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Analysing mobility and environmental impacts of automated ride-sharing services under mixed traffic

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ABSTRACT

Shared Automated Vehicles (SAVs) hold great promise for the future of urban mobility. Automated ride-sharing services are expected to alleviate traffic congestion, reduce traffic emissions, and significantly improve road safety by combining advanced connected and autonomous vehicle (CAV) technology with the ride and/or car-sharing concept. These benefits, however, are highly dependent on the deployment concept of the service and environment including network characteristics, CAV technology, traffic compositions, population acceptance, etc. This study aims to assess the mobility and environmental impacts of introducing a door-to-door automated ride-sharing (ARS) service under different deployment scenarios. Two calibrated and validated city-scale networks with different characteristics were used: a suburban area in the Greater Manchester (UK) and a city-centre area in Leicester (UK). An optimisation technique for the vehicle routing problem was developed to efficiently operate ARS at a network-level. The customers' preference for individual and shared rides with Willingness to Share (WTS) was investigated to gain a better understanding of the performance indicators (i.e., delay, travel time, speed, kilometres-driven and emissions) The introduction of ARS was investigated under two deployment scenarios: 1) mixed with conventional human-driven vehicles (HDVs) and 2) mixed with HDVs with varying CAV market penetration rates. Findings suggest that introducing ARS can adversely impact mobility and the environment under mixed traffic, especially in suburban areas, and the benefits of an automated ride-sharing system are highly dependent on WTS. The findings will assist local authorities in formulating automated ride-sharing policies to manage the traffic on roads.

1. Introduction

Traffic on the roadways has been growing fast over the past decades, increasing congestion and safety issues. The conditions on the roads are particularly worsened by single-occupancy vehicles that account for the majority of this (more than 62 % in the UK) traffic (Stewart, 2020). On-demand mobility services, such as car-sharing, ride-hailing, and ride pooling, have gained increasing popularity in recent years. They have become an increasingly common travel solution, as such mobility services are causing a dramatic shift in user mobility behaviour, especially in urban areas. Using ride-sharing services can potentially have beneficial impacts by reducing emissions, lowering travel costs, and alleviating traffic congestion. Furthermore, it can also reduce the search and demand of parking for personal vehicles which could save extra time and cost.

Introducing automation to this kind of service may significantly impact urban mobility and transport systems. Connected and automated vehicles (CAVs) are soon to be deployed on the roads in many countries (Department for Transport (UK), 2015). CAVs promise potential benefits in several areas, including traffic congestion, parking demand, energy

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consumption, and road safety. However, it is expected that during the early stage of deployment, owning and maintaining a CAV would be more expensive than conventional vehicles due to the cost of the technology underlying CAVs (Wadud, 2017). Therefore, the integration of CAVs into On-demand shared mobility services (such as car-sharing, ride-sharing, ride-hailing, and ride pooling) could be the first actual deployment of CAVs in the short term, especially in urban areas (Jagst, 2020). Previous researchers have examined the potential impacts of shared autonomous vehicles (SAVs), and they have found that SAVs could significantly reduce demand for private vehicles and land use for parking as SAVs will be serving customers at different times (Othman, 2021; Xia et al., 2021).

SAVs are expected to help reduce traffic congestion by reducing the number of vehicles on the roads. However, some studies forecast an increase in network congestion as well as in emissions due to increased Vehicle Kilometre Travelled (VKT) resulting from repositioning and empty trips (Lu et al., 2018; Overtoom et al., 2020). In general, the impact of introducing such a service is determined by the deployment environment, and strategies such as network characteristics and demand density and its distribution, fleet size, vehicle occupancy, etc. (Narayanan, 2019). Furthermore, deploying this service as a taxi or car-sharing service (single vehicle occupancy), as a shared ride service, or a mixed service (combine car-sharing and ride-sharing) could be also considered as an important factor that could significantly impact the potential benefits of this service.

The importance of potential effects that could come from merging automation with on-demand shared mobility services led to the study of an automated ridesharing (ARS) service in this paper. Various stakeholders, including transport planners, service operators, and cities, may be particularly interested in the implications on car ownership, congestion, land use, modal shift, and emissions in order to analyse the societal effects and weigh the costs and benefits. For this research, an automated ride-sharing service that offers door-to-door service was taken into consideration. The proposed service combines free-floating car-sharing, ridesharing, and fully autonomous vehicles operating in two city-scale networks in the United Kingdom: a suburban area in the Greater Manchester and a city-centre area in Leicester with mixed traffic conditions. This study examined various levels of passengers' willingness to use the service with shared trips, known as Willingness To Share (WTS). Additionally, the WTS varies only in independent scenarios. In any specific scenario, the demand group remains the same.

By employing an optimisation-based vehicle routing model and traffic microsimulation, the study provides insights into the effects of ARS on traffic performance, emissions, and passenger willingness to share (WTS), offering valuable guidance for policymakers in managing automated ride-sharing services effectively.

2. Literature review

A comprehensive review by Narayanan et al. (2020) synthesises the evolving landscape of Shared Autonomous Vehicles (SAVs), exploring service typologies, modelling approaches, and potential impacts. Their analysis reveals that SAVs consistently enhance mobility and system efficiency, with studies indicating reduced parking needs and a modal shift from conventional public transport. However, this shift highlights the need for efficient integration with public transport systems, a challenge compounded by the reliance on future-oriented scenarios with plausible yet untested assumptions. This underscores the importance of realistic modelling to accurately predict the outcomes of the SAV deployment.

A comparison of traditional taxis with shared automated taxis was undertaken by Lokhandwala and Cai (2018) using agent-based modelling and a New York City taxi dataset. The study has reported that a fleet size reduction of 59 % could be achieved from switching to shared automated taxis from traditional taxis without any significant increase in waiting time for occupants. The main benefits highlighted were increased occupancy rates, reduced travel distances, reduced carbon emissions and increased system flexibility. A similar study using agent-based modelling was carried out by Gurumurthy et al. (2019), replicating the travel patterns in the Austin, Texas with personal and shared AVs, Dynamic Ride Sharing (DRS), and road pricing policies. The results indicated that larger SAV fleets would increase single occupancy, leading to a reduction in DRS value. Therefore, in the future, operators should aim to have a moderate (rather than high) fleet size and keep fares relatively low to ensure the maximum benefits, which should limit any effects on rising traffic congestion. Additionally, future issues that need to be considered include the social-emotional matching of passengers in ride-sharing, acceptance of long trip durations due to picking up other passengers, longer waiting times and the types of vehicles (e.g. sizes) changing due to the changes in functions (Soteropoulos et al., 2019).

With regard to extra VKT, Fagnant et al. (2015) investigated the potential implications of a virtual shared autonomous fleet in a 12 x 24mile area of Austin, Texas. The authors assumed that a 1.3 % share of the total regional trips were to be served by SAVs and performed the simulation using MATSim dynamic traffic simulation software under different traffic conditions during the daytime. They concluded that each SAV could replace approximately 9.3 conventional vehicles while being able to maintain a good level of service and having an average of 1 min user waiting time. According to the findings, the new service generated around 8 % extra VKT due to pick-up and relocation empty trips. In terms of environmental impact, results by Yan et al. (2020) supported those in Zhang et al. (2015a, 2015b); Silva et al. (2021). Despite the additional VKT, SAV deployment will have a positive impact on emission and air quality since SAVs are supposed to be modelled as environment-friendly vehicles with a high turnover rate and less cold starts (Fagnant et al., 2015). Furthermore, Greenblatt and Shaheen (2015) stated that electric SAVs combined with low carbon electricity grid, can reduce Greenhouse Gas (GHG) emissions per mile by approximately 90 % compared with today's vehicles. Studies have reported that carsharing in general is associated with a decrease in GHG emissions which can reach up to 41 % per year for one household (Martin & Shaheen, 2011; Shaheen & Chan, 2015).

Oh et al. (2020) investigated the potential impacts of AMOD (Automated Mobility-On-Demand) on transportation in Singapore in 2030 using activity and agent-based simulation. The scenarios and performance measures used in the study included mode availability (all existing modes such as walking, car, car-pooling, bus, cycling etc., plus MOD and AMOD-single and shared), pricing (75 %, 100 % & 125 % of existing taxis), fleet sizing and performance measures such as demand patterns (mode shares/shifts), network performance and AMOD service metrics (request satisfaction rates, vehicle utilisation, average waiting times). The main findings were that AMOD use is likely to be greater than existing MOD and taxi services, but there was found to be an increase in Vehicle Km Travelled of up to 17 % when there was moderate adoption of AMOD and total vehicle ownership was not capped.

Extensive research has explored the benefits and challenges of shared automated vehicles (SAVs) and automated ride-sharing (ARS) systems. However, significant gaps remain in understanding their real-world deployment, particularly in mixed-traffic environments. While studies highlight potential improvements in congestion, emissions, and road safety (Fagnant et al., 2015; Zhang et al., 2015a, 2015b), the variability of these benefits across different network conditions and deployment scenarios remains under-explored. Many studies rely on theoretical models or limited simulations that overlook key factors such as suburban versus urban environments, varying market penetration rates of connected and autonomous vehicles (CAVs), and users' willingness to share rides (WTS). Additionally, the interaction between ARS and human-driven vehicles (HDVs) in mixed traffic remains insufficiently examined at an urban scale.

Further research is needed to develop data-driven strategies that optimise ARS deployment while mitigating adverse effects on traffic

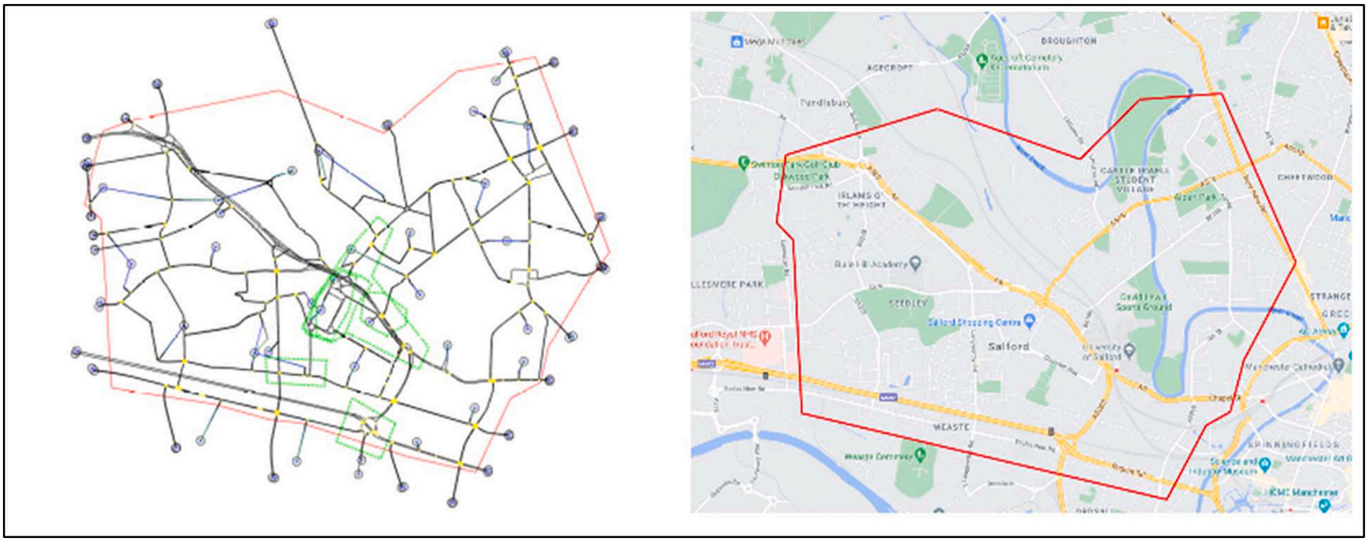


Fig. 1. Manchester network.

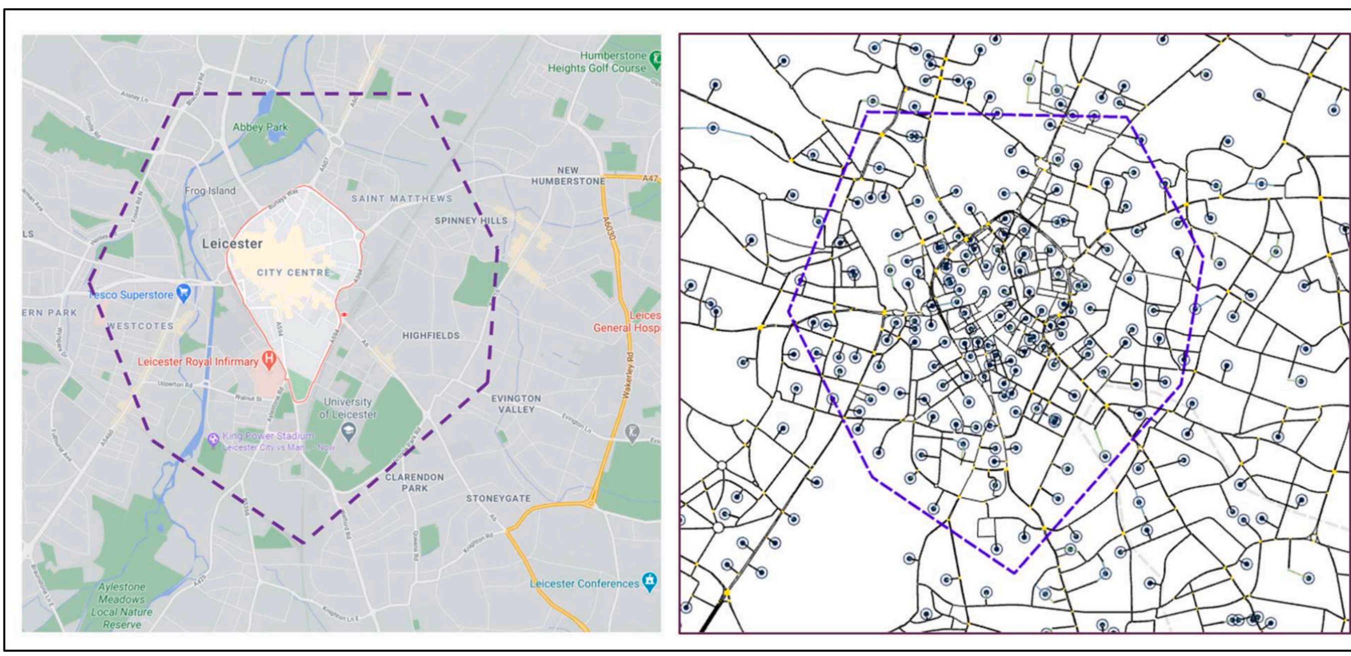


Fig. 2. Leicester network.

flow and the environment. Although some studies have investigated traveller preferences for SAVs (Krueger et al., 2016; Lavieri & Bhat, 2019), the role of WTS in practical deployment remains inadequately addressed. Current research relies heavily on stated-preference surveys or limited simulations, failing to capture key operational challenges such as real-time routing optimisation and fluctuating traffic conditions. There is a growing need for integrative studies that combine advanced optimisation techniques, sophisticated user acceptability modelling, and extensively calibrated networks to provide more accurate assessments of ARS impacts and inform policy decisions.

Overall, the findings of the literature presented above identified various strategies through which benefits of shared autonomous services can be maximised. In this regard, fleet size, willingness to share, and characteristics of the service area can play a key role in maintaining the potential for positive benefits.

3. Methodology

The aim of this study is to quantify the impact of introducing an automated ride-sharing service (ARS) under mixed traffic conditions in two different environments considering different deployment scenarios. The assessment approach adopted here is based on optimisation research and simulation models.

3.1. Simulation models

To illustrate the potential impacts of the proposed ride-sharing service, two calibrated and validated UK network models (the Greater Manchester and Leicester) developed in AIMSUN Next microsimulation software were used in this study. The Manchester Network represents a suburban area from Salford (around 13km^2)(Fig. 1). The model contains 308 nodes and 732 road sections with a 58 × 58 origin-destination (OD) matrix. The network and origin-destination (OD) matrices used in this study were provided by the study partner AIMSUN. These data were pre-calibrated by AIMSUN based on traffic counts from the study area, supplemented by their estimation and validation techniques. This approach ensures a reliable representation of travel demand across the network, consistent with industry-standard practices for OD matrix development. Further details on AIMSUN's methodology are available in their technical documentation (Aimsun, 2022a). Traffic data from evening peak-hour (1700–1800) was used, with an estimated traffic demand of 23,226 car trips, 1867 large goods vehicle (LGV) trips, and 63 heavy goods vehicle (HGV) trips.

The Leicester network is used to evaluate the impact of ARS services in a city-centre area (Fig. 2). The network model is around $10.2km^2$ and consists of 788 nodes and 1988 sections with an OD matrix of 183×183. The traffic demand for passenger cars, LGVs, and HGVs was 23,251 trips, 3131 trips, and 16 trips, respectively. In addition, public transport service was also considered for this network with 73 bus lines.

3.1.1. CAVs behavioural modelling

Two types of CAV behaviours were considered:1st Generation CAVs and 2nd Generation CAVs. Both types were assumed to be fully automated vehicles with Level 5 automation. The main idea behind modelling is based on the assumption that technology will advance over time. In general, the main assumptions regarding CAVs characteristics were:

- 1^{st} **Generation CAVs**: limited sensing and cognitive ability, long gaps, earlier anticipation of lane changes than Human-driven vehicles (HDV), and longer time in give way situations.
- 2^{nd} **Generation CAVs**: advanced sensing and cognitive ability, data fusion usage, confident in taking decisions, small gaps, earlier anticipation of lane changes than HDVs, less time in give way situations.

The implementation of these characteristics was done through adjusting various parameters of the default car-following model in Aimsun Next, the Gipps model (Gipps, 1981, 1986). The adjusted parameters include reaction time, time gap, parameters related to acceleration, deceleration, and to lane changing and overtaking behaviours, in addition to other parameters. More details about the parameters and their values can be found in (Chaudhry et al., 2022). The impact of ARS services was assessed in mixed traffic conditions that contain human driven passenger cars, freight, and public transport (PT) vehicles. The automation of freight vehicles was also considered. The present study assumed that all travellers have information about their journeys, and they will choose the shortest path. Optimisation was conducted to determine the optimal fleet size for 0 %, 50 %, and 100 % willingness to share, minimising the total travel cost while satisfying all customers. Finally, mobility and environmental impacts were analysed for the optimised fleet size using the simulation model.

3.2. Optimisation

For this study, the ARS is modelled as a Vehicle Routing Problem with Pickup and Delivery with Time Window (VRPPDTW) (Mahmoudi & Zhou, 2016; Savelsbergh & Sol, 1995), which is a variant of the Vehicle Routing Problem (VRP) that considers time frames and different pick up/delivery locations of trip requests. To formulate the VRPPDTW model the following notation is used. P is the set of pickup locations of all customers, D is the set of all customers drop-off locations, and W is the set of depot locations. The problem can be defined as complete graph $G = (V, E)$, where $V = P \cup D \cup W$ and E represents the arc set including all pairs of different locations $(i, j) \varepsilon P \times D$. Let K be set of the vehicle fleet and C_k denotes the set of vehicle capacities. Let n be the number of customers, each customer $q \varepsilon \{1, .., n\}$ has a preferred time window to be picked up from the origin denoted as a_{p_q}, b_{p_q} and the time window to arrive to its destination denoted as a_{d_q}, b_{d_q}, where $p_q \in P$ and $d_q \in D$. The time needed for vehicle k to travel from location i to j is denoted by t_{ij} and associated with a cost c_{ijk}. The objective of the VRPPDTW is to minimise the total travel cost in order to serve all customers in their required time windows using the following objective function (1):

$$\text{Minimize} \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} c_{ijk} x_{ijk} + M \sum_{k \in K} y_k \tag{1}$$

$$y_k \geq x_{ijk}, \forall i, j \varepsilon V, k \varepsilon K \tag{2}$$

Where x_{ijk} represent a binary variable that equal to 1 if the arc (ij) is used by vehicle k and 0 otherwise, y_k is a binary variable indicating whether vehicle k is used, and M is a large constant to penalize the use of additional vehicles. The objective function is subject to the following constraints:

$$\sum_{k \varepsilon K} \sum_{i \varepsilon V} x_{ijk} = 1, \forall j \varepsilon V \tag{3}$$

$$\sum_{w \in W} \sum_{i \in P} x_{wik} = 1, \sum_{w \in W} \sum_{j \in D} x_{jwk} = 1 \quad \forall k \in K \tag{4}$$

$$s_{ik} + t_{ij} \leq s_{jk} + M(1 - x_{ijk}), \quad \forall i, j \in V, \forall k \in K \tag{5}$$

$$a_i - M(1 - z_{ik}) \leq s_{ik} \leq b_i + M(1 - z_{ik}), \forall i \ \varepsilon V, \forall k \varepsilon K \tag{6}$$

$$L_{jk} \leq L_{i,k} + q_j + M(1 - x_{ijk}) \forall i \varepsilon V, \forall k \varepsilon K \tag{7}$$

$$L_{jk} \geq L_{i,k} + q_j - M(1 - x_{ijk}) \forall i \varepsilon V, \forall k \varepsilon K \tag{8}$$

$$0 \leq L_{ik} \leq C_k \forall i \varepsilon V, \forall k \varepsilon K \tag{9}$$

Constraint (3) ensures that each customer is visited only once, while constraint (4) makes sure that each vehicle starts and ends its route at one of the depots. Constraint (5) ensures that the service times at pickup and delivery locations respect the specified time windows. In this context, the term $M(1 - x_{ijk})$ acts as a large constant that relaxes the constraint via a large constant M. Further, the s_{ik} is the travel time variable that indicates the start of service at node/pickup location i when serviced by vehicle k. Constraint (6) ensures that the service start times at each location i fall within the preferred time window for the pickups, denoted as $[a_i, b_i]$, where z_{ik} is a binary variable indicating whether vehicle k visited node i. Constraints 7–9 address the load updates and capacities, where L_{ik} represents the load of vehicle k after leaving location i and q_i refers to the load picked up or dropped off at location i.

For this study, the VRPPDTW problem was implemented using the Google's OR-Tools (Perron & Furnon, 2019) to match ARS service customers with SAV fleet. It is worthwhile to note that the main objective is to minimise the travel time as well as the SAVs fleet size in order to respond to customer travel request within their specified pickup and drop-off time windows, i.e. to optimise the quality of service for passengers. Alternative optimisation approaches could be e.g. to minimise congestion or to maximise profitability.

4. Scenarios and assumptions

The impact of an automated on-demand mobility service was studied under three scenarios.

4.1. Baseline scenario

The traffic with the current situation, without any ride-sharing or automation considered.

4.1.1. Scenario 1: ARS with conventional fleet

An ARS is introduced into an urban environment with a traditional vehicle fleet in the background traffic. The automation is only

Table 1
CAV Deployment scenarios.

Vehicle Types	CAV Market Penetration Rate (HDV- 1st Gen CAV- 2nd Gen CAV)							
	100–0-0	80–20–0	60–40–0	40–40-20	20–40-40	0–40-60	0–20-80	0–0-100
Passenger Cars								
HDV	100 %	80 %	60 %	40 %	20 %	0 %	0 %	0 %
1st Generation CAV	–	20 %	40 %	40 %	40 %	40 %	20 %	0 %
2nd Generation CAV	0 %	0 %	0 %	20 %	40 %	60 %	80 %	100 %
Light Goods Vehicles (LGV)								
Human-Driven LGV	100 %	80 %	40 %	0 %	0 %	0 %	0 %	0 %
LGV-CAV	–	0 %	20 %	60 %	100 %	100 %	100 %	100 %
Heavy Good Vehicles (HGV)								
Human-Driven HGV	100 %	80 %	40 %	0 %	0 %	0 %	0 %	0 %
HGV-CAV	–	0 %	20 %	60 %	100 %	100 %	100 %	100 %

HDV = Human-Driven Vehicle; CAV = Connected and Autonomous Vehicles.

considered for the SAV fleet, while the other vehicle types in the network are considered to be HDVs. It was assumed that demand for this new service will replace 5 % of personal vehicle demand. The combination of the different levels of WTS and CAV technologies (1st and 2nd Generation CAVs) gives the following sub-scenarios:

1. 1st generation SAVs: 5 % of the total private vehicle travel demand (trips) is replaced by an SAV trip, with a variation in WTS (0 %, 50 %, 100 % of travellers).
2. 2nd generation SAVs: 5 % of the total private vehicle travel demand (trips) is replaced an SAV trip, with a variation in WTS (0 %, 50 %, 100 % of travellers).

4.1.2. Scenario 2: ARS with mixed conventional and CAV fleet

The ARS is analysed under a mixed fleet composition where the automation is considered for privately owned passenger cars, LGVs, and HGVs. The deployment of CAVs was tested from 0 % to 100 % market penetration rate (MPR) with 20 % increments (Table 1).

The impact of automated ride sharing is studied under the following sub-scenarios:

1. No policy intervention: No policy intervention scenario of increasing penetration of automated vehicles without an automated on-demand mobility service.
2. Shared CAVs: 5 % of the total private vehicle travel demand (trips) is replaced by an SAV trip, with a variable WTS (0 %, 50 %, and 100 % of travellers),

For both sub-scenarios, deployment of CAVs in the network was tested from 0 % to 100 % in 20 % increments with the two types of CAVs previously presented. The SAV capacity is four passengers, and the SAV fleet composition includes 1st and 2nd Generation CAVs. The presence of each type is based on its market penetration rate defined in Table 1. The investigated scenarios aim to depict the impact of ARS services under different deployment scenarios in terms of traffic compositions and CAVs implementations periods (early, medium, advanced).

The following assumptions have been made for this sub-use case implementation:

- In case CAVs and SAVs are EVs, the battery capacity can support full-day operations.
- The emissions generated from the electricity production used by the EVs were not taken into consideration.
- Parking spaces are sufficient for all SAVs in each station,
- The pick-up and drop-off locations and behaviour will not be addressed in this sub-use case,
- Preference for ridesharing is presented as a binary parameter (Yes, No),
- Cancellation of assigned SAV is not allowed,
- A SAV request refers to one traveller.
- The capacity of each SAV is 4 passengers.
- Automation was not considered for public transport.

5. Results and discussion

The results from the optimisation and research and simulation models are described and analysed in this section. The first subsection presents the findings from the optimisation method presented earlier in terms of SAV fleet size, total distance travelled, and empty distance travelled. Mobility impact results are presented in the second subsection, followed by the environmental impact analysis. Finally, the last subsection discusses the findings regarding the service-level impacts.

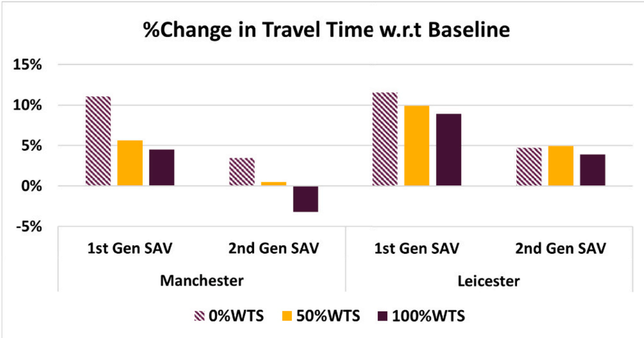
5.1. Results from the optimisation technique

Table 2 presents the optimisation results for the Manchester and Leicester network for the different passenger WTS studied. The optimisation process is conducted separately for each WTS level, with passenger preferences for shared or solo rides determined prior to the start of the optimisation. For this study, we assume a fixed fleet size and consider the number of used vehicles in operation. The optimal fleet size is defined as:

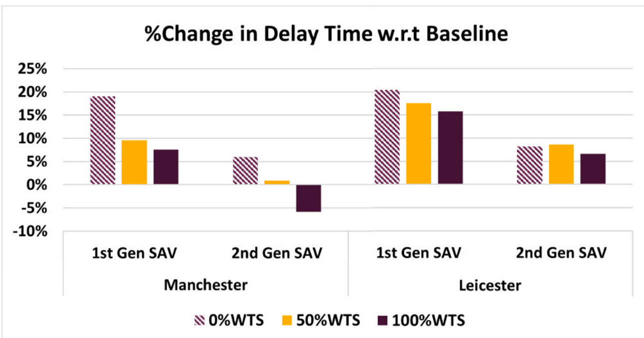
Table 2
Optimisation results for Manchester and Leicester network.

Network	No of Trips(*)	Willigness to share	Optimal SAV Fleet size	SAV Replacement Rate(**)	SAV Total km Travelled($)	Empty km Travelled
		0 %	682	1.66	5924.59	2998.50
Manchester	1134	50 %	570	1.9	5344.72	2435.30
		100 %	435	2.6	4420.16	1554.17
		0 %	730	1.28	3792.63	2084.05
Leicester	937	50 %	663	1,41	3574,37	1880.42
		100 %	547	1.71	3167,84	1529.42

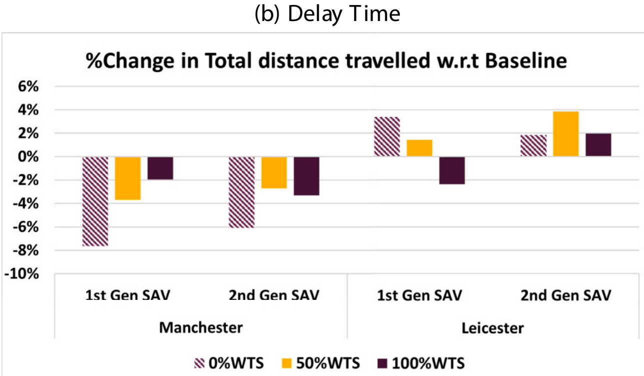
* The number of private personal vehicle trips that will be replaced with served by SAVs.
** Number of personal vehicles replaced by one shared AV (SAV)
$ The "Total km travelled" as an outcome of the optimisation process. This is not a Performance Indicator here.



(a) Travel Time



(b) Delay Time



(c) Distance Travelled

Fig. 3. Percentage change in (a) average travel time, (b) average delay, and (c) Total distance travelled with regards to baseline scenario for Manchester and Leicester network - Scenario1.

$$K^{*} = \sum_{k \in K} y_k \tag{10}$$

The results indicate that the fleet size required to replace conventional personal vehicle trips gradually decreases as more passengers are willing to share their rides. The decrease in the number of required SAVs is associated with an increase in the number of HDVs that one SAV can replace. Regarding SAV driven kilometres travelled, the results show that a higher WTS reduced the total and empty travelled distance covered by the SAV fleet in both networks. The results also revealed that the empty driven kilometres would gradually decrease with a higher willingness to share.

5.2. *Mobility impacts*

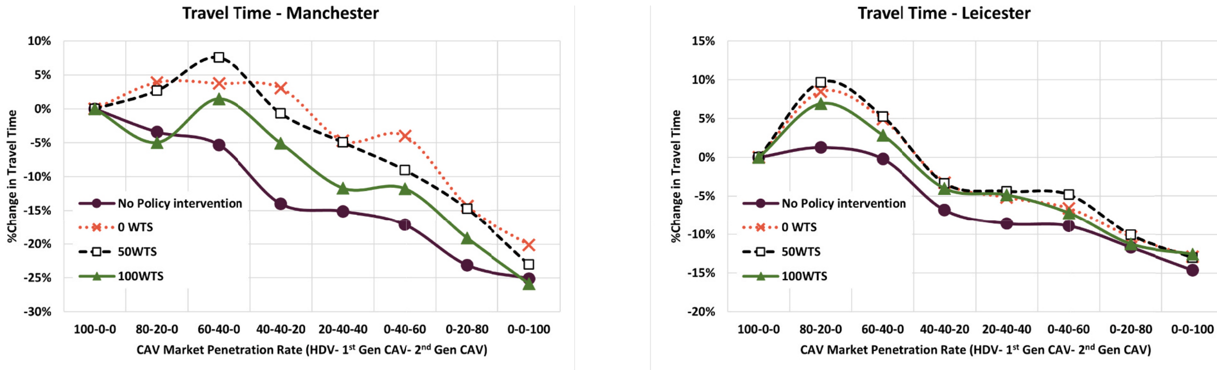
In this study, the mobility-related impacts have been quantified through microscopic simulation. These impacts include travel time, delay, average speed, and total distance travelled. In the simulation model, Delay Time is defined as the difference between the expected travel time (the time it would take to traverse the section under ideal conditions) and the actual travel time. Travel Time refers to the average time a vehicle needs to cross the section, calculated as the mean of all individual travel times, which are determined by subtracting the section entrance time from the section exit time for each vehicle that has left the section. Total Distance Travelled represents the total number of kilometres travelled by all vehicles that have crossed the network (Aimsun, 2022b). Fig. 3 depicts the results of Scenario 1, where an ARS service is deployed with a conventional background fleet. Introducing an ARS service has triggered an increase in travel time and delay in both networks compared to their corresponding baseline (current situation). The increase in the studied Key Performace Indicators (KPIs) is strongly and inversely related to the rate of WTS as well as the CAV technology since a decreasing trend could be observed with increasing WTS and advanced CAV (2nd generation CAVs). In the Greater Manchester suburban network, the increase in delay and travel time are associated with traffic congestion potentially caused by the interaction between SAVs and human-driven vehicles and the SAV empty repositioning trips (pick-up trips). Another contributory factor could be the circulating behaviour of SAVs since they tend to use low capacity and secondary roads to reach their destinations, causing more traffic congestion (Overtoom et al., 2020).

The increased delay and travel time in the Leicester network could also be attributed to congestion caused by the aforementioned factors. However, as congestion increased, an increase in the number of freight and PT vehicles entering the network was also observed (Table 3), indicating a slight improvement in network performance compared to the Manchester network, which experienced a considerable drop in the number of entering vehicles (Table 5). Therefore, the improvement in the Leicester network could be attributed to network characteristics (dense road network with more options for alternative routes), which are substantially different from the Manchester network.

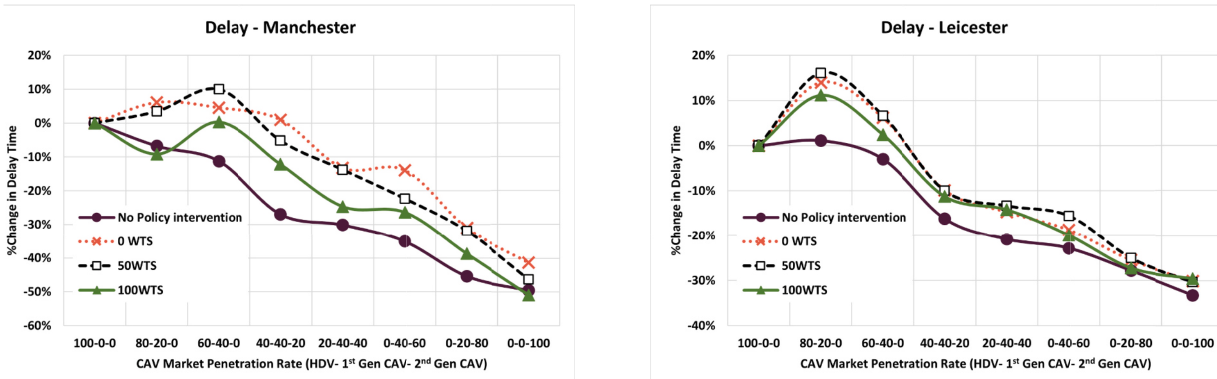
Similar to delay and travel time, the total distance travelled results (Fig. 3c) also suggest that the impact of deploying ARS depends on the WTS. In the case of Manchester, a reduction in total distance compared to the baseline with 1st and 2nd generation CAVs could be observed. The reduction is related to fewer vehicles entering the network (less traffic flow), as shown in Table 3. The reduction in the (traffic flow) is not just associated with replacing a share of passenger cars with SAVs but also with reducing the number of other vehicle types entering the network (Table 3). However, the results show that with high levels of WTS, an improvement could be observed. Leicester network results show

Table 3
Impact on average number of vehicles entering the network (traffic flow) due to ARS service - Scenario 1.

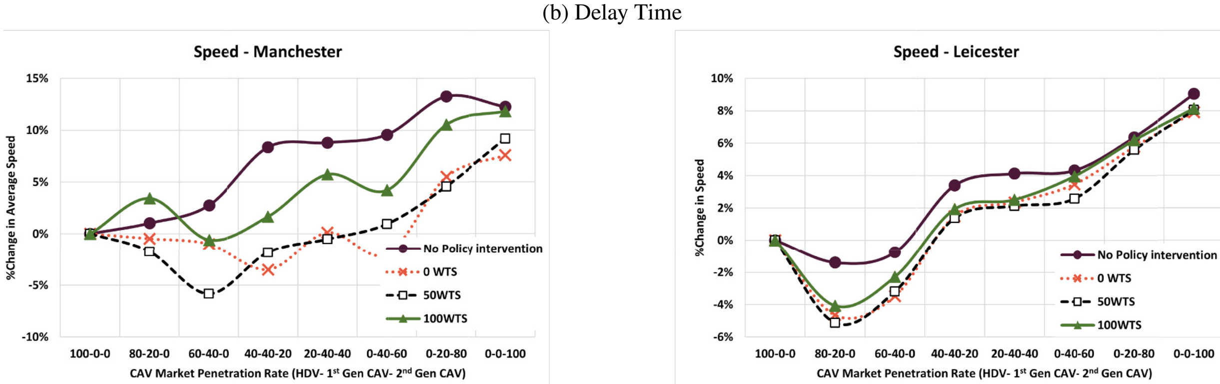
Wilingness to Share	All	Manchester Passenger Car + SAV	Freight Vehicles	All	Leicester Passenger Car + SAV	Freight vehicle+PT
1st Generation CAVs						
0 %	−9 %	−9.1 %	−8.5 %	−1.2 %	−1.5 %	1.2 %
50 %	−6.1 %	−6.3 %	−4.4 %	−2.7 %	−3.2 %	0.1 %
100 %	−4.4 %	−4.6 %	−2.9 %	−2.8 %	−3.2 %	−0.3 %
2nd Generation CAVs						
0 %	−7.6 %	−7.7 %	−7.2 %	−1.5 %	−1.8 %	0.8 %
50 %	−4.9 %	−5.1 %	−3.2 %	−1.9 %	−2.3 %	1 %
100 %	−5.4 %	−5.5 %	−4 %	−1.4 %	−1.7 %	1.1 %



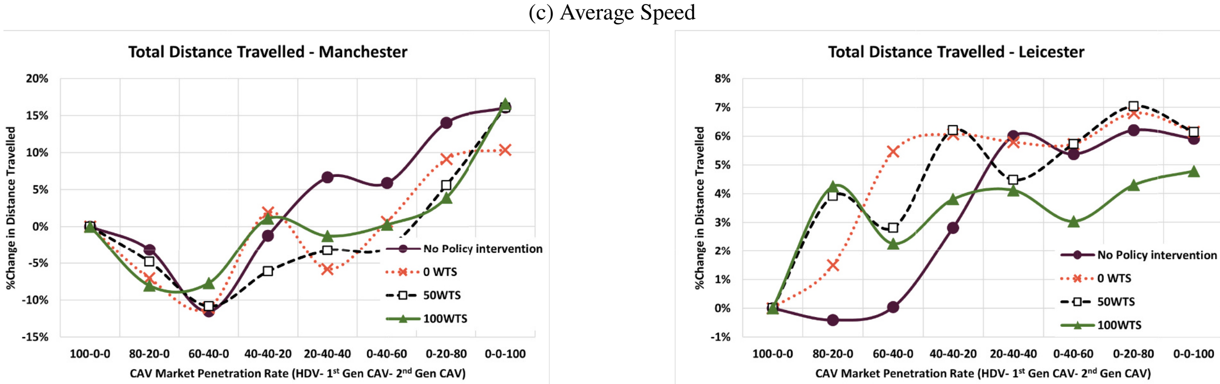
(a) Travel Time



(b) Delay Time



(c) Average Speed



(d) Kilometres travelled

Fig. 4. Mobility impact results in terms of Percentage change with respect to Baseline scenario for Manchester and Leicester networks - Scenario 2.

Table 4
Emissions impact results in terms of Percentage change with respect to baseline scenario for Manchester and Leicester networks - Scenario 1.

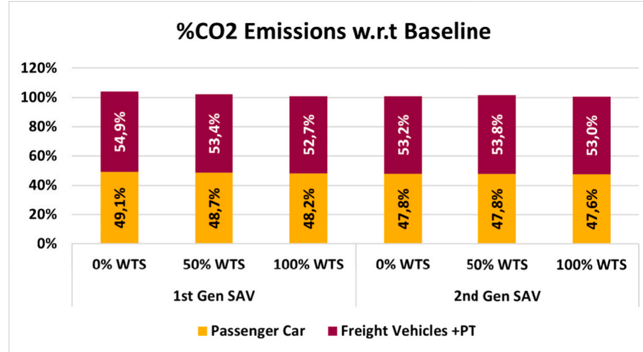
Wilingness to Share	Manchester			Leicester		
	CO2	NOX	PM	CO2	NOx	PM
1st Generation CAVs						
0 %	−2.11 %	4.15 %	−7.06 %	3.98 %	6.12 %	4.27 %
50 %	−2.34 %	1.45 %	−5.25 %	2.12 %	5.02 %	1.74 %
100 %	−2.26 %	0.08 %	−4.03 %	0.90 %	5.29 %	−0.48 %
2nd Generation CAVs						
0 %	−3.46 %	1.76 %	−7.66 %	0.99 %	3.27 %	0.84 %
50 %	−2.90 %	0.86 %	−5.50 %	1.63 %	2.72 %	2.28 %
100 %	−3.64 %	−0.77 %	−5.63 %	0.55 %	2.18 %	0.72 %

increased distance compared to the corresponding baseline scenario. The increase could be attributed to the slight increase in freight vehicles and PT (Table 3) and the SAV empty VKT resulting from SAVs pick-up trips. However, with a higher WTS, a decreasing trend could be observed.

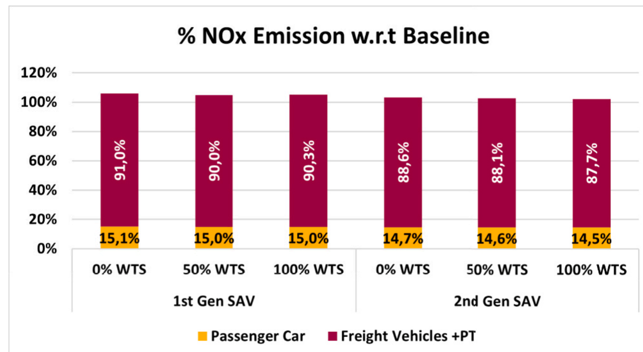
The results regarding the introduction of ARS service with a mixed conventional and automated background fleet are presented in Fig. 4. The results indicate that automation (No policy intervention) will improve network performance. More specifically, automation leads to decreased values of delay and travel time with increasing CAV MPR (Fig. 4a and b), reaching a maximum percentage of −25 % and − 49.5 %, respectively, for the Manchester network and − 14.62 % and − 33.25 % for Leicester Network at full MPR with 2nd Generation CAVs (0−0−100).

In terms of ARS service, the results show that introducing this type of service negatively impacts network performance compared to no policy intervention (Fig. 4). More specifically, travel time results for ARS scenarios appear to be higher than the no-policy-intervention scenario, particularly at low CAV MPR (80–20–0 and 60–40–0), where the ARS performed worse than the baseline scenario (100−0−0) in both networks. A similar pattern could be seen for delay time. Regarding distance travelled and average speed, an increasing trend could be seen with increased CAV MPRs for all scenarios. When ARS scenarios are compared to no policy intervention scenarios, it is clear that ARS scenarios perform worse. However, at 100 %WTS the conditions are improved compared to 0 % WTS specially in travel time and delay (Fig. 4a and b). The adverse impact of ARS could be related to the interaction between the different vehicle types accessing the network (HDV, CAVs, and SAVs) with different driving characteristics especially at low MPR where HDV and 1st Gen vehicles are the dominant modes. Furthermore, SAVs circulating behaviour can also aggravate the traffic conditions as the routing algorithm favours shortest routes that could include low capacity and secondary roads, which could create traffic congestion.

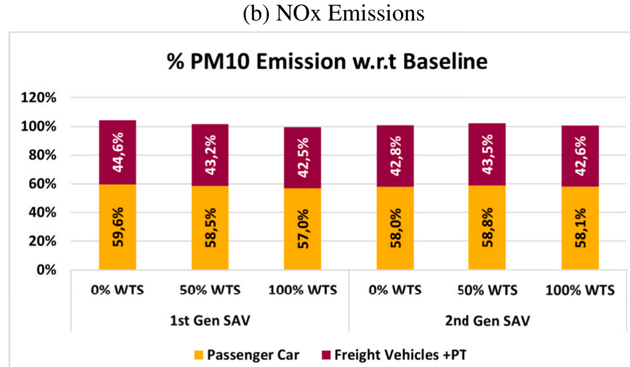
Comparing the ARS scenarios with each other, it could be seen that increase in delay and travel time is significant, inversely related to the rate of travellers WTS as well as the CAV MPR. The results suggested that with low WTS, delay time seems to be higher compared to higher WTS. For example, at full CAV MPR (0–0-100), the delay time decreases from 67,17 s/km with 0 % WTS to 56,21 s/km in the Manchester network and from 65,88 s/km to 62,41 s/km in Leicester Network. The same observation applied to average speed results as higher values could be observed with higher WTS (100 %WTS). One of the potential reasons for this is the number of SAVs trips that increases when a large portion of passengers decide to use SAV for individual trips (0 % WTS), which means less vehicle occupancy and more empty trips to reach new passengers. In general, more SAV trips imply more travelled distance. In



(a) CO2 Emissions



(b) NOx Emissions



(c) PM10 Emissions

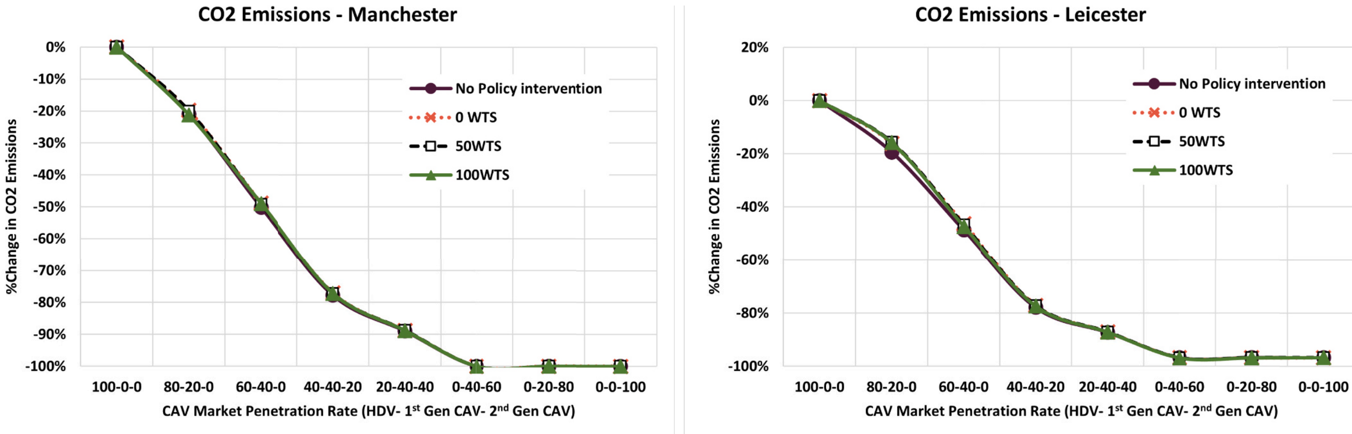
Fig. 5. Percentage change in emissions with regards to Baseline scenario for Leicester network.

other words, the distance travelled is expected to increase with low WTS. However, the results in Fig. 4d show an inconsistent trend due to traffic congestion and trip length that prevents SAVs from finishing their scheduled trips and many vehicles from entering the network by the end of the simulation period.

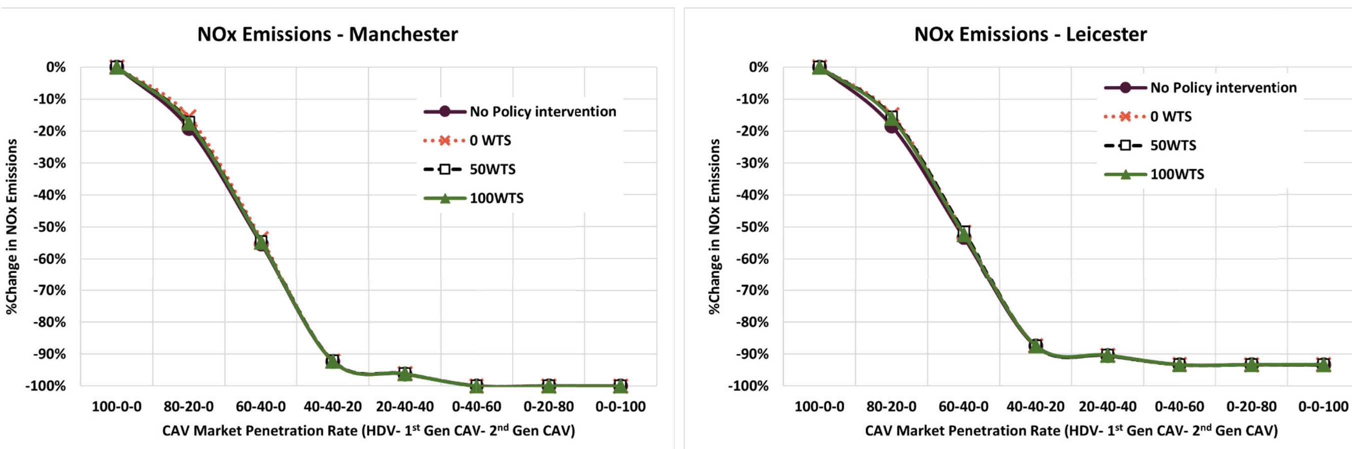
5.3. Environmental impact

The environmental impacts were directly obtained from the AIMSUN Next microscopic simulation for automated ride-sharing using the model of Panis et al. (2006). This model considers three emission indicators named Carbon Dioxide (CO2), Nitrogen Oxides (NOx) and Particulate Matter (PM10).

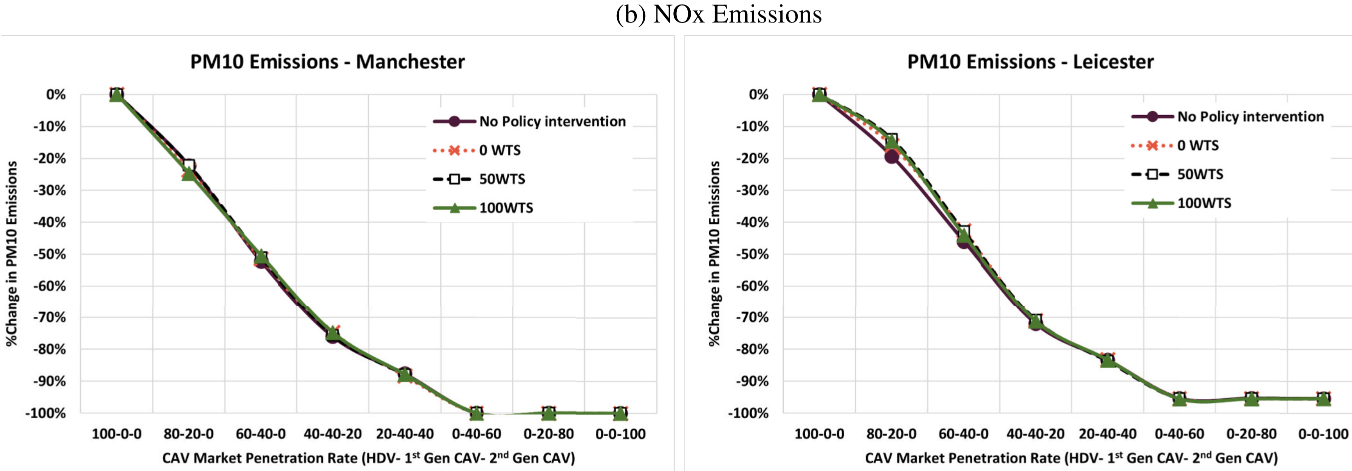
Table 4 presents the findings from Scenario1 in terms of percentage changes with regards to the baseline scenario. Despite the presence of electrically powered SAVs, the three indicators are increasing for the Leicester network. Also, emissions are reduced with increased passenger willingness to share (WTS) and advanced CAV technology. The additional emissions are mainly caused by an improvement in traffic



(a) CO2 Emissions



(b) NOx Emissions



(c) PM10 Emissions

Fig. 6. Environmental impact results in terms of Percentage change with respect to Baseline scenario for Manchester and Leicester networks.

conditions, which allowed more freight and public transport vehicles to enter the network (3), especially with the introduction of 2nd Generation SAVs. As shown in Fig. 5, the majority of the additional emissions are attributed to freight and public transport.

Regarding the Manchester network, with 1st Generation or 2nd Generation SAVs, the results show an overall decrease in CO2 and PM10 emissions and a slight increase in NOx emissions which is attributed to freight vehicles in the network. The reduction is linked to the decrease in the number of vehicles entering the network caused by congestion (Table 3).

Results regarding the introduction of ARS service into a mixed conventional and CAV traffic are shown in Fig. 6. The CO2, NOx, and PM10 emissions follow a consistent decreasing trend with increasing CAVs MPR for all studied scenarios compared to the baseline scenario (100–0-0), which is expected since CAVs are assumed to be electric vehicles. Regarding ARS impacts, Table 5 displays the percentage change of CO2 emission indicators concerning the automation scenario (no policy intervention). The impact of ARS introduction varied with WTS level.

Table 5
Percentage change of CO2 Emissions with respect to No Policy intervention (Automation without ARS service) – Scenario 2.

Market Penetration Rate (HDV–1st Gen CAV-2nd Gen CAV)	Manchester			Leicester		
	0 %	50 %	100 % WTS	0 % WTS	50 % WTS	100 % WTS
80–20–0	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
60–40–0	1.49 %	1.27 %	−0.34 %	4.14 %	4.71 %	4.41 %
40–40-20	2.63 %	1.94 %	2.39 %	4.97 %	4.01 %	2.79 %
20–40-40	3.40 %	2.56 %	2.66 %	3.41 %	3.22 %	2.39 %
0–40-60	–	–	–	1.48 %	1.29 %	0.61 %
0–20-80	–	–	–	−0.56 %	−1.31 %	−3.23 %
0–0-100	–	–	–	−0.87 %	−0.54 %	−2.92 %

The table shows that there is an increase in CO2 compared to no policy intervention regardless of the WTS level. However, the impact of ARS improves with high WTS levels, especially at high CAV MPR. Overall, the results indicated that the WTS level is a key factor in determining the impacts of ARS on emissions. With low WTS, vehicle occupancy decreases, resulting in additional empty trips and distance travelled. These findings are consistent with those in Lu et al. (2018), which suggest that the autonomous taxi system could increase GHG and SO2 emissions despite using electric Taxi.

6. Conclusion

This paper investigates the impacts of introducing automated ride sharing (ARS) on mobility and the environment through optimisation and microsimulation assessment methods. The evaluated service is a door-to-door service that combines ridesharing and CAVs. This study investigated two deployment scenarios: an early deployment stage in which CAVs were introduced as SAV sharing the road with a conventional vehicle fleet in the background, and an advanced deployment scenario in which SAV operates in an environment with a mixed fleet of conventional and automated vehicles. Both scenarios were evaluated in two city-scale networks with distinct characteristics: a city-centre area in Leicester (UK) and a suburban area in Greater Manchester (UK), taking into consideration passenger WTS their rides with others. In the early implementation scenario, the findings indicated that ARS would have a different impact depending on the network characteristics, CAV technology, and the level of passengers' WTS. A negative impact on network performance was observed in the Manchester suburbs with the introduction of ARS service, as there was a significant increase in delay and travel time, in addition to a decrease in the number of vehicles entering the network. The negative impact could be caused by the following factors: 1) interaction between HDVs and CAVs, which are expected to have different driving styles and capabilities, 2) SAV repositioning trips (pick-up trips), 3) SAV circulating behaviour because they tend to use low capacity and secondary roads to reach their destinations. An increase in the delay was also observed in the Leicester city-centre network, along with an increase in traffic flow, implying a slight improvement in network performance compared to the Manchester suburban network. The findings also suggest that users' (WTS) trips with other travellers can significantly impact traffic by reducing the number of automated taxi vehicles and trips in the network.

Regarding environmental impacts, emissions were reduced with increased WTS and advanced CAV technology. However, the impact on the two networks was different. In the suburban area (the Greater Manchester) a decrease was observed but is not necessarily considered an improvement since it is associated with the reduced number of vehicles in the network. On the other hand, in the Leicester city-centre network, the opposite was observed as the results describe an increase in emissions due to an improvement in the traffic conditions. This could be attributed to network characteristics (dense road network with more options for alternative routes), which are substantially different from the Greater Manchester network. In addition, the analysis showed that most emissions come from freight and PT vehicles and since more non-electric powered vehicles are entering the network, additional emissions could be expected.

Regarding introducing an ARS service into a mixed conventional and automated fleet, the results showed that the proposed service adversely impacts mobility and the environment in both test networks. More specifically, an increase in delay and travel time was observed compared to the scenario where only automation was considered due to additional empty trips of SAVs and interactions between the different vehicle types in the network. However, the impact is significantly related to the level of WTS, as findings suggest that traffic conditions can be improved with high WTS. Concerning environmental impacts, an increase in emissions was found under mixed fleet scenarios, possibly due to congestion resulting from interactions between the different driven styles of simulated vehicles and SAV repositioning trips and circulating behaviour.

The findings from this study provide a useful insight for traffic network operators on how ARS can be implemented on urban mobility during the early stage of deployment of autonomous vehicles. The convenience and cost-effectiveness of SAVs can motivate individuals to shift from owning private vehicles to utilising shared services (Zhang et al., 2018). Additionally, the rising popularity of ridesharing can result in a lower demand for parking (Zhang et al., 2015). Policymakers and practitioners should promote the usage of such services as shared rides not only as shared vehicles. In addition, the most optimal policy can likely differ from one city to the other as the effects of ride-hailing services can vary based on the state of public transit of a city (Hall et al., 2018). The benefits of an automated ride sharing system are highly dependent on users' willingness to combine trips, and it has the potential to increase congestion due to empty repositioning trips. Therefore, before implementing an automated ride sharing system, the suitability of local conditions should be investigated first. Future research should be tested and analysed these impacts when real-world data become available.

The current study assumed that sufficient battery capacity for all-day operations and adequate parking spaces for all shared autonomous vehicles at each station are available, which does not represent the most realistic scenario. In the future, the impacts could be observed by varying these variables. The current study also plans to explore the potential for assessing the economic impact of ARS in terms of travel time value and environmental impacts in future research.

CRediT authorship contribution statement

Rajae Haouari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Hua Sha:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Mohit Kumar Singh:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Conceptualization. **Evita Papazikou:** Writing – review & editing, Writing – original draft, Formal analysis. **Amna Chaudhry:** Writing – review & editing. **Pete Thomas:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Andrew Morris:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Mohammed Quddus:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Data availability

The authors do not have permission to share data.

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