Effect of Human-Robot Interaction on the Fleet Size of AIV Transporters in FMS

Lancelot Martin
Faculty of Engineering and Science
University of Greenwich
Chatham, UK
Lancelot.Martin@greenwich.ac.uk

Mario González-Romo
College of Engineering
Mathematics and Physical Sciences
University of Exeter
Exeter, UK
m.j.gonzalez-romo@exeter.ac.uk

M'hammed Sahnoun
LINEACT/CESI
Research Department
Saint-Etienne-du-Rouvray, France
msahnoun@cesi.fr

Belgacem Bettayeb
LINEACT/CESI
Research Department
Lille, France
bbettayeb@cesi.fr

Naihui He
College of Engineering
Mathematics and Physical Sciences
University of Exeter
Exeter, UK
n.he@exeter.ac.uk

James Gao
Faculty of Engineering and Science
University of Greenwich
Chatham, UK
J.Gao@greenwich.ac.uk

***Abstract*—The execution of material handling tasks using *autonomous guided vehicles* (AGVs) has proven a real success during the last decade. Nevertheless, the installation of AGVs is costly as it needs to modify the workshop's configuration by defining dedicated movement zones. Recently, more flexible and collaborative mobile robots known as *autonomous intelligent robots* (AIV) can be used in manufacturing systems. This new generation of intelligent mobile robots does not need specific zones and can interact with unexpected or mobile obstacles such as human operators. This paper focuses on AIV fleet size definition in a variable and unexpected environment with humans while keeping AIV assigned transportation tasks on time. A simulation that model the complexity of the AIV travel time estimation under the mentioned circumstances and the improvement brought by IoT, Big Data and sensors by using them as the real-time data source is developed.**

***Index Terms*—Industry 4.0, Industry 5.0, Fleet management optimization, Simulation, Human operator behavior, Scheduling**

I. Introduction

The term Industry 5.0 refers to people working alongside robots and smart machines. It's about robots helping humans work better and faster by leveraging advanced technologies like the Internet of Things (IoT) and big data. It adds a personal human touch to the Industry 4.0 pillars of automation and efficiency. Industry 5.0 aims at centering the human into highly digitized industrial organizations. It creates a human-centered environment where painful and non-added value tasks are automated. Humans are then working alongside robots and smart machines [1].

A material handling system is an essential component in any production system, especially in *flexible manufacturing systems* FMS. Designing and managing automation components in material handling systems play an important role to improve the whole manufacturing system. Relevant issues in the designing and management of facilities using *automated guided vehicles* AGVs as material handle units are classified in the areas of guide-path design, estimation of the required number of vehicles, vehicle scheduling, idle-vehicle positioning, vehicle-battery management and vehicle with conflict-free routing [2].

When humans in a production environment share transportation paths with mobile robots, the material handling system are affected. This problem is more to happen in FMS or legacy manufacturing systems that might be considering upgrading into a flexible approximation to the current and future market demand. Therefore, the idea is to analyze human density traffic on shared paths to find the optimal number of AGVs working under these circumstances. Another reason to include a relationship between the number of AGVs and human density traffic is that AGVs are costly factory assets; they need to be used in both functional and safety best operative capacities, especially if working alongside humans. Also, considering human density traffic in material handling systems gives a more realistic approximation to develop, implement, upgrade, and model productions systems in the current and next-generation industry. Finally, this problem is not yet documented as more of the traffic conflict studied issues only see the traffic due to factories' layouts path configuration and other mobile robots as a traffic source.

Current advances in technologies provide *simulation platforms* that model or implement industrial schemes as a first aid to analyse industrial problems quickly. Thus, to calculate the

This research was made possible thanks to €2.6 million financial support from the European Regional Development Fund provided by the Interreg V France Channel England Programme in context of CoRoT Project

optimal number of AGVs in a handling system under human density traffic condition, an initial analysis using the Netlogo simulation software platform with the Netlogo's System Dynamics Library is completed. The Netlogo is a programmable modelling environment well suited for modelling complex system and operations; it based on *agent-based modelling* (ABM) philosophy providing tools to design digital factories with detailed models to implement production and storage facilities and manage material workflows.

In this work, a relationship between the estimated number of optimal AGVs and conflict-free routing problem incorporating human density traffic to fulfil the production plan is investigated.

II. Literature review

Estimating the optimal number of AGVs is a complex task related to two main problems; the *integrated scheduling of machines and AGVs problem* and the *conflict-free vehicle routing problem* (CFRP) [3], [4]. The first problem, the integrated scheduling of machines and material transport; performance with the number of AGVs is estimated using measured parameters such as *vehicle travel time*, *vehicle utilisation*, *queue length*, and *material handling cost*. Most of the integrating scheduling of machines and vehicles research has the main objective to process all tasks on time with a sufficient number of vehicles while minimising the *makespan* [5].

On the other hand, one of the most reported used technique is the Djakarta algorithm combined with a time window to solve the CFRP. Thus the problem is divided into two stages: scheduling and routing. According to [6], if the problem is divided into two parts, the minimal number of AGVs can be determined by the development of a job-task heuristic assignment module for AGVs; the heuristic methodology takes into consideration all available AGVs and dispatches the necessary ones so that transportation order is performed given a maximum order fulfilment time in a specific time-window [7]. The initial and consecutive number of AGVs is calculated for each job routing as the round integer number to the nearest integer above the current value of the ratio between the total time spent by an AGV to perform all job tasks (order fulfilment) and the time spent by each job task. The job scheduling task (AGV assignment task) is implemented by the heuristic of the shortest job first (SJF) or the Tabu search meta-heuristic algorithm. Both algorithms are later compared without a straightforward winning. A downside in this approximation is that the routing part calculates all the routes, which minimise the cost and number of maneuvers to be executed by the AGVs without considering collisions and dead-lock between mobile robots. Thus, it is only valid for pre-planning stages where a particular task and relocating activities are generally known in advance as in the static case [8].

Analytical methods to find the optimal number of AGVs are studied in [9]. Researchers concluded that the analytical methods under analysis lead to underestimate or overestimate the numbers of AGVs making the analytical methods suitable for an initial estimation of the number of AGVs.

Statistical analysis using regression analysis to determine the vehicle requirements in an automated material handling system is presented in [10]. In this analysis, the number of required vehicles is based on the most statistical influencing parameters for a given production facility such as the number of production machines, total vehicle routing distance, job shop's layout number of intersection and number of nodes, maximum machine utilisation, total loaded and empty vehicle travel distance and layout complexity. Overall results showed that the developed model obtains reliable predictions on the number of AGVs required in a production facility.

Less research integrates AGVs tasks assignments and AGVs *routing* for estimation of the optimal number of AGVs. In [11], an approach to solving the integrated scheduling problems considering the optimal number of AGVs with a conflict-free routing in an FMS production environment is presented. To find the optimal number of AGVs, with the shortest transportation time, a path planning problem, and a conflict-free routing problem (CFRP) simultaneously, researchers propose a genetic algorithm combined with the Dijkstra algorithm that is based on a time window.

Modelling and Simulation using a stochastic method to find the optimal number of AGVs with vehicle positioning, dispatching, routing and charging is presented in [12]. Researchers proposed a two-stage simulation optimisation mechanism where simulation models with different charging system are constructed using FlexSim simulation software. By applying a *global metamodel-based optimisation* such as *response surface methodology* (RSM), the obtained responses on the AGV utilisation and throughput are optimised. Sahnoun et al [13] proposed a simulation based approach to define optimal AGV fleet size where mobile robots reduce their speed in traffic jam. Another methodology to analyse, implement and simulate complex systems is the ABM. ABM methodology can model the system's components-interactions as a dynamic *system of interacting agents* [14], [15]. According to [16], an *agent* is an encapsulated computer system situated in some environment, capable of flexible, autonomous action in that environment to meet its design objectives. More simulations tools and methodologies on scheduling algorithms and routing problems while optimizing the number of AGVs are described in [5].

III. Problem description

This paper tackles the problem of determining the optimal number of AIVs in an open environment where humans and robots share the same traffic space, with the objective of minimizing the total tardiness of transportation tasks. Intelligent mobile robots have several possible paths to transport and reach a given destination; path selection is usually based on a priority rule of shortest transportation time, i.e., the path requiring minimum transportation time will be given the highest priority. Assumptions in the simulation model are: first, an intelligent robot travels at a constant speed and it stops for

5 seconds when meeting a human. This time is assumed to be sufficient for human to clear the way for the mobile robot. A similar time-assumption is made when an unexpected obstacle appears in the robot's embedded map. An intelligent mobile robot can avoid any detected obstacle but needs 5 seconds to find a local alternative path. Secondly, the density of human traffic in mobile robots path is varied. The variation in human traffic density is because the number of people occupying the displacement area of mobile robots is dynamically changed from a moment to another during a working day. There are two main periods of human traffic concentrations; the first one is at the beginning of the day and at its end, where the density of people present in corridors is high. The second period of human traffic concentration is at lunchtime. Periods of high-human density traffic due to humans is shown in Figure 1. The x-axis represents scheduled working hours, and the y-axis the number of human traffic detected by sensors at corridors. Third, the complexity to calculate the number of the necessary

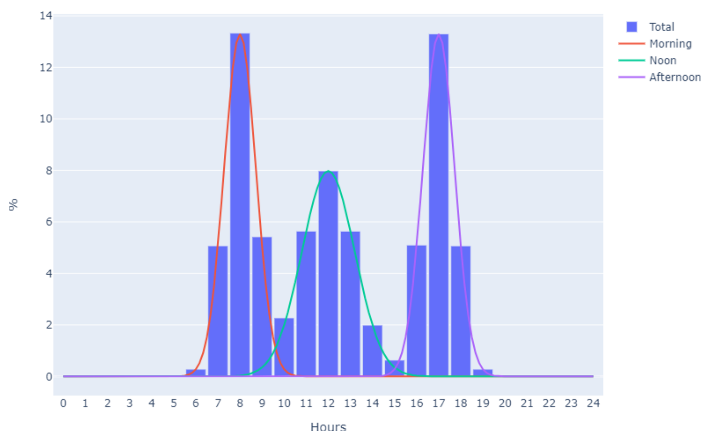

Fig. 1: Distribution of human-traffic density due to human operators in mobile robots traffic space

mobile robots to satisfy the daily transportation tasks does not only depend on the daily production demand but also the number of persons present in robots' movement areas. As the number of people is stochastic, dynamic scheduling, in this context, is the most promising approach to allocate task allowing mobile robots to choose the best path and the best moment to execute a transportation task. IoT, sensors and data analysis play an important role in increasing the efficiency of the decision made per each robot. Another aspect of the complexity concerns the decision levels. Three decision types must be taken in order to manage collaborative robots. Figure 2 shows the different levels of decisions that affect the correct functioning of robots. The travel time of each mobile robot is affected by the number of persons present in its path and its ability to avoid these dynamic obstacles. This situation is depending on the tasks allocated to the robot, which are defined through advanced scheduling included in the operational level decision-making process. The performance of the whole system depends on the number of robots deployed in the production system. This number is defined in the tactical level decision-making process. The high interaction between these three levels makes the complex definition of fleet size. We will proceed with simulation in order to define the optimal number of used robots in different situations of human interaction.

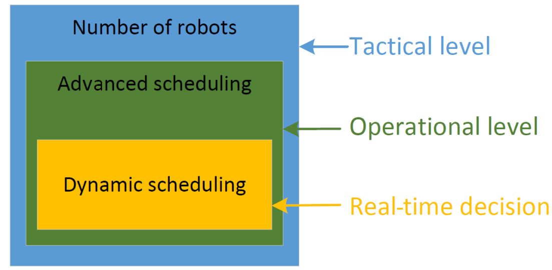

Fig. 2: Different decisions in smart mobile robot management

IV. METHODOLOGY

In order to define the optimal number of mobile robots, it is essential to consider deadlocks and traffic jam caused by other mobile robots or by human presence on the path of the mobile robot. We propose to evaluate the choice of fleet size by simulation following a greedy approach. A multi-agent simulation model is proposed to define the behaviour of each component of the system. As shown in figure 3, the model is composed of five agents as following:

- Humans: this agent represents all the human workers in a workshop. They follow a stochastic behaviour based on the global observation of their presence in corridors as shown in Figure 1. The probability of human traffic density in corridors can be adjusted as a simulation parameter.
- Robots: they represent autonomous and smart entities agents able to transport products from one stock location to another. Each mobile robot can make local decisions, such as avoiding an obstacle, charging its battery etc.
- Supervisor: modelled agent responsible for defining the sequence and scheduling of operations and tasks and supervising the communication between different production system elements. It can be understood as a Manufacturing Execution System (MES).
- Workshops: this agent can be one of the production workshops (different departments), production cells, production workstations.
- IoT/BMS: these agents include all the sensors installed in the building and connected to the building information systems and the IoT devices present in the production system, such as connected operator interfaces, connected stock and machines.
- Corridors: they constitute agents to implement ways linking workshops, which are the common resource between robots and humans.

Agents are interacting as shown in Figure 3. Link (1) represents the interaction between robots and humans, where each mobile robot has to stops for 5 seconds when it crosses a human. The interaction (2) represents the movement of the mobile robot in corridors. The same kind of interaction, represented by link (5), exists between Human agents and corridors. This represents the use of the same resource by robots and humans for displacement. The interaction between the IoT/BMS can be direct through the link (3) and indirect through the supervision system (links (9) and (4)). Therefore link (4) allows the supervision system to transmit an order to a mobile robot and collect data. Link (6) represents data collection about human operators behaviour and their interaction with the environment. Link (7) defines the physical links between workshops using corridors. The role and presence of operators in the workshop are represented by the link (8). The link (9) ensures the transmission of collected data to the supervision system, and, finally, the interaction (10) represents the communication of the stat and configuration of each workshop.

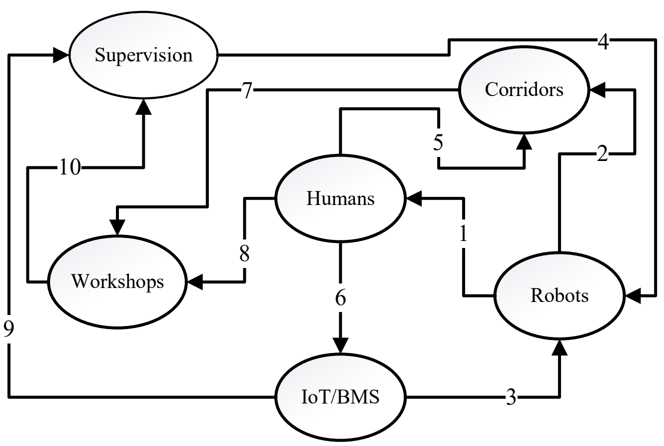

Fig. 3: Multi-agent model

V. Simulation experiments

The multi-agent-based simulation model detailed in the previous section is developed using NetLogo Software, a discrete-event simulation programming tool. The interface is in 2D and contains the map of the workshop, which includes human operators and mobile manipulators agents in movement. The simulator allows modifying the number of used robots and the rate of persons present in corridors. This rate can be fixed or variable following the probability of presence defined in Figure 1. The simulation model is presented in the figure 4 where it is possible to observe human operators present in corridors at the same time as robots.

This simulation aims to measure the effect of operators presence on the transportation time of mobile robots and to define the robot fleet size with consideration of this dynamic transportation time. Two main scenarios are designed and executed. The first one executes a given production planning without any operator present in corridors. This scenario is considered the reference situation representing the lower bound of the optimal solution in fleet size. Other scenarios will consider different

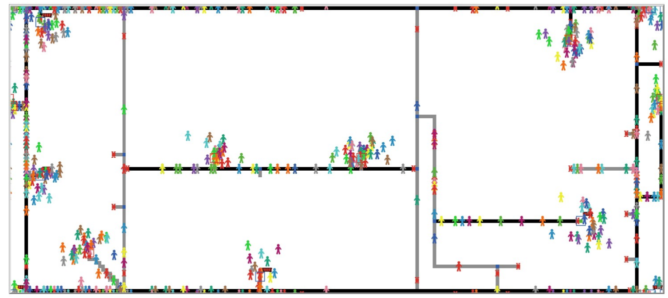

Fig. 4: Multi-agent based simulator

rates of human presence in corridors. Even the transportation displacement strategy has a natural effect on performance indicators of the production system; we will assume that it will not get any effect on our experimentation study because the same strategy is adopted for all scenarios. Experimentation on a real system has shown that transportation time increases with the probability of meeting a human in corridors, which means that we need more mobile robots to satisfy the same demand with a higher probability of human presence in corridors. On the other hand, many mobile robots will create more traffic jam, which slows down the execution of transportation tasks.

VI. Conclusions

This paper explores the problem of defining transportation robots fleet size in a collaborative workshop environment, where humans and robots share the same working space. The literature and real experimentation reported by industrial practitioners demonstrated a significant correlation between the transportation time and the number of humans present in the shared working space. However, as the correlation is not accurately quantified, defining the appropriate fleet size for mobile robots is not trivial. This problem concerns not only manufacturing systems in Industry 4.0 but also related to manufacturing systems in the new era of industry 5.0. Therefore, this paper proposes a simulation-based approach to get an accurate estimation of this robot fleet size. The structure of the simulator is explained with a presentation of the first version of the simulation environment. The experimentation strategy based on the use of this simulator is also detailed. Subsequent work will expose the results of simulation for scenarios with different product demands. A transportation strategy will be developed based on the estimation of number of operators in each space zone of the production system and each time zone of the working day.

Acknowledgment

This research was made possible thanks to € 2.6 million financial support from the European Regional Development Fund provided by the Interreg V France Channel England Programme in context of CoRoT Project.

References

[1] K. A. Demir, G. Döven, and B. Sezen, "Industry 5.0 and Human-Robot Co-working," in *Procedia Computer Science*, vol. 158, pp. 688–695, Elsevier B.V., jan 2019.

[2] M. De Ryck, M. Versteyhe, and F. Debrouwere, "Automated guided vehicle systems, state-of-the-art control algorithms and techniques," *Journal of Manufacturing Systems*, vol. 54, pp. 152–173, 2020.

[3] D. Antakly, J. J. Loiseau, and R. Abbou, "A temporised conflict-free routing policy for AGVs," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 11169–11174, 2017.

[4] T. Le-Anh and M. B. De Koster, "A review of design and control of automated guided vehicle systems," *European Journal of Operational Research*, vol. 171, pp. 1–23, may 2006.

[5] H. Fazlollahtabar, M. Saidi-Mehrabad, H. Fazlollahtabar, and M. Saidi-Mehrabad, "Methodologies to Optimize Automated Guided Vehicle Scheduling and Routing Problems: A Review Study," *J Intell Robot Syst*, vol. 77, pp. 525–545, 2015.

[6] K. Vivaldini, L. F. Rocha, N. J. Martarelli, M. Becker, and A. P. Moreira, "Integrated tasks assignment and routing for the estimation of the optimal number of AGVS," *The International Journal of Advanced Manufacturing Technology*, vol. 82, pp. 719–736, jan 2016.

[7] Ü. Bilge and G. Ulusoy, "A time window approach to simultaneous scheduling of machines and material handling system in an FMS," *Operations Research*, vol. 43, no. 6, pp. 1058–1070, 1995.

[8] H. Hasan, M. S. Zainal Abidin, S. Azimi, and M. F. Muhamad Said, "Automated Guided Vehicle Routing: Static, Dynamic and Free range," *International Journal of Engineering and Advanced Technology*, vol. 8, pp. 1–7, sep 2019.

[9] P. Valmiki, A. Simha Reddy, G. Panchakarla, K. Kumar, R. Purohit, and A. Suhane, "A Study on Simulation Methods for AGV Fleet Size Estimation in a Flexible Manufacturing System," in *Materials Today: Proceedings*, vol. 5, pp. 3994–3999, Elsevier Ltd, jan 2018.

[10] R. Arifin and P. J. Egbelu, "Determination of vehicle requirements in automated guided vehicle systems: A statistical approach," *Production Planning and Control*, vol. 11, pp. 258–270, jan 2000.

[11] X. Lyu, Y. Song, C. He, Q. Lei, and W. Guo, "Approach to Integrated Scheduling Problems Considering Optimal Number of Automated Guided Vehicles and Conflict-Free Routing in Flexible Manufacturing Systems," *IEEE Access*, vol. 7, pp. 74909–74924, 2019.

[12] G. Fragapane, R. de Koster, F. Sgarbossa, and J. O. Strandhagen, "Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda," *European Journal of Operational Research*, jan 2021.

[13] M. Sahnoun, Y. Xu, F. B. Abdelaziz, and D. Baudry, "Optimization of transportation collaborative robots fleet size in flexible manufacturing systems," in *2019 8th International Conference on Modeling Simulation and Applied Optimization (ICMSAO)*, pp. 1–5, IEEE, 2019.

[14] D. Z. Zhang, A. I. Anosike, M. K. Lim, and O. M. Akanle, "An agent-based approach for e-manufacturing and supply chain integration," *Computers and Industrial Engineering*, vol. 51, pp. 343–360, oct 2006.

[15] N. R. Jennings and M. Wooldridge, "Applications of Intelligent Agents," in *Agent Technology*, pp. 3–28, Berlin, Heidelberg: Springer Berlin Heidelberg, 1998.

[16] N. R. Jennings, "On agent-based software engineering," *Artificial intelligence*, vol. 117, no. 2, pp. 277–296, 2000.