented in Chapter 7, where an example realisation of such a proposed transition from a pedestrian circulation to pedestrian evacuation simulation has been developed in the buildingEXODUS CPAF Plug-in.

10.2. Revisiting the Research Questions

After having described the CPAF in detail in this thesis, the research questions which have been the starting point of this thesis' research are revisited.

10.2.1. Purposeful and Goal-Directed Pedestrian Behaviour

In the context of complex multi-purpose environments, how can purposeful and goal-directed pedestrian behaviour be represented in a pedestrian behaviour simulation?

a) How can the environment's purpose be represented?

b) What effect does the environment's purpose have on the occupying pedestrians?

c) In a complex multi-purpose environment, how can several other purposes available in the environment be represented?

d) How are the environment's purposes reflected in the individual pedestrian?

e) How does the complex multi-purpose environment lead to goal-driven pedestrian behaviour?

The modelling of purposeful and goal-directed pedestrian behaviour is realised in the CPAF by several components and their interplay. The notion of purpose or goals are introduced both in the environment model as well as in the agent model.

The goals which are viable in the chosen environment are collected in the CPAF's Global Goal Set. Goals in the CPAF can represent different kinds of purposes, which are determined by the goals' modelled parameters. A goal definition in the CPAF includes a goal category (for example "activity", "navigation" or "procedural"), parameters to indicate the importance of the goal and parameters to indicate the type of action that is required to satisfy this goal. With these parameters, it is possible to simulate different kinds of purpose, such as for example the general purpose of the environment or the purposes of facilities contained in the modelled environment.

Procedural goals are used to represent the purpose of the environment. For example in the comprehensive verification case of a railway station terminal, three procedural goals have been modelled (see Section 9.2): the goal to acquire a ticket, the goal to reach the platform well in time and the goal to board an assigned train. Depending on the realisation of such procedural goals, they may have an explicit effect on the agents' behaviour. In the example of the railway station terminal, the procedural goals have been realised such they have the highest possible importance. Therefore, the agents will always prefer satisfying these procedural goals rather than any other goal of lower importance. In addition, the goal to reach the platform on time and the goal to board the assigned train have been realised such that they determine the constraints for the agents' time keeping. The agents will hence monitor their time situation with regard to these time constraints and therefore will subordinate any other plans to meeting the given time constraints.

The goals in the CPAF's Global Goal Set constitute the goal representation in the environment model. In the agent model, these goals are mirrored by the agent's individual Agent Goal Set. The parameters of an agent goal are derived from the parameters of the associated environment goal. Especially, an agent's agent goal is assigned a determinate individual importance value, within the environment goals' importance range. This simulates the effect, that a goal or purpose can be of different individual importance to different pedestrians.

The agents in the CPAF aim to satisfy their assigned agent goals. They plan their trip in the environment such that they can satisfy as many of their initially assigned agent goals as possible, subject to their modelled familiarity with the environment. During their sojourn in the environment, the agents may become motivated to satisfy other agent goals, which have not been initially assigned to them. The agents might also decide to explore the modelled environment or even to actively seek further information in order to satisfy their assigned agent goals. When planning their activities in the environment, the agent will however always prefer to satisfy more important agent goals rather than less important agent goals. With these features of the CPAF, goal-driven and purposeful pedestrian behaviour is simulated.

10.2.2. Individual Pedestrian Decision Making

In the context of complex multi-purpose environments, how can the individual pedestrian's decision processes be represented in a pedestrian behaviour simulation?

a) How do humans draw decisions?

b) What characteristics does a decision making model require in order to enable the simulated individual pedestrian to draw informed decisions?

c) What triggers the individual pedestrian's decision making process?

d) How are the individual pedestrian's decisions related to the purposes of the complex multi-purpose environment?

The CPAF contains a sophisticated decision making component which is inspired by theories in the cognitive and behavioural human science disciplines, see Section 3.2.1 for a detailed literature review of these theories and approaches. During the literature review it has been found, that none of the main theories is applicable in every situation. Instead it appears, that humans draw decisions in different ways, depending on the characteristics of the specific decision situations. When humans can unhurriedly evaluate different choice alternatives, they often choose the optimal choice alternative for their decision problem. On the other hand, if humans need to draw a decision quickly and potentially under stress, they seem to be employing time-efficient heuristics rather than determining an optimal solution. People who are more experienced in drawing decisions in specific situations thereby tend to find more optimal solutions than unexperienced people. For these reasons, the CPAF's decision making component consists of two different decision making models. The first decision making model always finds an optimal solution to a decision problem by implementing mathematical optimisation techniques [158–160]. The second decision making model implements a time-efficient decision heuristic, the Take-the-Best decision heuristic from the Adaptive Toolbox [97].

Both decision making models realised in the CPAF require, that the different choice alternatives in a decision situation need to be both comparable amongst each other and evaluable for the agent to make the decision. Consequently, a notion of reference that the agent can refer to and a notion of decision attributes for the different choice alternatives has been introduced in the CPAF. For example, in the case that the agent needs to decide for a facility within the environment to satisfy one of their assigned agent goals, the agent will compare the different facilities based on the price range of their vended products, their brand and potentially the size of the facility. The agent will both compare the different facilities amongst each other and also compare the facilities to their individual expectations or preferences.

In the CPAF it has been postulated, that the main driving force of the agents' actions are their individual goals and needs. This postulate is in accordance with psychological science theories [4, 127–129]. In the CPAF, the agents therefore need to make decisions if and how they can satisfy their goals. The agents draw these decisions at various opportunities. They plan their trip prior to entering the simulated environment. While travelling in the environment, they can react to information they have perceived, to their external circumstances and their internal motivations. In all these situations, the agents will decide on any further actions to be taken regarding their current plans and their goals within the environment.

10.2.3. Experience and Knowledge

In the context of complex multi-purpose environments, how can individual knowledge and different levels of experience be represented in a pedestrian behaviour simulation?

a) What environmental and situational information needs to be taken into account in a pedestrian behaviour simulation in order to represent an individual pedestrian's knowledge and experience of the environment?

b) How can the process of gaining environmental knowledge and experience be represented in a pedestrian behaviour simulation?

c) How does the individual pedestrian make use of their acquired experience and knowledge and how can this be represented in a pedestrian behaviour simulation?

Since the CPAF is intended to simulate individual behaviours in a pedestrian behaviour simulation, the CPAF agents need to have an individual knowledge. This knowledge representation in the CPAF is tailored to the task that the agents are meant to exhibit purposeful behaviours and situational as well as contextual awareness within a simulated complex multi-purpose environment. Hence, the agents in the CPAF need to be aware of what they want to do, where they can achieve what they want to do and how they can achieve it. In the case of simulating pedestrians which make use of their complex multi-purpose environment, the agents would need to know what needs they want to satisfy, at which locations in the environment they can satisfy them and what they have to do once they have decided where to satisfy a given need. Hence, the individual agent's knowledge representation consists of a goal memory component – their Agent Goal Set; a spatial memory component – their Spatial Memory Set, and a memory of the agent's concrete plans – their Agent Task List.

The CPAF agents typically start their travel in the environment with a pre-defined amount of knowledge. The amount of this pre-defined knowledge that is at disposal to the individual agent depends on the case that shall be studied in a pedestrian behaviour simulation of a given environment. Therefore, the CPAF has been designed to allow for the user of the pedestrian behaviour simulation model to specify different levels of prior spatial familiarity and the availability of goals to the agent population prior to the start of the simulation. Depending on this information provided by the user, the CPAF agents are capable of both planning their trip within the environment but they may also elect to explore the environment. Their spatial memory is the agent's knowledge base when they wonder whether to take actions in order to satisfy one of their goals. The agent can evaluate information from their Spatial Memory Set with regard to goals in their Agent Goal Set, which might result in adjusting the agent's Agent Task List.

While travelling through the modelled environment, the agents are capable of completing their spatial knowledge with the CPAF's visual perception feature. The CPAF agents are also capable of developing or disregarding needs. The agent's individual Agent Goal Set is hence not fixed, but goals might be added or might become suppressed during the course of the simulation. Likewise, the agent's plans also develop over time. Some plans might be changed, when finding a better suited location; some plans might be dropped, when the agent is running out of time; or some plans might be added, when finding a location where to satisfy one of the agent's goals.

10.2.4. Situational Awareness and Contextual Behaviour

In the context of complex multi-purpose environments, how can the individual pedestrian's situational and contextual awareness be represented in a pedestrian behaviour simulation?

a) What is needed to reflect the individual agent's current situation in the individual agent in a pedestrian behaviour simulation?

b) How do humans evaluate a given situation and context?

c) How can adaptive behaviour be represented in a pedestrian behaviour simulation?

The CPAF realises situational and contextual awareness by enabling the agent to perceive the relevant information from their surrounding environment, to evaluate this information and to take appropriate actions. In this thesis, the CPAF comprises four features to simulate the situational and contextual awareness of pedestrians in complex multi-purpose environments. The first two features are the modelled awareness to population density and time pressure. The third feature is the agents' capability to relate perceived structural information to their individual needs, and the fourth feature is the agents' capability to decide to actively seek additional structural information.

The awareness to the agent's surrounding population density and their time situation is achieved in the CPAF by emotion modelling techniques. The agent periodically collects the required information from the environment and relates this information to their current individual situation. In the case of the CPAF's Urgency feature which enables the agent to monitor their time situation, the agent regularly checks the time they have got at their disposal and compares this to an estimate of how much time they need for their current remaining plans. Based on this time assessment, the agent can react and decide to alter their behaviour or even their current plans in order to still meet their time constraints. Similarly, the agent assesses the general population density in the environment and the population density around their next targeted location with the CPAF's Perceived Crowd feature. Depending on whether the level of population density has significantly risen, the agent might react to this information by deciding to assess their time situation. The aim of the time assessment is then to determine whether the heightened population density might lead to the agent being no longer capable of achieving all of their current remaining plans.

The last two features for modelling situational and contextual awareness in the CPAF are the agent's capability to react to recently perceived structural information and the capability to realise that they don't possess enough knowledge to satisfy all their goals. Upon perceiving new structural information that is relevant to the agent's current goals, the agent might decide to adjust their current plans by deciding to visit the just perceived facility rather than a previously planned facility. The agent might decide so because they prefer the just perceived facility or because the just perceived facility proves to be more convenient in terms of serving more goals than the previously planned facility. After having completed their planned tasks, the agent assesses their goal situation whether they still have unsatisfied needs. If so, the agent can decide to actively seek for further structural information as to where they can best satisfy their remaining needs.

10.2.5. Pedestrian Circulation Modelling

In the context of complex multi-purpose environments, how can the normal usage behaviour of pedestrians be represented?

a) How and on what basis do pedestrians choose their targeted facilities within complex multi-purpose environment? How can this be represented in a pedestrian behaviour simulation?

b) How and on what basis do pedestrians choose their path within a complex multi-purpose environment? How can this be represented in a pedestrian behaviour simulation?

c) How can the process of a pedestrian planning their itinerary in a normal usage scenario with multiple target locations be represented in a pedestrian behaviour simulation model?

The CPAF provides the means to assist the user in simulating normal pedestrian usage behaviour in complex multi-purpose environments. The CPAF comprises a Trip Planning feature, where the agents choose an initial route in the environment based on their assigned familiarity with the modelled environment and their initially assigned set of goals that they shall accomplish. After having planned their initial itinerary, the CPAF agents "automatically" make use of the modelled environment when travelling through the structure. This is achieved by the CPAF agents' capabilities to exhibit goal-driven behaviour together with their sophisticated decision making entity and their individual knowledge representation. Based on these fundamental features, the CPAF agents are capable to learn relevant information from the environment and to exhibit contextual and situational aware behaviour. This individual behaviour thus results in an emergent global agent population behaviour, which is logical and comprehensible at the level of each individual agent.

With the CPAF's Trip Planning feature, the agent at first evaluates all of their known facilities within the environment. They then choose those facilities which best match their individual personal preferences and their assigned agent goals. After having chosen their targeted facilities, the agents choose a connecting route. The route choice algorithm of the CPAF's Trip Planning feature thereby implements an algorithm inspired by empirical findings in research on human wayfinding performance [7, 8].

10.2.6. Alarm Response Behaviour Modelling

> *How can the influence of the individual pedestrian's previous environment usage onto the individual pedestrian's behaviour in response to an emergent alarm event be represented in a pedestrian behaviour simulation model?*
>
> *a) How can the simulation of previous environment usage under normal usage conditions help to improve the representation of the individual pedestrian's initial conditions at the time of an emergent alarm event?*
>
> *b) How can the simulation of previous environment usage under normal usage conditions help to improve the representation of the individual pedestrian's decision processes and activities after an occurred alarm event?*

The pedestrians' alarm response behaviour in a given environment is strongly dependent on the pedestrians' previous usage of the environment, their familiarity with the environment and the pedestrians' current occupation at the time of the occurred alarm event [142–144, 149]. Expert researchers have recently drawn more attention to the fact, that pedestrian circulation models and evacuation models need to be combined in order to realistically reproduce pedestrian alarm response behaviour. For example Gwynne and Kuligowski [9], Gwynne and Boswell [34] have formulated this requirement by introducing their ICE concept.

The CPAF provides the basic information to simulate such a transition from an earlier normal circulation phase to an evacuation simulation of the modelled environment. For the purpose of demonstrating how the CPAF can be used to inform an evacuation simulation, an experiential alarm response behaviour has been incorporated in the buildingEXODUS CPAF Plug-in.

The buildingEXODUS CPAF Plug-in allows to simulate the direct transition from a normal usage scenario simulation to an evacuation simulation of the environment in question. By enabling such a direct transition, the initial conditions of the ensuing evacuation simulation are a direct result of the agents prior behaviour. As such, the agents' locations within the environment at the time of the emergent alarm event as well as their familiarity with the environment and the activities with which they are occupied don't need to be explicitly modelled by the user but can be inferred from the normal usage simulation.

In the buildingEXODUS CPAF Plug-in's response behaviour model, the agent makes use of their individual knowledge of the structure when choosing a suitable target exit in the case that an alarm event has occurred. The exit choice thereby distinguishes between those exits known to the agent by prior experience and those exits which have been learned by the agent during their travel in the environment. Some of the learned exits may have been forgotten by the time of the alarm event, some may have recently been perceived. This information is provided in the CPAF's agent knowledge model. From the agent's known exits and under consideration of the known information's different levels of reliability, the agent is capable of making an informed exit choice by using the CPAF's sophisticated decision making entity.

Furthermore, the buildingEXODUS CPAF Plug-in provides three Response Phase Models to simulate the actual alarm response behaviour of the individual pedestrian. In the most simple response phase model, the user can specify both the amount of time required by the agent to initiate their evacuation and the activities that the agent performs during their response phase. In the second response phase model, the user can again specify the agents' response time distribution, but in this model, the activities that the agent performs prior to initiating their evacuation are determined from the agent's current plans at the time of the alarm event. Finally, the third response phase model determines both the agent's response time and their pre-evacuation activities depending on the agent's current plans at the time of the alarm event. The buildingEXODUS CPAF Plug-in's Response Phase Models only model limited options for the agents pre-evacuation activities. However, the models illustrate the buildingEXODUS CPAF Plug-in's concept of how information from an earlier environment usage and information about the individual agent's situation at the time of the alarm event can be used to adequately inform a subsequent evacuation simulation.

10.3. Conclusion

The Cognitive Pedestrian Agent Framework (CPAF) proposes a holistic pedestrian agent model to replicate advanced pedestrian behaviour such as purposeful behaviour, human cognition as well as adaptive behaviours to the surrounding conditions. With the CPAF it is hence possible to study pedestrians interacting with their surrounding environment. Although some of these behaviours have already been implemented into some pedestrian behaviour simulation tools, no other pedestrian behaviour simulation did realise these behaviours in a comprehensive and consistent agent model.

In order to achieve this, the CPAF has been designed to combine concepts from various research disciplines such as psychology, human behaviour research, artificial intelligence and virtual reality simulations. The concepts that the CPAF comprises have been chosen to be either empirically proven in human behaviour research or to be well-established in the respective research domain. Several new insights have been incorporated in the CPAF that no other current pedestrian behaviour simulation represents:

1. a comprehensive decision making model,
2. a regional-based wayplanning heuristic,
3. the effect of forgetting of learned information,

4. different levels of experience.

The CPAF has been designed by using a bottom-up approach for modelling pedestrian behaviour. Most other pedestrian behaviour simulation tools employ a top-down modelling approach, where collected data is used to inform and calibrate the model in order to reproduce the observed behaviour. With the bottom-up approach used for the CPAF, reproducing a specific set of empirical pedestrian behaviour data is more difficult. The CPAF has been designed to be parameterisable to a high degree, see Table 8.1. The CPAF allows to freely define: the goals of interest in the environment; the set of goal location feature attributes and the corresponding set of personal preference agent attributes; the agent motivation functions; the agents' previous experience with the environment; and thresholds relating to the CPAF's emotion model. When trying to reproduce empirical pedestrian data, information on how to set these parameters is needed in order to correctly parameterise the CPAF. As such, the strengths of the CPAF lie more in simulating the general pedestrian behaviour in a given environment rather than correctly replicating a specific observation of pedestrian behaviour.

10.4. Future Work

This section comprises suggestions for future work regarding the Cognitive Pedestrian Agent Framework (CPAF) proposed in this thesis. Suggestions for further development and extensions of the CPAF itself are described, but also suggestions for further research in the field of pedestrian behaviour simulation in general, motivated by the work presented in this thesis.

10.4.1. Extending the Cognitive Pedestrian Agent Framework's Emotion Representation

In the current verion, the CPAF realises a limited set of so called emotions, meaning the agent's ability to assess and react to external stimuli. Depending on the actual case to be studied, it may be of interest to add other emotions to the CPAF.

An example for a useful emotion which has not been integrated in this thesis' version of the CPAF could be boredom. In the case of simulating a long-distance traffic facility, pedestrians might get into the situation that they have completed all of their planned activities, but they still have an ample amount of time until their scheduled departure. In this situation, pedestrians might decide to engage in activities with the simple goal to "pass some time". Such activities might include going for window shopping, browsing through a random shop, going to a coffee shop or sitting down someplace and read. When choosing their "pass some time" activity, the pedestrian might check the state of their motivations. For example if the pedestrian isn't hungry, but might have a slight appetite, they will probably be more likely to choose to go to a coffee shop to pass their time.

10.4.2. Modelling Agenda Re-Scheduling in the Cognitive Pedestrian Agent Framework

In the current version of the CPAF, the agent is capable of adding new plans to their current agenda, of dismissing plans and of altering existing plans. An area for future research might be how advanced agenda re-scheduling might be incorporated in the CPAF. For example in some situations, the agent might elect to rearrange the order of their current plans.

10.4.3. Study of Real-World Use Cases

An important part of the development of pedestrian behaviour simulation tools is to verify or calibrate the modelled features [66, 161–164]. A bottom-up approach has been used for ensuring the validity of the CPAF: the CPAF's individual components have been designed such that they are either flexibly parameterisable or based on existing models and theories. Those components of the CPAF which are parameterisable are summarised in Table 8.1. It is hence the task of the user to choose appropriate model parameters for the study of their intended use case to appropriately inform the CPAF. On the other hand, the remaining components of the CPAF which are not parameterisable are summarised in Table 10.1. These components of the CPAF are all based on suitable models found in the literature or in other pedestrian behaviour simulation models. The models have been chosen to be themselves validated on empirical data on human performance.

Table 10.1.: Non-parameterisable components of the Cognitive Pedestrian Agent Framework.

CPAF Component	Entity	CPAF Model Basis
Knowledge Model	Short Term Memory	Generic Memory Model of the ACT-R Cognitive Architecture
Decision Making Model		Review of Human Decision Making Theories
Visual Perception Model		buildingEXODUS Exit Signage Model
Stimuli Representation	Urgency Model	buildingEXODUS Urgency Model
Usage-Cycle Simulation	Human Path Planning Heuristic	Theories of Wiener et al. [7], Tenbrink and Wiener [8]

The interplay of the various CPAF components has been demonstrated and discussed in a comprehensive use case of a railway station terminal, see Chapter 9. In addition to this demonstration, it would however be desirable in future to further apply and assess the CPAF in real-world use cases and based on real-world data.

For such future application studies, the parameters required to inform the CPAF would need to be acquired. These parameters can be obtained by observing pedestrian behaviour in the desired complex multi-purpose environment and thereby collect information about the nature of the agent population, the main characteristics of the environment, the pedestrians' goals in visiting the environment and the pedestrians' entry and exit points. In addition to this required input data, data on the pedestrians' building usage needs to be collected, for example using video footage or counting the pedestrians entering and leaving the environment's facilities. This usage data can then be compared to the outputs of a pedestrian behaviour simulation tool which incorporates an implementation of the proposed CPAF.

10.4.4. Goal-Driven and Cognitive Social Behaviour

The CPAF aims to simulate goal-driven cognitive individual pedestrian behaviour. The agent does behave in accordance with their own goals, agenda and preferences. An area for future research may be to extend the proposed framework to include social and group behaviours. Possible real-life scenarios to be researched could include

- Groups of pedestrians (families, friends, couples) who visit an environment together, but split up during their travel in the environment and later re-unite.
- Pedestrians enquiring other pedestrians or members of staff for further information.
- Pedestrians following other pedestrians, for example when they are observing a large crowd within a store.

Appendix

Appendix A:

Mathematical Notations and Derivations of Model Parameters

A.1. Probability Distributions

Discrete Uniform Distribution $\mathcal{U}(\mathfrak{X})$

Let $\mathfrak{X}$ be a non-empty discrete constraint set of size $n \in \mathbb{N}$. The Discrete Uniform Distribution $\mathcal{U}(\mathfrak{X})$ on the set $\mathfrak{X}$ is given by its probability density function:

$$f_{\mathcal{U}(\mathfrak{X})} \colon \mathfrak{X} \to [0,1], \qquad f_{\mathcal{U}(\mathfrak{X})}(x) := \frac{1}{n} \tag{A.1}$$

Continuous Uniform Distribution $\mathcal{U}([x_{min}, x_{max}])$

Let $x_{min}, x_{max} \in \mathbb{R}$ be given real numbers. The Continuous Uniform Distribution $\mathcal{U}([x_{min}, x_{max}])$ on the interval $[x_{min}, x_{max}]$ is given by the probability density function:

$$f_{\mathcal{U}([x_{min},x_{max}])} \colon [x_{min}, x_{max}] \to [0,1], \qquad f_{\mathcal{U}([x_{min},x_{max}])}(x) := \frac{1}{x_{max} - x_{min}} \tag{A.2}$$

Normal Distribution $\mathcal{N}(\mu, \sigma^2)$

Let $\mu \in \mathbb{R}, \sigma \in \mathbb{R}^+$ be given real numbers. The Normal Distribution $\mathcal{N}(\mu, \sigma^2)$ with mean μ and variance σ^2 on the real numbers is given by the probability density function:

$$f_{\mathcal{N}(\mu,\sigma^2)} \colon \mathbb{R} \to [0,1], \qquad f_{\mathcal{N}(\mu,\sigma^2)}(x) := \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) \tag{A.3a}$$

$$F_{\mathcal{N}(\mu,\sigma^2)} \colon \mathbb{R} \to [0,1], \qquad F_{\mathcal{N}(\mu,\sigma^2)}(x) := \int_{-\infty}^{x} f_{\mathcal{N}(\mu,\sigma^2)}(x) \tag{A.3b}$$

Log-Normal Distribution $\mathcal{L}(\mu, \sigma^2)$

Let $a\mu \in \mathbb{R}, \sigma \in \mathbb{R}^+$ be given real numbers. The Log-Normal Distribution $\mathcal{L}(\mu, \sigma^2)$ on the real numbers with mean $\exp(\frac{\mu+\sigma^2}{2})$ and variance $\exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)$ is given by the probability density function:

$$f_{\mathcal{L}(\mu,\sigma^2)}\colon\ \mathbb{R} \to [0,1], \qquad f_{\mathcal{L}(\mu,\sigma^2)}(x) := \begin{cases} 0 & \text{if } x \leq 0 \\ \frac{1}{\sqrt{2\pi}\sigma}\frac{1}{x}\exp\left(-\frac{1}{2}\left(\frac{\ln x-\mu}{\sigma}\right)^2\right) & \text{if } 0 < x \end{cases} \tag{A.4}$$

The cumulative distribution function is given by:

$$F_{\mathcal{L}(\mu,\sigma^2)} = \frac{1}{2} + \frac{1}{2}\mathrm{erf}\left(\frac{\ln x - \mu}{\sqrt{2\pi}\sigma}\right) \tag{A.5}$$

Log-Normal Distribution on limited support $(0,a]$ $\mathcal{L}_{[0,a]}(\mu,\sigma^2)$
Let $\mu \in \mathbb{R}, \sigma, a \in \mathbb{R}^+$ be given real numbers. The Log-Normal Distribution on the interval $[0,a]$ $\mathcal{L}_{[0,a]}(\mu,\sigma^2)$ is given by the probability density function

$$\begin{aligned} f_{\mathcal{L}_{[0,a]}(\mu,\sigma^2)} &: \quad \mathbb{R} \to [0,1], \\ f_{\mathcal{L}_{[0,a]}(\mu,\sigma^2)}(x) &:= \begin{cases} (F_{\mathcal{L}(\mu,\sigma^2)}(a))^{-1} f_{\mathcal{L}(\mu,\sigma^2)}(x) & \text{if } x \in [0,a] \\ 0 & \text{else} \end{cases} \end{aligned} \tag{A.6}$$

A.2. Mathematical auxiliary definitions

Identity Function
The identity function on a set $\mathfrak{X}$:

$$\mathbb{1}_{\mathfrak{X}}(x) := \begin{cases} 1, & \text{if } x \in \mathfrak{X} \\ 0, & \text{if } x \notin \mathfrak{X} \end{cases} \tag{A.7}$$

p-Norm
The p-Norm function $\|.\|_p$ on the vector space $\mathbb{R}^n$ is defined as:

$$\|.\|_p\colon\ \mathbb{R}^n \to \mathbb{R}_0^+, \quad \|x\|_p := \sqrt[p]{\sum_{i=1}^{n} x_i^p} \tag{A.8}$$

Sequence Set
Let $\mathfrak{X}$ be a discrete constraint set and let $n := |\mathfrak{X}|$ denote its quantity. The **sequence set** $\mathfrak{S}(\mathfrak{X})$ of the set $\mathfrak{X}$ is defined as the set of all possible permutations of all elements in $\mathfrak{X}$:

$$\mathfrak{S}(\mathfrak{X}) := \{(x_1,\ldots,x_n) \in \mathfrak{X}^n \mid x_i \neq x_j \text{ for } i \neq j\} \tag{A.9}$$

A.3. Derivations of chosen simulation parameters

A.3.1. Recall Probability

The ACT-R theory (see Sections 3.1 and 3.1.1.3 for a detailed review), proposes – amongst others – a sophisticated declarative human memory model, which has been motivated by and tested on a large number of empirical human memory performance data [86, 112].

As described in Anderson et al. [3], the ACT-R's declarative memory module is designed to fit in the holistic ACT-R cognitive architecture. Therefore, the cognitive access to the model's memory module is achieved by an interconnected memory buffer which can process a single memory unit, a so called *chunk*, at a time. In order to retrieve a suitable memory chunk and further process and interpret this memory with the underlying procedural module, one memory chunk needs to be chosen from all available memory chunks within the declarative memory module. The ACT-R theory proposes, that memory chunks are compared on basis of their *activation*, i.e. the more "active" a given memory chunk is, the more likely it is to be chosen. As has been pointed out by Anderson et al. [86], the activation model for memory chunks reproduces empirical human memory performance data to a high degree upon proper model set-up. For this reason, it has been decided to model the CPAF's short-term spatial memory functionality with the help of the ACT-R activation concept.

In the ACT-R theory as proposed by Anderson et al. [3, 86], the activation A_i of a memory chunk i is given by the formula:

$$A_i = B_i + \sum_j W_j S_{ji} \tag{A.10}$$

where B_i is the chunk's base level activation and for each element j that is associated to the chunk i, the value W_j depicts the element's attentional weight and S_{ji} the strength of association from element j to the memory chunk i [3].

The base-level activation of a chunk memory i is dependent upon the individual's history with the memory chunk i in terms of time. In the ACT-R, it is postulated that the impact of an experienced memory falls with the amount of time since the last time that the memory has been called to mind. But not only the latest time that the memory has been accessed is taken into consideration, but all encounters, thereby not only modelling the retention of a memory but also the effects of training and gaping [86]. Thereby, the base-level activation of a memory chunk i is given by the formula:

$$B_i = \ln \left(\sum_{j=1}^{n} \frac{1}{\sqrt{t_j}} \right)$$

where n denotes the number of the sources of activation, i.e. encounters, of the memory chunk and t_j for $1 \leq j \leq n$ denote the time since the j-th encounter.

The activation's attentional weight W_j and the strength of association S_{ji} are in general set such that:

$$W_j = \frac{1}{n}, \qquad S_{ji} = 2 - \ln(fan_j)$$

where fan_j denotes the number of facts associated to the element j [3].

With this definition of the activation A_i, the probability of recalling the memory chunk i is then set to:

$$P_i = \frac{1}{1 + e^{\frac{A_i - \theta}{0.4}}}$$

for a threshold θ [3].

The ACT-R's activation model can be applied to the specific situation of modelling the goal-related spatial memory of agents in the CPAF. In terms of the spatial memory which is incorporated in the CPAF, a memory chunk is of the form:

"the goal location l can satisfy the set of goals $\mathfrak{G}$"

The chunk's elements of consideration are thereby the goal location l and the agent goal set $\mathfrak{G} \subseteq$ AGS.

In the specific situation of the goal-related spatial memory model for agents, the base-level activation at simulation time τ of the memory chunk "the goal location l can satisfy the set of goals $\mathfrak{G}$" is simply given by the formula:

$$B(l, \tau) = \ln\left(\sum_{j=1}^{n} \frac{1}{\sqrt{T_j(l, \tau)}}\right), \quad \text{where } T_j(l, \tau) := \tau - \tau_{perc}(l, j) \text{ for } 1 \leq j \leq n$$

Hereby denotes $\tau_{perc}(l, j)$ the absolute simulation time that the goal location l has been perceived for the j-th time.

Since the elements of the memory chunk "the goal location l can satisfy the set of goals $\mathfrak{G}$" are the goal location l and the agent goals $g \in \mathfrak{G}$ within the agent goal set $\mathfrak{G}$, the strength of association S_l respectively S_g for $g \in \mathfrak{G}$ are given by determining the number of known facts fan_l respectively fan_g.

For the element of the goal location l, the relevant facts about this memory element are the goals that can be satisfied at the given location, $\mathfrak{G}(l)$. Therefore, it is $S_l = |\mathfrak{G}(l)|$. Similarly, for each $g \in \mathfrak{G}$ it is $S_g = |\mathfrak{L}^{\mathrm{M}}(g)|$.

In conclusion, the activation of the memory chunk "the goal location l can satisfy the set of goals $\mathfrak{G}$" at the simulation time τ is given by

$$\begin{aligned}
&A(l,\tau,\mathfrak{G}) \\
&= \ln\left(\sum_{j=1}^{n}\frac{1}{\sqrt{T_j(l,\tau)}}\right) + \frac{2\cdot(|\mathfrak{G}|+1)}{n} - \frac{1}{n}\left[\ln(|\mathfrak{G}(l)|) + \sum_{g\in\mathfrak{G}}|\mathfrak{L}^{\mathrm{M}}(g)|\right] \\
&= \ln\left(\sum_{j=1}^{n}\frac{1}{\sqrt{T_j(l,\tau)}}\right) - \frac{\ln(|\mathfrak{G}(l)|)}{n} + \frac{1}{n}\left[2\cdot(|\mathfrak{G}|+1) - \sum_{g\in\mathfrak{G}}|\mathfrak{L}^{\mathrm{M}}(g)|\right] \qquad \text{(A.11)}
\end{aligned}$$

Following the ACT-R theory, the probability of recalling this memory chunk is thereby:

$$P(\tau,\mathfrak{G}) = \frac{1}{1+e^{-\frac{5}{2}A(\tau,\mathfrak{G})}} \qquad \text{(A.12)}$$

where the probability threshold θ has been set to zero in this thesis due to default of appropriate human performance data.

A.3.2. Wait Task Termination Time

Situation

Determine a time τ_{term} to terminate a critical time task with originally assigned critical time τ_{wait} after an alarm has been operated at time τ^{Alarm}, where:

$$\tau^{\mathrm{Alarm}} \leq \tau_{term} \leq \tau_{wait}$$

Define the task's originally remaining duration as:

$$T_{wait} := \tau_{wait} - \tau^{\mathrm{Alarm}}$$

and further the task's remaining duration to be set as:

$$T := \tau_{term} - \tau^{\mathrm{Alarm}}$$

Problem

Model T as a random variable which is distributed according to a log-normal distribution:

$$T \sim \mathcal{L}(\mu,\sigma^2)$$

The parameters μ and σ are to be chosen such that the distribution is centred around a quarter of the originally remaining duration T_{wait} and such that the probability that T

differs from its mean value μ_T by more than μ_T is less than $\frac{1}{4}$:

$$P\left(|T - \mu_T| \geq \mu_T\right) \leq \frac{1}{4}$$

With the Chebyshev's inequality, this leads to the following conditions on the mean μ_T and standard deviation σ_T of T:

$$\mu_T = \tfrac{1}{4} \cdot T_{wait} \tag{A.13}$$
$$\sigma_T = \tfrac{1}{2} \cdot \mu_T \tag{A.14}$$

Solution
In general, for the log-normal distributed random variable $T \sim \mathcal{L}(\mu, \sigma^2)$, the distribution parameters of T are given in terms of the parameters μ and σ by:

$$\begin{aligned} \mu_T &= e^{\mu + \frac{\sigma^2}{2}} \\ \text{median}(T) &= e^{\mu} \\ \text{var}(T) = \sigma_T^2 &= e^{2\mu+\sigma^2}(e^{\sigma^2} - 1) \\ \text{mode}(T) &= e^{\mu - \sigma^2} \end{aligned}$$

Let ξ denote the median of T and let η denote the ratio of the median of T and its mode:

$$\xi := \text{median}(T) = e^{\mu}, \qquad \eta := \frac{\text{median}(T)}{\text{mode}(T)} = e^{\sigma^2}$$

From the definition of ξ and η, it can be seen that:

$$\xi > 0 \quad \text{and} \quad \eta > 1$$

With these definitions, the mean μ_T and variance σ_T^2 of T can then be expressed in terms of ξ and η:

$$\mu_T = \xi\sqrt{\eta} \tag{A.15}$$
$$\sigma_T^2 = \xi^2\eta(\eta - 1) \tag{A.16}$$

As a result, Equations (A.15) and (A.16) together with Condition (A.14) lead to:

$$\tfrac{1}{2}\xi\sqrt{\eta} \overset{\substack{\text{(A.14),}\\ \text{(A.15)}}}{=} \sigma_T \overset{\substack{\text{(A.16),}\\ \xi>0}}{=} \xi\sqrt{\eta(\eta - 1)}$$

Since $\xi > 0$ and $\eta > 1$, this is equivalent to:

$$\tfrac{1}{2}\xi\sqrt{\eta} = \xi\sqrt{\eta}\sqrt{\eta - 1} \iff \tfrac{1}{4} = \eta - 1 \iff \eta = \tfrac{5}{4}$$

Substituting in the definition of η leads to:

$$\sigma^2 = \ln\left(\tfrac{5}{4}\right) \tag{A.17}$$

With the obtained solution for η, it follows that

$$\begin{aligned}
\mu &= \ln \xi \\
&\overset{(A.15)}{=} \ln\left(\frac{\mu_T}{\sqrt{\eta}}\right) \\
&\overset{(A.13)}{=} \ln\left(\tfrac{1}{4}T_{wait}\right) - \ln\left(\sqrt{\tfrac{5}{4}}\right) \\
&= \ln(T_{wait}) - \ln\left(2\sqrt{5}\right) \qquad \text{(A.18)}
\end{aligned}$$

Appendix B:

The Cognitive Pedestrian Agent Framework Scenario Specification Generator

The Cognitive Pedestrian Agent Framework Scenario Specification Generator (CPAF-SSG) is a dialog-based graphical user interface to retrieve required simulation parameters for the buildingEXODUS CPAF Plug-in, see Table 8.1 for an overview of which parameters are needed to inform the generic CPAF.

The parameters acquired with the CPAF-SSG are fed into buildingEXODUS as a Scenario Specification File, see Section 4.2. From this Scenario Specification File, buildingEXODUS generates an agent population which is then further adjusted by the buildingEXODUS CPAF Plug-in. Furthermore, the buildingEXODUS CPAF Plug-in uses the provided parameters to build its advanced environment model and realise the usage-cycle simulation of the modelled environment.

The CPAF-SSG lets the user specify for each goal in the Global Goal Set (Section 5.2.2) the proportion of the agent population that will be assigned the corresponding agent goal during the simulation initialisation phase, see Section 6.2. A screenshot of the dialog can be found in Figure B.1. In the current implementation of the buildingEXODUS CPAF Plug-in and the CPAF-SSG, the number and type of the goals included in the buildingEXODUS CPAF Plug-in's Global Goal Set are fixed. This implementation has been sufficient for the purpose of this thesis. However, it would be desirable to enhance the buildingEXODUS CPAF Plug-in and the CPAF-SSG to be able to freely generate any desired goal.

As has been described in Section 5.2.3, the second important part of the CPAF's environment model are so called goal locations. The CPAF-SSG assists the user in setting up their goal location environment in the buildingEXODUS CPAF Plug-in. Therefore, the CPAF-SSG is capable of parsing buildingEXODUS's .MAT geometry files to extract compartment zones and relevant nodes from a given buildingEXODUS geometry. The user can then categorise the extracted zone information. Subsequently, the CPAF-SSG allows for setting the Goal Location Feature Attributes $F(l)$ for each identified goal location l, see

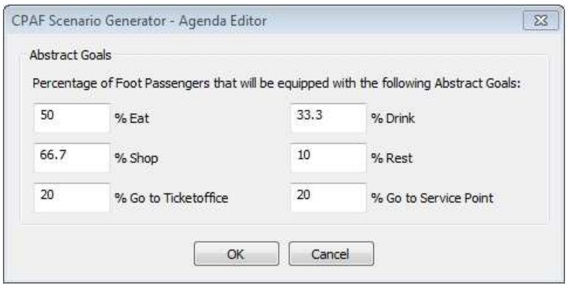


Figure B.1.: The “Agenda Editor” dialog of the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

Figure B.2 for a screenshot of the CPAF-SSG dialog.

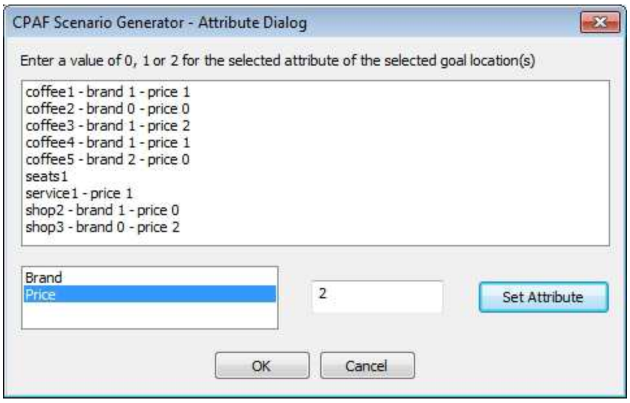


Figure B.2.: The “Goal Location Features” dialog of the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

The CPAF-SSG assists the user in setting up the required agent population parameters for the buildingEXODUS CPAF Plug-in. A screenshot of the CPAF-SSG’s “Population Editor” dialog is depicted in Figure B.3. The user can specify the size of the agent population to be simulated, the prior spatial knowledge distribution (see Section 6.2.1), the distribution of the agents’ personal preferences P (see Section 5.3.1) as well as the minimum and maximum threshold for the distribution of the agents’ Perceived Crowd Threshold C^{*} (see Section 5.6.2.1).

Using the CPAF-SSG, the user can elect to enable or disable selected features of the buildingEXODUS CPAF Plug-in, see Section 8.1.3 and Table 8.4 for an overview of the buildingEXODUS CPAF Plug-in feature interdependencies. When the user elects to simulate an occurred alarm event using the buildingEXODUS CPAF Plug-in’s Alarm Response Feature, they can choose between the buildingEXODUS CPAF Plug-in’s three possible Alarm Response Phase Models, see Section 7.2. Depending on the chosen Alarm Response Model, the user further needs to specify the parameters required for the model’s simulation. The parameters that need to be specified depend on the chosen model. The CPAF-SSG therefore assists the user in inputting the parameter. For example see Figure B.4 for a screenshot of the CPAF-SSG’s “Evacuation Scenario” setup dialog, where the use has chosen the Imposed-

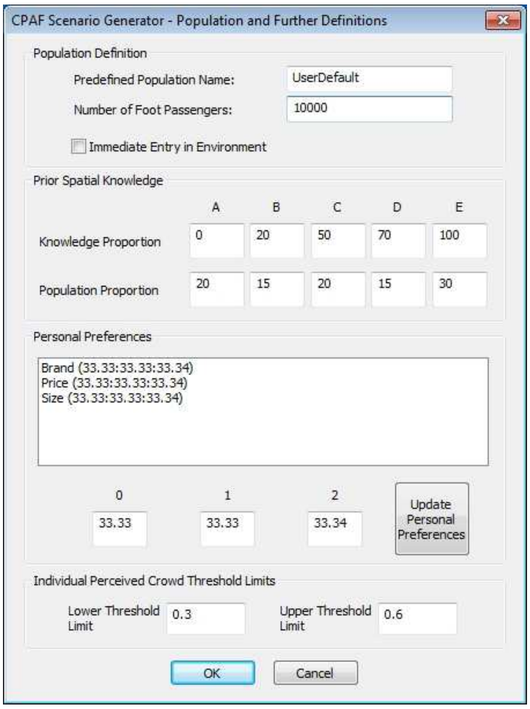


Figure B.3.: The "Population Editor" dialog of the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

Time Predicted-Activities Response Phase Model.

For this thesis' comprehensive verification case of a train station terminal (see Chapter 9), it had been required to setup a train schedule and assign agents to particular trains of this simulated train schedule. This task has also been realised with the CPAF-SSG, see Figure B.5 for a screenshot of the CPAF-SSG's "Departure Schedule" dialog.

The CPAF-SSG allows for an easy specification of a train schedule. Afterwards, it assigns the agent population (the "foot passengers") to the specified trains based on a random distribution. This random distribution is thereby given by the distribution of "train passengers" that arrive at the simulated environment on the train in question. This feature of the CPAF-SSG is generic and can be used to facilitate the setup of other long-distance traffic facilities, such as for example airports, or to setup environments where there are only specific exit routes to be taken.

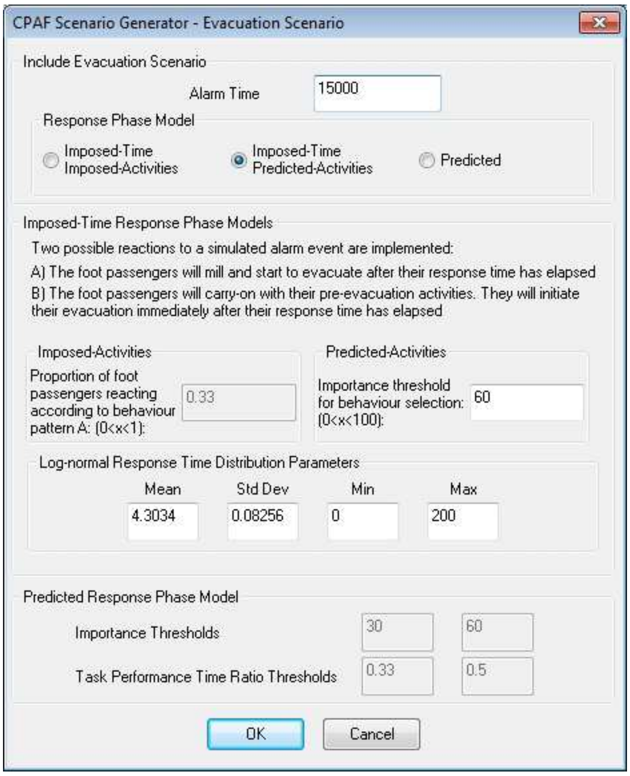


Figure B.4.: The "Evacuation Scenario" dialog of the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

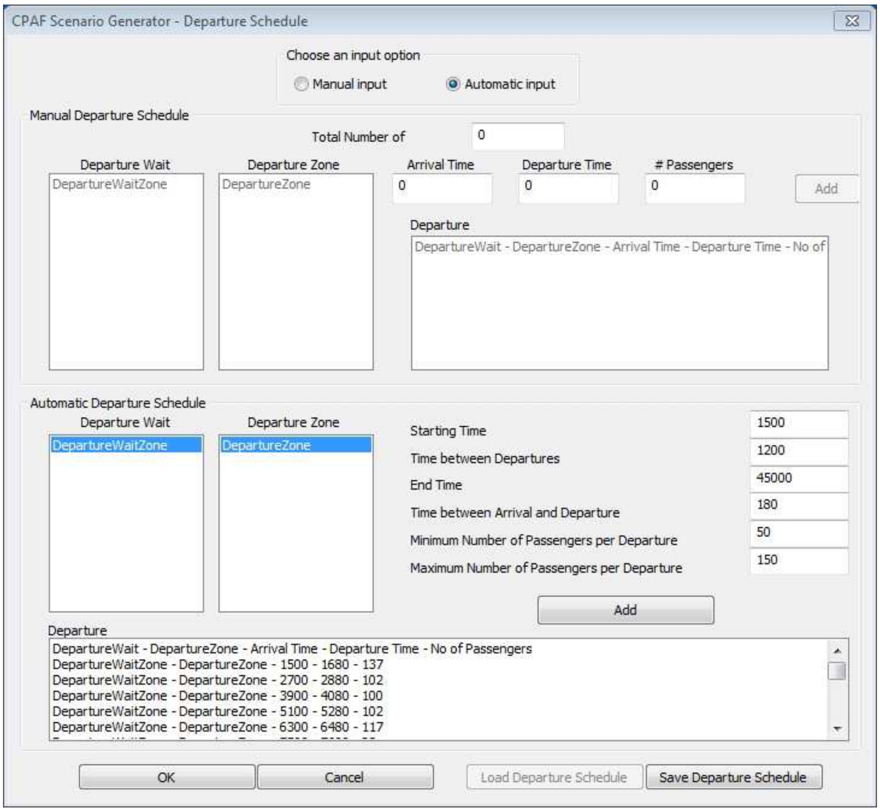


Figure B.5.: The "Departure Schedule" dialog of the Cognitive Pedestrian Agent Framework Scenario Specification Generator.

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