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The short-term impacts of cooperative, connected, and automated mobility on passenger transport

Deliverable D6.2 – WP6 – PU

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The short-term impacts of cooperative, connected, and automated mobility on passenger transport

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List of abbreviations

ACC	Adaptive Cruise Control
AIT	Austrian Institute of Technology
API	Application Programming Interface
AV	Automated Vehicle
CACC	Cooperative Adaptive Cruise Control
CATS	Connected and Automated Transport Systems
CAV	Connected and Autonomous Vehicle
CCAM	Cooperative, Connected and Automated Mobility
CC	City centre
C-ITS	Cooperative Intelligent Transport Systems
CV	Connected Vehicle
DRS	Dynamic Ride Sharing
ERP	Expected Penetration Rate
ERTRAC	European Road Transport Research Advisory Council
EU	European Union
EV	Electric Vehicle
GLOSA	Green Light Optimal Speed Advisory
HDV	Human Driven Vehicles
HGV	Heavy Goods Vehicle
HOV	High Occupancy Vehicle
HOT	High Occupancy Toll
IC	Inner city
IP	Intra peripheral
ldm	Longest distance mode
LGV	Large Goods Vehicles
MPR	Market Penetration Rate
mUoM	Marginal utility of money
NHTSA	National Highway Traffic Safety Administration
NRC	National Research Council
PCU	Passenger car unit
PST	Policy Support Tool
PT	Public Transport
RUP	Road use pricing
SAE	Society of Automotive Engineers
SAV	Shared Autonomous Vehicle
SD	System dynamics
SRG	Stakeholder Reference Group
SUC	Sub-use Case
TTC	Time to Collision
UC	Use Case
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle

V2X	Vehicle to everything
VHT	Vehicle Hours Travelled
VKT	Vehicle Kilometres Travelled
VMT	Vehicle Miles Travelled
VTTS	Value of travel time saved
VRPPDTW	Vehicle Routing Problem with Pickup and Delivery with Time Window
XP	Extra peripheral
WTS	Willingness to share

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Executive summary

The aim of the LEVITATE project is to prepare a new impact assessment framework to enable policymakers to manage the introduction of cooperative, connected, and automated transport systems, maximise the benefits and utilise the technologies to achieve societal objectives. As part of this work, the LEVITATE project seeks to forecast societal level impacts of cooperative, connected, and automated mobility (CCAM).

The aim of this report is to provide an analysis of the short-term impacts, described in Deliverable 3.1 (Elvik et al.,2019), of different passenger car transport sub-use cases (policy interventions). The short-term impacts analysed include travel time, vehicle operating cost, and access to travel. Based on several discussions with the stakeholder reference group (SRG) including city officials and industry professionals, a list of key interventions, termed sub-use cases (SUCs), were selected to be tested through different applicable methods. These include road use pricing (rup), provision of dedicated lanes on urban highways, parking price policies, parking space regulations, automated ride sharing, and green light optimal speed advisory (GLOSA). For assessing the travel time impact, mesoscopic and microscopic simulation as well as Delphi method have been used. The Delphi method was also used to estimate impacts on vehicle operating cost and access to travel. Road Use Pricing was modelled through mesoscopic simulation using the full-scale city-level model of Vienna. All other sub-use cases were analysed through microscopic simulation method using Manchester network for Dedicated Lanes, Automated Ride Sharing and GLOSA, Leicester network for Parking Space Regulations, and Santander model for testing Parking Price Policies.

CAVs deployment was tested from 0 to 100% with 20% increments under all applicable sub-use cases. The behaviours of CAVs were defined based on an extensive literature review performed as part of the LEVITATE project. Two types of connected and automated vehicles (CAV) were included in the analysis, 1st Generation CAVs and 2nd Generation CAVs, where 2nd generation CAVs were assumed to have improved driving characteristics and enhanced cognitive capabilities, which will lead to shorter time gaps as compared to the 1st generation CAVs and human-driven vehicles (HDV).

Overall, results from the policy interventions tested under passenger transport provided useful insights with regard to their implications and short-term impacts. Regarding the impact on travel time, the findings from different assessment methods were in line for the majority of studied policy measures. The implementation of a static road use pricing strategy in the city of Vienna indicated more consistent benefits due to static pricing with respect to the average travel time, while the impact due to dynamic road use pricing implementation was found difficult to predict due to the added complexity in traffic operation. The responses from majority of the Delphi study participants also indicated similar trends, suggesting that the introduction of city tool policies would positively impact travel time.

Findings from the microsimulation results of provision of a dedicated lane for CAVs on urban highways indicated maximum travel time savings under innermost lane configuration and at moderate market penetration rate (MPR) of CAVs (60% HDVs, 40% CAVs). The experts' opinions in this regard also indicated maximum travel time reduction under the innermost lane placement scenario. Parking management was identified as one

of the key areas of interest by SRG. In this regard, various on-street parking space regulations were tested, including replacing parking lanes with driving lanes, cycle lanes, public spaces, pick-up drop-off areas, and removing half of the on-street parking. Results indicated positive impacts on traffic operation when parking spaces were replaced with driving lanes, cycle lanes, and public spaces, compared to replacement with pick-up/drop-off areas and removing half of the parking spaces. In addition to parking space replacement interventions, a parking pricing policy was also tested in the inner-city domain to evaluate the impact of various parking strategies on travel time. Under all the tested parking price schemes, on average, the results showed an increase in travel time with respect to no policy intervention (baseline) scenario. It was identified that the right policy decision on parking pricing is critical in avoiding negative impacts on traffic.
Under passenger transport, an automated ridesharing service was also analysed in one of the study networks which showed an increase in travel time due to congestion caused by the empty pick-up trips and circulating behaviour of shared vehicles (using low capacity and secondary roads). It was found that benefits from such services can only be obtained with an increased willingness to share.

With regard to connectivity, the Green Light Optimal Speed Advisory system was tested on a busy corridor in the Manchester network with three signalized intersections, sufficiently apart for GLOSA implementation. All CAVs were assumed to be GLOSA equipped. Results exhibited reduction in number of stops and travel time with GLOSA application as compared with No-GLOSA (baseline) scenario. Maximum travel time savings can be achieved when applied at multiple intersections or at corridor level.
The findings from Delphi study showed that introduction of automated vehicles are expected to increase operating cost in the short term which can expected to be reduced with higher MPR while access to travel was indicated to progressively increase with increasing MPR of automated vehicles. Automated ride sharing services were foreseen to have a significant impact in reducing vehicle operating costs and increasing access to travel.

Overall, the results provide some important messages for city departments of governments to manage potential consequences due to the introduction of CAVs in the transport system. The findings from different policy interventions, tested in this deliverable, exhibit that increasing MPR of CAVs solely may not have positive impacts and the right policy measures are critical for achieving positive impacts (e.g., travel time savings) with the introduction of CAVs. The results also indicate the importance of the transition phase to full fleet penetration of CAVs.

1 Introduction

1.1 LEVITATE

Societal **Lev**el **I**mpacts of Connec**t**ed and **A**utoma**t**ed Vehicl**e**s (LEVITATE) is a European Commission supported Horizon 2020 project with the objective to prepare a new impact assessment framework to enable policymakers to manage the introduction of connected and automated transport systems, maximise the benefits and utilise the technologies to achieve societal objectives.

Specifically LEVITATE has four key objectives:

1. To establish **a multi-disciplinary methodology** to assess the short, medium and long-term impacts of CCAM on mobility, safety, environment, society and other impact areas. Several quantitative indicators will be identified for each impact type.
2. To develop a range of **forecasting and backcasting** scenarios and baseline conditions relating to the deployment of one or more mobility technologies that will be used as the basis of impact assessments and forecasts. These will cover three primary use cases – automated urban shuttle, passenger cars and freight services.
3. To apply the methods and forecast the impact of CCAM over the short, medium and long term for a range of use cases, operational design domains and environments and an extensive range of mobility, environmental, safety, economic and societal indicators. A series of case studies will be conducted to validate the methodologies and to demonstrate the system.
4. To incorporate the established methods within a **new web-based policy support tool (PST)** to enable city and other authorities to forecast impacts of CCAM on urban areas. The methods developed within LEVITATE will be available within a toolbox allowing the impact of measures to be assessed individually. A Decision Support System will enable users to apply backcasting methods to identify the sequences of CCAM measures that will result in their desired policy objectives.

1.2 Work package 6 and deliverable 6.2 within LEVITATE

Work Package 6 (WP6) considers the specific case of passenger cars which are used across the transport system so forecasting of impacts involved the use on urban, rural and highway infrastructure, consequently.

Forecasting will be based on the methodology developed in WP3 and the scenarios developed in WP4 to identify and test specific scenarios regarding the impacts of CATS on urban transport. More specifically, the objectives of Work Package 6 (WP6) are:

- To identify how each area of impact (safety, mobility, environment, economy, and society) will be affected by the transition of passenger cars into Connected and automated transport systems (CATS), with focus on the transition towards higher levels of automation. Impacts on traffic will be considered cross cutting the other dimensions.
- To assess the short, medium, and long-term impacts, benefits, and costs of cooperative and automated driving systems for passenger cars

- To test interactions of the examined impacts in passenger cars, and
- To prioritise considerations for a public policy support tool to help decision making.

The purpose of Deliverable 6.2 is to present the *short-term impacts* of connected and automated passenger cars with regards to increasing CAV deployment rates. The exact impacts of interest and how to measure these have been previously defined in WP3 and WP4. The specific nature of short-term context has been defined in D6.1 (Boghani et al., 2019). Focus in this report is placed on impacts on travel time, vehicle operating cost, and access to travel. The main methodological approaches used to forecast the short-term impacts are microscopic traffic simulation modelling, mesoscopic mobility simulation modelling, and Delphi method. The simulation modelling approaches are used to estimate the road network-level impacts of the integration of different impacts for different transport types, modes and actors. Those which could not be analysed through simulation modelling techniques, are assessed through Delphi study.

Table 1.1 presents an overview of the list of impacts considered in the PST for WP6, along with a short description and the unit of measurement. Highlighted are those handled in this deliverable.

Table 1.1: Overview of the impacts in WP6. Highlighted are the short-term impacts for this deliverable.

Impact	Description	Method
Short term impacts / direct impacts		
Travel time	Average duration of a 5Km trip inside the city centre	Mesoscopic simulation/ Microscopic simulation/Delphi
Vehicle operating cost	Direct outlays for operating a vehicle per kilometre of travel	Delphi
Access to travel	The opportunity of taking a trip whenever and wherever wanted (10 points Likert scale)	Delphi
Medium term impacts / systemic impacts		
Congestion	Average delays to traffic (seconds per vehicle-kilometre) as a result of high traffic volume	Microscopic simulation
Amount of travel	Person kilometres of travel per year in an area	Mesoscopic simulation/Microscopic simulation/Delphi
Modal split using public transport	% of trip distance made using public transportation	Mesoscopic simulation/ System dynamics/Delphi
Modal split using active travel	% of trip distance made using active transportation (walking, cycling)	Mesoscopic simulation/ System dynamics/Delphi
Shared mobility rate	% of trips made sharing a vehicle with others	Delphi
Vehicle utilisation rate	% of time a vehicle is in motion (not parked)	Delphi
Vehicle occupancy	average % of seats in use	Delphi

Long term impacts / wider impacts		
Road safety	Number of traffic conflicts per vehicle-kilometre driven (temp. until crash relation is defined).	Road safety method
Parking space	Required parking space in the city centre per person (m2/person)	System dynamics/Delphi
Energy efficiency	Average rate (over the vehicle fleet) at which propulsion energy is converted to movement	Delphi
NO_X due to vehicles	Concentration of NO_x pollutants as grams per vehicle-kilometre (due to road transport only)	Microscopic simulation
CO_2 due to vehicles	Concentration of CO_2 pollutants as grams per vehicle-kilometre (due to road transport only)	Microscopic simulation
PM_{10} due to vehicles	Concentration of PM_{10} pollutants as grams per vehicle-kilometre (due to road transport only)	Microscopic simulation
Public health	Subjective rating of public health state, related to transport (10 points Likert scale)	Delphi
Accessibility in transport	The degree to which transport services are used by socially disadvantaged and vulnerable groups including people with disabilities (10 points Likert scale)	Delphi
Commuting distances	Average length of trips to and from work (added together)	System dynamics

2 Sub-use cases

The term 'sub-use case' (SUC) in this deliverable refers to subcategory (policy intervention) under passenger car use-case developed to study the quantifiable impacts of CCAM on passenger transport. From the stakeholder reference group (SRG) workshop, detailed in D 6.1 (Boghani et al., 2019), consultation was obtained from the experts from city administrations and industry on the generation and prioritization of the sub-use cases. Within LEVITATE, this list has been prioritized and refined within subsequent tasks in the project to inform the interventions and scenarios related to passenger transport. In turn, these SUCs will be included in the LEVITATE Policy Support Tool (PST).

The prioritisation of the sub-use cases mainly took these three input directions into account:

- Scientific literature: Indicating the scientific knowledge and the available assessment methodologies for the sub-use cases. However, this might not be directly linked to their importance / relevance for practice.
- Roadmaps: Indicating the relevance of sub-use cases from the industrial/ political point of view, independent of available scientific methodologies.
- SRG Workshop: Containing first-hand feedback for the sub-use cases but might only reflect the opinions of organisations and people who participated.
- Results of the backcasting city dialogues conducted in LEVITATE WP4 for Vienna, Greater Manchester and Amsterdam (Zach, Sawas, Boghani, & de Zwart, 2019; Papazikou et al., 2020)

Considering the input from all three sources, six key sub-use cases have been defined within WP6 and covered in the present report, which are as follows:

1) Road use pricing (RUP)
2) Provision of dedicated lanes on urban highways
3) Parking price policies
4) Parking space regulation:
5) Automated ride sharing, and
6) Green Light Optimal Speed Advisory (GLOSA).

2.1 Road use pricing (RUP)

The term road-use pricing refers to charges for the use of infrastructure, including distance and time-based fees, road tolls and various charges with the scope to discourage the access or long-stay of vehicles within an area.

Within LEVITATE the two different price charging schemes are considered as defined above for all passenger vehicles for a commercial mixed traffic zone. Here, "dynamic toll" is to be understood as a toll with dependency on occupancy (empty km or car sharing), time (system entry time), and space (road class or/and zone) while the unit pricing for those parameters could be fixed per respective unit (e.g., peak-hours/off-peak hours, km, persons). Differently, the "static toll" refers to a fixed fee or tax paid by users to enter a tolling area.

2.1.1 Literature review

Existing urban systems

Existing road-use pricing systems concern a specific highway or highway network, or a well-defined city centre area. The major city systems in operation include London, Singapore, Stockholm and Milan. The charge can be modified during peak-hours or increased congestion. The performance of each system depends heavily on their specificities. Table 2.1 summarises the characteristics of the road-charging schemes in these four cities.

Table 2.1 Characteristics of existing road-use pricing schemes (IEA/OECD, 2009)

Town	Name	Date implemented	Scheme type	Area (km²)	Operating hours	Price	Enforcement system
Singapore	Electronic road pricing	1975	Cordon ring (in)	7	Mo-Sa 7.00 - 22.00	Gantry / time dependent EUR 0 to 1.5	Radiofrequencies + cameras
London	Congestion charge	2003	Cordon ring (in)	40	Mo-Fr 7.00-18.30	Flat rate, GBP 8/day	CCTV cameras
Stockholm	Congestion tax	2006 (became permanent in 2007)	Cordon ring (in and out)	35	Mo-Fr 6.30-18.30	EUR 1 to 2/crossing depending on time of day	Laser + cameras
Milan	Ecopass	2008 (temporary through end of 2009; extension possible)	Cordon ring (in)	8	Mo-Fr 7.30-19.30	EUR 2 to 10/day	Digital cameras

In terms of the impact of such policies, they decrease congestion as they affect the amount of traffic and also, the amount of vehicle utilisation. Other beneficial impacts concern emissions drop, CO_2 emissions reductions and safety (Transport for London, 2007; Eliasson, Hultkrantz, Nerhagen & Rosqvist, 2009). It is generally supported that implementation of cordon schemes of congestion pricing in large urban areas could have a beneficial and wider impact in the society (IEA/OECD, 2009).

2.1.2 Political sensitivity of the sub-use case and implications

Road-use or congestion pricing schemes have faced opposition and protests, it has been criticised as not equitable, with negative effects in the economy of neighbourhoods and on retail businesses, or as another tax. Nevertheless, under appropriate supporting conditions economical evaluations mostly agree on the viability of the intervention to reduce congestion and control traffic in the city centre (Kopp & Prud'Homme, 2010; Anas & Lindsey, 2011; Croci, 2016).

Within the LEVITATE project outcomes from the mesoscopic simulation on this intervention are disseminated via deliverables D6.2 and D6.3 (Sha et al., 2021) for short-term and medium-term impact assessment. Emphasis will be given wherever appropriate within the deliverables or case study documents that they are only case studies to see the effects of road use pricing intervention in those cities, and not necessarily their intention or decision to implement such intervention.

The road use pricing has raised significant interest and attention during the dialogue with cities and stakeholders, who made apparent that they would like to investigate both pricing models/options in order to adopt the optimum policy according to their priorities and their city vision.

In the initial list of interventions to explore there was also a differentiation in tolls between the human driven and fully automated vehicles. However, after the dialogue with the cities' representatives, it became clear that their *vision focuses on the reduction of any private motorised vehicle in their city centre*, rendering the toll variance meaningless.

2.1.3 Implementation

The method identified as most applicable to derive conclusions on changing mobility behaviour that is caused by variation of mobility pricing schemes, is an agent based macroscopic mobility simulation of activity chains with an underlying calibrated choice model. This method has been applied previously to investigate RUP measures at several implementation sites:

- Meyer de Freitas, Schuemperlin, and Balać (2016): Different toll levels in Zurich were simulated until a reduction of 20% vehicle kilometres travelled was reached.
- Kaddoura and Kickhöfer (2014): Application of road pricing to the MATSim Sioux Fall scenario.
- Simoni, Kockelman, Gurumurthy, and Bischoff (2019): The authors applied road pricing strategies in combination with AV vehicles.

Further assumptions made to investigate the SUC's scenarios for tolling imposed on the inner-city region of the overall model area, are detailed in section 3.2. These assumptions allow for consideration of both static pricing upon toll-area entry as well as dynamic pricing depending on the travelled distance within the toll-area.

2.2 Provision of dedicated lanes on urban highways

According to Connected Automated Driving Roadmap from ERTRAC (2019), Dedicated AV Lane is a lane where vehicle(s) with specific automation level(s) are allowed but the area is not confined (it would be segregated in that case). It is envisaged that where a dedicated public transport lane is in operation, the dedicated AV lane would be integrated with the dedicated public transport lane, allowing both types of vehicles.

The discussions within SRG meeting and findings from recent literature suggest that certain policies and regulations can directly influence the adoption of CAVs such as, road use pricing, parking fee, dedicated lanes, price of owning and operating car and many more. Within LEVITATE Project the policy intervention of Dedicated Lanes is thoroughly investigated as a sub-use case. The main objectives of this sub-use case included:

- Determining the minimum market penetration rate (MPR) required for dedicated lane to be viable option
- Investigating the optimal configuration for dedicated CAV lanes,
- Finding the societal level impacts of dedicated CAV lanes

2.2.1 Literature review

In principle, the concept of dedicated lanes originates from the high occupancy vehicle (HOV) and toll (HOT) lanes. This type of lanes was reserved for the exclusive use of vehicles with a driver and one or more passengers including carpools, vans and transit buses. The first application of HOV lane can be placed around the 1970s. In theory, the implementation of this type of lanes was supposed to encourage people to car share and car-pool. However, the evaluation of the HOV lanes showed that they were underutilised and hence the concept of HOT lanes was introduced where single-person vehicles are allowed to drive in these lanes if they pay a fee. Another type of lane that has been discussed in relevant literature over the years is electric-vehicle only lanes, an intervention that could provide incentive to buy an electric vehicle.

Dedicated AV lanes have been the topic of research for several research papers and European literature (Mohajerpoor & Ramezani, 2019; Vander, Laan & Sadabadi, 2017; Ye & Yamamoto, 2018). Theoretically, the introduction of dedicated AV lanes is supposed to provide an incentive to people to buy an automated vehicle and, especially during the first years of AV implementation, limit the interaction between humans and AVs which could be proven problematic. In this regard, literature review was performed to identify various lane allocation strategies under different fleet compositions, and their resulting traffic performance.

Mohajerpoor and Ramezani (2019) analysed the characteristics of mixed-traffic flow of AVs and NVs (Normal Vehicles) on arterials and highways to model the impact of AVs on saturation flow rate using analytical models to determine headways and their variability. As part of this study, the impact on delays on a two-lane road under various lane allocations, including dedicated AV lanes, was also investigated. In total, four lane allocation policies were analysed for their delay effects on the specified two-lane link road: (a) dedicated lanes (one AV, one normal vehicle (NV)), (b) mixed-mixed lanes (both lanes for mixed traffic), (c) mixed-NV lanes (one for NV and one for mixed traffic), and (d) mixed-AV lanes (one for AV and one for mixed traffic). The best lane-allocation policy was found to be the mixed-NV lanes policy when the expected penetration rate (ERP) is less or equal to 50%; the dedicated lanes policy for 50%< EPR <65%; and the mixed-AV lanes policy for 65%≤ EPR ≤100%.

Previously, an autonomous vehicle behaviour has been modelled at the macroscopic level in a study by Vander Laan and Sadabadi (2017), which considered the impact of the operational performance of autonomous vehicles (AV) on a multi-lane freeway corridor with separate lanes dedicated to AV and non-AV traffic. Newell's linear car-following model is used and applied to a 22 mile stretch of the 4-lane I-95 corridor between Washington, DC and Baltimore, MD during the afternoon peak period (1600-1800), when congestion levels are generally high. The impact of introducing an AV-only lane is assessed at numerous AV penetration rates, with Vehicle Hours Travelled (VHT), Vehicle Miles Travelled (VMT), average speed and vehicle throughput all are plotted against AV penetration rate. Under one AV dedicated lane, the results showed that as penetration rates increased up to 30, 40 or 50%, overall corridor performance metrics (VHT, VMT, speed, throughput) improved; however, further AV penetration considerably worsened the overall traffic performance.

Ye and Yamamoto (2018) also analysed the behaviour of CAVs in mixed traffic conditions with a dedicated lane through fundamental diagrams. A cellular automaton model was developed with no specific road environment but using the penetration rates, densities, dedicated lane numbers and time to determine the impact on flow. Their results indicated degradation in the performance of the total traffic flow throughput with CAV dedicated lanes at a low CAV penetration rate, particularly at a low-density level. At higher penetration rate, the benefits of establishing dedicated lanes were found to diminish as well. Their findings suggested that benefit of providing a dedicated CAV lane is only achievable within a moderate density range. The penetration rate of CAVs and their individual performance are critical elements in determining the performance of a CAV dedicated lane. The higher the performance of the CAV, the more value it will derive from the implementation of a CAV dedicated lane. Additionally, the performance of the CAV dedicated lane can be increased by requiring CAVs to go at a faster speed than vehicles on other conventional lanes.

Ma and Wang (2019) studied the impact of CAV dedicated lanes on traffic flow in heterogeneous traffic condition. A cellular automata model was used as the car-following (longitudinal) and lane-changing (lateral) model in this study and a one-way four lane scenario was modelled, based on a freeway similar to Interstate 15 north of San Diego. The paper verifies that setting up exclusive lanes for CAV will greatly improve the traffic condition of the freeway under different penetration rates of CAV. However, when the proportion of CAVs is much less or much higher, the dedicated lanes do not show great impact on capacity. Based on the results on traffic flow, the study suggested one dedicated lane to be the most suitable option under CAV penetration rate ranging from 10 to 40% whereas with further increase in CAVs percentage i.e., 50-90%, two dedicated lanes were recommended as the optimal option.

In many studies identified across this literature review, two and four lane freeways/motorways were used in the simulations, and speed, speed variances, travel time and traffic density were identified as the main impacts, with penetration rates of between 30-60% leading to the best outcomes for the impacts (e.g., faster times, speeds and minimal speed variance).

2.3 Parking price policies

In the stakeholders' reference group meetings, there has been a special emphasis on parking space management within CATS. Following that this sub-use case investigates various possible interventions related to parking to analyse various impacts within LEVITATE project.

2.3.1 Literature review

Parking price is one of the key factors for deciding personal vehicle use as a mode of transportation. Currently, there are around 30million cars in Great Britain (Department of Transport [DfT], 2017). As the number of cars increases, the need for parking spaces will increase. Parking spaces may not always be available, so policymakers want to reduce the demand for parking spaces as well as low occupancy cars. This is one of the reasons for implementing the parking prices (Institute for Transport Studies, 2019).

Autonomous vehicles do not need to park near the destination or park at all. Hence, this could solve the problem of parking. As autonomous vehicles do not require parking, then they could do one of the following actions: a) roam around until the passenger needs them again, b) they can go back to origin or park outside, c) there could be an intermediate situation where some of the vehicles return to the parking, and some remain in the network.

The strategy of increased parking prices to reduce parking behaviour is not new. These have been implemented since the 90s for better management of spaces. A survey of UK local authorities by Healey and Baker (1998) revealed that at that time 25% of the authorities were trying to cut parking spaces. Whereas around 50% of them were planning to increase the parking price.

A study by Simićević, Vukanović, and Milosavljević (2013) used a stated preference survey to quantify the effects of parking price on the use of parking spaces. The authors developed the relationship between parking price and time limitation. It was found that parking price affected car use, whereas the time limitation decides whether people use on-street or off-street parking. Further, it was also found that parking price could help manage the parking spaces and it could also destroy the attractiveness of some zones. Studies also show that the parking price could affect the travel time (Qian & Rajagopal, 2014)

A study by Calvert, Schakel, and van Lint (2017) has shown the effects of autonomous vehicles on travel time. It was observed that the travel time reduces with the incremental introduction of autonomous vehicles. Another study by Santana et al. (2021) also supported this and shown that the travel time reduces with the introduction of AVs. Another study by Rezaei and Caulfield (2021) also supported this and demonstrated that the travel time reduces with the introduction of AVs, but the incremental trend is not uniform, and it shows a fluctuating trend.

A study by (Cheng & Qi, 2019) investigated the impact of the parking price on the quality of service at Hongqiao International Airport parking. The results were compared before and after implementing the parking price. It was found that this method helps to reduce long term parking demand and improved parking availability at the airport. Further, the income of the airport was also increased significantly.

Liu (2020) analysed the impact of pricing on public parking spaces. The author concluded that increasing the parking price would increase the government revenue from parking and buses. Further, the parking prices would discourage passengers from using personal vehicles and promoting public transport. The maximum benefit of this scheme could be obtained with optimal parking prices.

Parking prices are introduced to reduce the personal and single occupancy vehicles on the roads. These strategies also help in increasing the traffic flow, decreasing the travel time (Qian & Rajagopal, 2014) and improving the safety of vehicles. Several other studies also proved similar results to decrease the travel time with the increasing MPR of CAVs. However, these studies were done for varying parking price conditions. The results may be different when multiple parking choices are available to the passengers.

2.4 Parking space regulations

On-street parking is the most common parking prototype that comprises all paid and unpaid parking activities along the roadside in urban cities (Biswas, Chandra, & Ghosh, 2017). It allows drivers to park their vehicles close to their destination and share the same road width with other vehicles moving on the street (Prakash, Bandyopadhyaya, & Sinha, 2020). On-street parking has some natural contributions to the economy. However, the negative effects have drawn attention from governmental bodies and academic institutions in terms of causing congestion, capacity reduction and increasing road traffic accidents. Theoretically, the introduction of autonomous vehicles offers the potential to improve road safety and reduce the urban space requirements for roads and parking, and this opens up new opportunities to create more space for high-quality and liveable areas (González-González, Nogués, & Stead ,2019; 2020).

2.4.1 Literature review

As described in the previous section, on-street parking can significantly impact traffic performance and may create or exacerbate various problems for urban cities. In this respect, a recent study conducted by Hasan, Haider, and Islam (2021) revealed the effects of on-street parking in Chittagong City, Bangladesh. The results showed that on-street parking could have the following negative effects: narrows down the road (47%); footpath crisis (29%); noise and air pollution (23%), shops get blocked (5%), and loss of time (30%).

Some previous studies indicated that on-street parking may bring negative impacts on the travel time. Guo, Gao, Yang, Zhao, and Wang (2012) applied the hazard-based duration model and attempted to quantify the influential factors related to on-street parking. In the study, 938 vehicles were observed in two-lane, two-way streets. The results showed a significant impact of on-street parking on travel time. This study also provided several important insights on factors that influence the travel time including: (a) the distribution of travel time can be an influential factor; (b) the effective lane width; and (c) the frequency of parking/unparking manoeuvres can be considered as the most significant influencing factors on travel time. A similar finding was reported by Lim, Hallare, and Briones (2012). The authors used the analytical survey method and the experimental method in Metro Manila. The results revealed that the manoeuvring of vehicles in and out of an on-street parking space have increased the travel time of moving vehicles. A recent study conducted by Putri and Prahara (2021) investigated the relationship between travel time and on-street parking. The Manual Kapasitas Jalan Indonesia (MKJI) 1997 and linear regression model has been applied in this study. The results showed that on-street parking has a strong influence on vehicle’s travel time to get through to the study area.

Meanwhile, on-street parking has a high association with traffic congestion. According to Biswas et al. (2017), on-street parking normally reduces the road capacity in two ways and eventually contributes to the capacity loss of urban roads. Firstly, on-street parking narrows down the carriageway width and vehicles are forced to move into this reduced carriageway leading to a reduction in overall stream speed. Secondly, frequent parking and unparking manoeuvres creates congestion on the roads. Hence, up to 90% of the capacity reduction was reported in the study consequence of the on-street parking. A study from Fadairo, (2013) indicated that nearly 14% of all congestion on urban roads were caused by on-street parking or parking manoeuvring vehicles. Guo et al. (2012) observed that traffic volume decreased when the proportion of parking manoeuvres was increased, and 35% of parking manoeuvres can eventually reduce the capacity up to 35%.

There are a number of studies that investigated the relationship between on-street parking and traffic delay. Nahry, Agah, Thohirin, and Hamid (2019) examined the effect of on-street parking in Jakarta by modelling the relationship between various variables, (i.e., parking turnover, parking index, flow-in and flow-out). The modelling results showed that the variable of parking turnover has a significant impact on the traffic delay. In other words, the higher the volume and the parking turnover, the higher the delay will be. A similar finding was reported by Borovskoy and Yakovleva (2017). The authors developed a dynamic simulation model that integrated AIMSUN software with a Vehicle Tracking application for AutoCAD to study parking turnover impact on traffic flow. The results revealed that the increase in the on-street parking turnover led to an increase in traffic delays. Sugiarto and Limanoond (2013) examined the impact of on-street parking manoeuvres on travel speed and capacity, particularly on urban artery roads in the city of Banda Aceh. The traffic simulation showed that with the presence of on-street parking, the average delay time was increased by 32%, and the speed was reduced by 24%.

Several previous studies have also indicated speed reduction on urban roads to be an immediate consequence generated by parked vehicles (Biswas et al.,2017; Kladeftiras and Antoniou, 2013). A recent study conducted by Praburam and Koorey (2020) has reported that on-street parking has a significant impact on traffic speed. The results showed that the mean speeds were reduced by around 10km/h between empty and full on-street parking levels and fell at a rate of 1km/h for an increase of 10% in the parking levels.

A number of studies attempted to predict the impacts of on-street parking using traffic simulation approach, especially in the context of autonomous vehicles (such as Chai, Rodier, Song, Zhang, & Jaller, 2020; International Transport Forum [ITF], 2018; Biswas et al., 2017). A study by Chai et al. (2020) used the SUMO traffic model and local travel activity data to simulate AV parking scenarios in the central business district of San Francisco. In the study, three scenarios have been simulated: (a) demand for drop-off and pick-up travel versus parking; (b) the supply of on-street and off-street parking; and (c) the total demand for parking and drop-off and pick-up travel due to an increase in the cost to travel. The results showed that the shift from parking trips to drop-off and pick-up trips improves traffic flow due to reduced parking search time and more efficient use of parking spaces. The results also indicated that over-allocation of drop-of and pick-up spaces could further increase CO2 emissions from vehicles that got stuck in traffic congestion and suggested that such convention of parking spaces to drop-off and pick-up spaces must be street specific and dynamic over-time to adjust to the changes in AV market shares.

A study conducted by International Transport Forum (ITF,2018) provided a modelling exercise to quantify the impact of re-allocating curb space from parking to pick-up and drop-off zones for passengers and freight in an area of central business district of Lisbon, Portugal. The results showed that the curb-release lay-bys have a better fit between the supply and demand for pick-up/drop-off capacity and significantly reduce queuing and resulting delays. The results also suggested that city councils should consider how to dynamically manage the spaces from the street to the curb over the course of the day.

The review of literature indicated that besides some natural contributions to the economy, on-street parking can cause some prominent negative impacts on traffic performance and create hazards to road users in several ways, i.e., increasing journey time, causing congestion, reducing road capacity, increasing traffic emissions, and increasing road traffic accidents. It is envisaged that the introduction of autonomous vehicles can potentially mitigate some of the negative impacts as well as provide new opportunities in the cities for high-quality and liveable areas.

2.5 Automated ride sharing

Ridesharing is a conventional model where the private car is shared via pre-arranged journeys. Ridesharing is pre-arranged within, for example, neighbourhoods, community, the workplace, or informally via ride-matching websites and applications.

Sharing taxis has been done informally at taxi stands by identifying similar destinations via 'word of mouth'. However, app-based taxi sharing is an emerging business model where the user can call a taxi via the app and share it with others if they wish to. Ride matching is handled by optimising algorithms and matched ride options are available to users via the apps. CCAM can play a significant role in this model as connectivity will enhance the taxi sharing options.

However, it is important to identify that micro-transit services and on-demand mini-bus services can be operated along fixed or flexible routes based on demand. These are usually commercial services, and the number of seats is usually greater than taxis. This option seems to overlap with the urban shuttle sub-use case within the LEVITATE project and does not seem to be a passenger car sub-use case.

Out of the possible options, it has been recognised that automated taxi sharing is the fastest emerging business and is already in operation in many cities worldwide. Considering the suitability under the passenger transport use case, automated taxi sharing was taken forward as one of the sub-use cases within this work package.

2.5.1 Literature review

The emergence of autonomously driven vehicles holds great promise for the future of on-demand shared mobility services. On-demand mobility services, such as car-sharing, ride-hailing, and ride pooling, have gained increased popularity over the past few years. Due to becoming an increasingly common travel solution, such mobility services are causing a dramatic change in the mobility behaviour of the users, especially in urban areas. On-demand mobility services can positively impact transportation, land use, the environment, and society, and combining them with the emergent technology of autonomously driven vehicles could amplify these benefits.

In this regard, a comprehensive review of relevant studies in the field of Shared Autonomous Vehicles (SAVs) was presented by Narayanan, Chaniotakis, and Antoniou, (2020). The authors discussed SAV services from different aspects, including service typology, characteristics, modelling, and potential impacts. They found most studies showing an increase in mobility and efficiency of the transportation system. A comparison of the studies over the years was also undertaken and further showed the change in impacts due to certain variables. For example, a decrease was found in the potential of SAVs to reduce parking requirements between 2015 and 2018. Data detail, accessibility, and reliability were identified as some of the main challenges of using the current tools to estimate the need for shared services. It also appeared to be the case that shared services will lead to a modal shift from public transport, and so SAVs would need to be integrated efficiently with public transport in the future. The authors also reported that assumptions within the previous studies are often based on current travel data rather than being based on future projections. In order to realistically understand the impacts of introducing SAVs, scenarios need to be based on plausible assumptions that may occur in the future. From the review, it was found that the main areas where there is a lack of research include fleet size, elasticity, short-term car sharing systems, dynamics pricing, social equity, and public health.

It is also important to predict the potential impacts of shared autonomous mobility services on travel behaviour and land use. In this context, Soteropoulos, Berger, & Ciari, (2019) presented their findings through a review of modelling studies investigating the impacts of SAVs on travel behaviour and land use. The review found that shared AV fleets could have positive impacts, reducing vehicles numbers and parking spaces as well as VHT. However, there could also be potential for a slight increase in the inner-city population. The results also suggested that in rural areas, a greater number of vehicles may be needed to replace the current fleet due to more empty rides. The authors indicated the need for more research on empirical travel costs and perception of time in AVs, especially with shared rides. Additionally, future issues that were identified 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.

With regard to extra vehicles miles (VMT) travelled, Fagnant, Kockelman, and Bansal (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 are going to be served by SAVs and performed the simulation using MATSIM dynamic traffic simulation software under different traffic conditions during the daytime using 5-minute departure time windows. 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 minute user wait times. In terms of distance travelled, the results showed the new service generate around 8% extra VMT due to pick-up and relocation empty trips. The results also showed that in spite of the additional VMT, SAV deployment will probably 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.

In terms of the benefits and costs of SAVs, Gurumurthy, Kockelman, and Simoni, (2019) performed an analysis across Austin, Texas, through agent-based modelling using MATSim, replicating the travel patterns in Austin, Texas with personal and shared AVs, and Dynamic Ride Sharing (DRS) and road pricing policies in use. The impacts of fleet size, pricing and fare levels were scrutinized, with the results showing that inconvenience and privacy issues were overcome by the cost-effectiveness of travelling with strangers when fares were at a low-medium level. Lower fares for those using Dynamic Ride Sharing appeared to increase passenger's willingness to share rides and therefore resulted in a higher Average Vehicle Occupancy. Regarding fleet size, 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 also keep fares relatively low to ensure the maximum benefits, which should limit any effects on rising traffic congestion.

In order to identify the overarching advantages and disadvantages Lokhandwala and Cai (2018) analysed taxi sharing using agent-based modelling with New York city data. A comparison of traditional taxis with shared automated taxis was undertaken. A potential fleet size reduction of 59% could be achieved from the switch to shared automated taxis from traditional taxis without any significant increase in wait time for occupants. The main benefits highlighted were increased occupancy rates, reduced travel distances, reduced carbon emissions and increased system flexibility. One disadvantage highlighted was that a reduced fleet size caused by dynamic ride sharing could lead to taxis focusing on higher demand areas, so some areas would be left with limited services, particularly in the suburbs.

The review of the literature presented above identifies several positive benefits of SAV services on mobility. However, fleet size and willingness to share elements play a key role in maintaining the potential for positive benefits. More research is needed in areas like fleet size, elasticity, short-term car-sharing systems, dynamics pricing, social equity and public health, travel costs, and perception of time in ridesharing.

2.6 Green Light Optimal Speed Advisory (GLOSA)

Cooperative Intelligent transport Systems (C-ITS) functions are employed to improve traffic safety and efficiency and are realized through communication between road vehicles and infrastructure together with on-board vehicle software. Among these, there are the so-called Day 1 services that build on mature technologies and are expected to be available on the short term (Mellegård & Reichenberg, 2019).

Green Light Optimal Speed Advisory (GLOSA) is a Day 1 C-ITS signage application enabled by the C-ITS service "Signalised Intersections". The application utilises traffic signal information and the current position of the vehicle to provide a speed recommendation in order for the drivers to pass the traffic lights during the green phase and, therefore, reduce the number of stops, fuel consumption, and emissions. The distance to stop, the plans for signal timing and the speed limit profile for the area are taken into account to calculate the speed recommendation displayed to the driver. GLOSA service is provided through ETSI G5 into the on-board computer of the vehicle or via mobile network into a smartphone app.

Road transport entails undoubtfully benefits to society but does not come without externalities. The negative effects on the environment and the society include traffic crashes, pollution and congestion (Santos, Behrendt, Maconi, Shirvani, & Teytelboym, 2010). Congestion entails interrupted flow, lower speeds, larger travel times and delays. This has an environmental impact as when a vehicle faces delays on the road, with multiple stops and waiting in the traffic lights, due to mostly speed alterations and frequent acceleration and deceleration manoeuvres, the fuel consumption and pollution is increasing.

In recent years, technological achievements have rendered vehicle wireless communications available. Connected vehicle technology includes vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication and has several safety and mobility applications (Radivojevic, Stevanovic, & Stevanovic, 2016). As traffic information becomes accessible, connected vehicles are able to adapt their behaviour according to traffic conditions which can contribute to beneficial changes in traffic flow and emissions (Masera, Imprialou, Budd, & Morton, 2019). One emerging vehicle to infrastructure application that intends to improve emissions through optimizing traffic flow on signalized road networks is the Green Light Optimal Speed Advisory (GLOSA). The basic concept and working of the system is elaborated through a schematic diagram in Figure 2.1 .

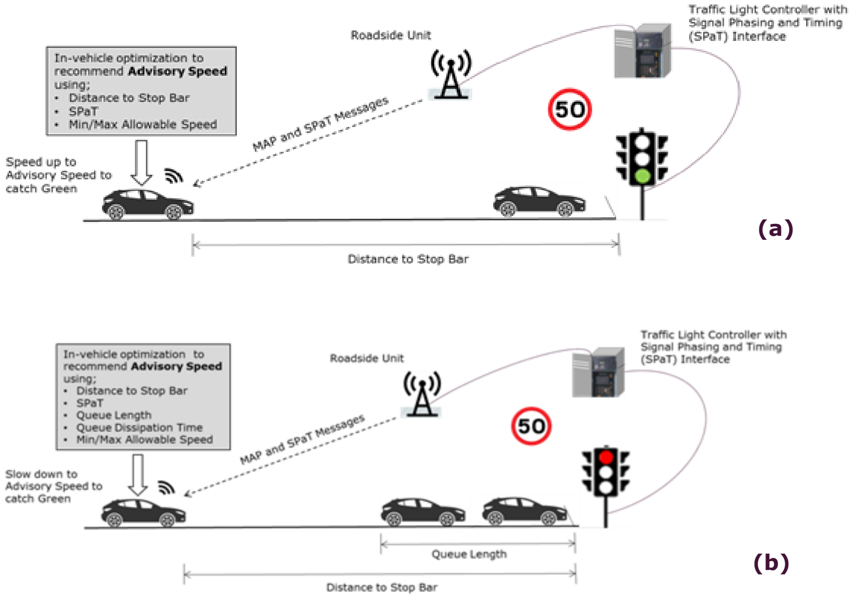


Figure 2.1: GLOSA system and application overview: (a) Communication initiated when current phase is Green, (b) Communication initiated when current phase is Red

In automated and connected vehicles era, it would be useful for cities, various stakeholders, and transport planners to assess the societal impacts of such an application in an urban area and attempt to evaluate the benefits in relation to the relevant costs.

2.6.1 Literature review

With regard to previous studies exploring the impacts of GLOSA system, Mellegård and Reichenberg (2019) provided a review of 64 publications between 2006 and 2019 investigating GLOSA (Figure 2.2). Most based their findings on simulation, with a much smaller amount using real-world methods (e.g., pilots, FOTs). The on-board GLOSA algorithm was proposed as the main solution in the majority of the studies, with less proposing the whole system and/or predicting signal changes as the solution. The focus was on the equipped vehicle in most studies, as opposed to fellow road users or other societal issues. In terms of impacts, many of the studies looked at the effect of varying traffic levels on GLOSA effectiveness. No publications examined drivers' ability to follow the advised speed. Travel time increases, as well as decreases, were seen across the 64 studies.

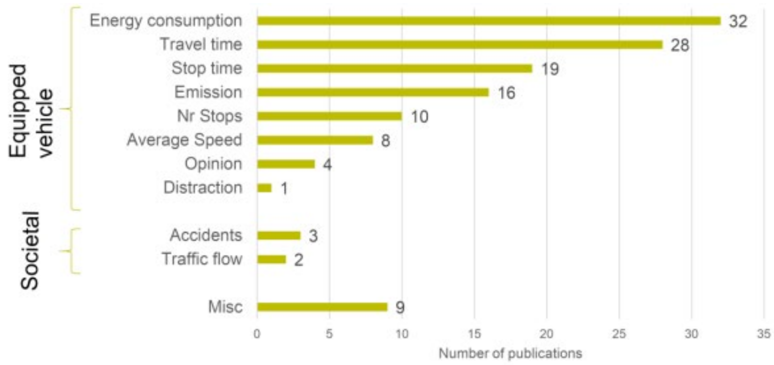


Figure 2.2: Overview of the effects/impacts evaluated across the 64 papers (from Mellegård and Reichenber, 2019)

The potentials and limitations of GLOSA systems in realistic large-scale simulations were investigated by Eckhoff, Halmos, and German (2013). This study mainly looked at environmental-related impacts (e.g., emissions) but also analysed impacts on waiting times and the number of stops. The simulation framework Veins was used, coupling OMNeT++ and the traffic simulator SUMO. An area of Munich was used to develop the simulation, and four levels of traffic density were investigated in the study, two were in free flow, one was in semi-free flow, and one was in synchronised flow. CO_2 emissions were lowered by up to 11.5% in low traffic densities, waiting times by 17% and amount of stops potentially by around 6%. But in heavier traffic conditions, some issues were detected, such as longer waiting times higher CO_2 emissions for non-equipped vehicles.

Gajananan et al (2013) used an integrated traffic, driving and communication simulator to investigate the effects of GLOSA on emissions, travel times and stopped times. GLOSA introduction led to a reduction in all 3 of these areas (40-68% reduced stopped times, 10-16% reduced travel times, 8-20% reduced CO_2 emission). Lebre et al (2015), have also reported reductions in travel time through a simulation study under experimental and real traffic conditions.

Karabag (2019) modelled two intersections on a section of road in the city of Tallahassee, Florida, USA, using VISSIM simulation software. The reduction in delay was found to be significant including decrease in stop delay by 84% and number of stops by 88%.

Previous studies have also reported that benefits on GLOSA system can be achieved if used with fixed time signal controllers. For instance, Stevanovic, Stevanovic, & Kergaye (2013), who used VISSIM simulation model of 5-intersection corridor in the US while testing fixed and actuated signal timings, found improvement in travel time, number of stops, and fuel consumption under fixed timings, but not under actuated operation. Under fixed-time controllers, the authors also reported improvement in traffic performance with higher MPR and increased frequency of GLOSA system activation. Signal retiming/optimization before implementing GLOSA was suggested as increasing the benefits from such an application.

Overall, findings from the previous studies indicate reduction in travel time with application of GLOSA system particularly when used with fixed time signals. However, percentage reduction reported was found to vary across the existing literature. Previous studies also indicated that expected benefits can be attained at low traffic densities whereas under congested traffic situations the system could be counterproductive.

3 Methods

The types of impacts that are presented in Deliverable 3.1: A taxonomy of potential impacts of connected and automated vehicles at different levels of implementation (Elvik et al.,2019) have been estimated and forecast using appropriate assessment methods, such as traffic simulation, system dynamics and Delphi panel method. For example, traffic simulation can directly provide short-term impacts. Therefore, it was used to forecast short-term impacts to be able to develop relationships that can infer dose (in terms of introduction of sub-use case) and response (selected impact). Traffic simulation also provides further input to assess medium-term impacts by processing those results appropriately to infer such impacts. System level analysis (such as by tools found within system dynamics) can provide measure of long-term impacts. For the sake of simplicity and applicability of assessment methods, it is assumed that for the appropriate level of automation, adequate infrastructure exists. It is also assumed that the pure technological obstacles for the sub-use cases in consideration are solved. All these results relating to the relationships between sub-use cases, impacts and any intermediate parameters will be provided to WP8 of LEVITATE, which concerns the development of the LEVITATE Policy Support Tool (PST). The results will be integrated within the PST modules and functionalities so that impact assessment can be carried out by the user.
An overview of the methods used to estimate the short-term impacts in this deliverable is presented in Table 3.1.

Table 3.1: Overview of the methods used to estimate short-term impacts of connected and automated vehicles under WP6

Sub-use Cases	Methods		
	Microscopic Simulation	Mesoscopic Simulation	Delphi
Road use pricing (RUP)		✓	✓
Provision of dedicated lanes for AVs on urban highways	✓		✓
Parking price policies	✓		✓
Parking space regulations	✓		✓
Automated ride sharing	✓		✓
Green Light Optimal Speed Advisory (GLOSA)	✓		✓

3.1 Microscopic simulation

Traffic simulation has been widely applied to estimate the potential impacts of connected and automated vehicles. As identified in LEVITATE Deliverable on Impact Assessment Methods (Elvik et al., 2020), many studies have used microsimulation technique to estimate the potential impacts of CATS on traffic performance indicators. It is envisaged that the microsimulation approach can be used to calculate the direct impacts of CAVs. In most cases, a commercially available traffic microsimulation tool (such as AIMSUN, VISSIM, Paramics or SUMO) is used along with an external component. The microsimulation tool is applied to represent the infrastructure and creates the traffic in the predefined road system, while the external component aims to simulate the CATS functionalities.

Within WP6, the traffic microsimulation method is used to model and analyse the sub-use cases of dedicated lanes, parking price policies, parking space regulation, automated ridesharing, and GLOSA. AIMSUN Next Microsimulation tool has been used in all the sub-use cases, utilising calibrated and validated city networks, including Manchester and Leicester in the UK and Santander in Spain. CAV functionalities/behaviours were modelled by adjusting a wide spectrum of parameters in the simulation framework.

Two types of CAVs (1st Generation CAVs and 2nd Generation CAVs) were modelled to analyse the sub-use cases, details of which are provided in the following section. The deployment of CAVs was tested from 0 to 100% MPR with 20% increments as shown in Table 3.2 .

Table 3.2: CAV Deployment scenarios

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Vehicle - passenger vehicle	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV - passenger vehicle	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (ambitious) CAV - passenger vehicle	0%	0%	0%	20%	40%	60%	80%	100%
Human-Driven LGV	100%	80%	40%	0%	0%	0%	0%	0%
LGV-AV	0%	20%	60%	100%	100%	100%	100%	100%
Human-Driven HGV	100%	80%	40%	0%	0%	0%	0%	0%
HGV-AV	0%	20%	60%	100%	100%	100%	100%	100%

3.1.1 Modelling of CAVs behaviours

Two types of CAVs were considered in this study:1st Generation CAVs and 2nd Generation CAVs. Both types are assumed to be fully automated vehicles with level 5 automation. The main idea behind modelling these two types is based on the assumption that technology will advance with time. Therefore, 2nd Gen CAVs will have improved sensing and cognitive capabilities, decision making, driver characteristics, and anticipation of incidents etc. In general, the main assumptions made on CAVs characteristics are as follows:

- 1st Generation: limited sensing and cognitive ability, long gaps, early anticipation of lane changes than human-driven vehicles and longer time in give way situations.

- 2nd Generation: advanced sensing and cognitive ability, data fusion usage, confidence in taking decisions, small gaps, early anticipation of lane changes than human-driven vehicles and less time in give way situations.

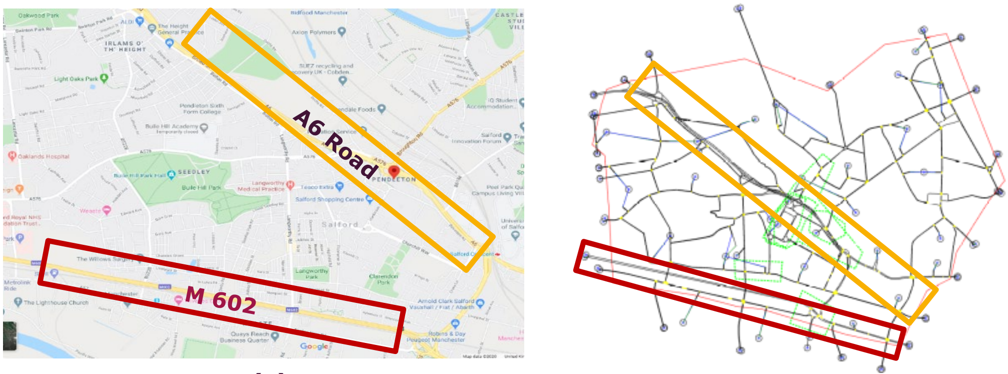
These characteristics were defined through various model parameters in AIMSUN Next including reaction time, time gap, acceleration and deceleration characteristics, parameters related to lane changing and over taking behaviour and several others. The default car-following model in AIMSUN is based on Gipps model (Gipps,1981,1986). Various parameters of the car-following model were adjusted to implement HDV and CAV behaviours. The assumptions on CAV parameters and their values were based on a comprehensive literature review, including both empirical and simulation-based studies (Cao et al.,2017; Eilbert, Berg, & Smith,2019; Goodall & Lan,2020; de Souza & Stern ,2021; Shladover, Su, & Lu ,2012), as well as discussions in meetings with various experts within the project. Some guidance on the behaviours was also obtained through studies on adaptive cruise control (ACC) and cooperative ACC (CACC) systems.

Traffic impact of CAVs were assessed in mixed traffic conditions that contain, in addition to passenger cars, freight and public transport (PT) vehicles. The automation of freight vehicles was also considered; however, due to limited knowledge on automation of freight vehicles, only a few parameters were adjusted to model the behaviours of freight CAVs.

3.1.2 Implementation based on SUC

3.1.2.1 Provision of dedicated lanes on urban highways

A calibrated and validated traffic microsimulation model of Manchester area (provided by Transport for Greater Manchester) was used for this sub-use case. In general, the model development and calibration involved details of road network in the study area, peak hour traffic demand, vehicle types, signal timing data, vehicular behaviour and lane usage, journey times, bus routes, stations, and timetable information. A comprehensive set of traffic counts was used to compare and validate the modelled flows with observed traffic counts. Modelled journey times were also compared and validated against observed journey times during the peak hours. This model provides a good foundation for the experiment as it includes a motorway and a major arterial road (M602 and A6, respectively) (Figure 3.1) which connect the centre of Manchester with the suburbs.



(a) (b)

Figure 3.1: The modelling area in the city of Manchester (a) and Manchester network in AIMSUN software (b)

Assumptions and parameters

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

- When introduced, the dedicated lane will be mandatory for CAVs and public transport (if applicable). That means that the CAVs are not allowed to travel in any other lane unless they cannot follow their route in any other way.
- The dedicated lane will be located either on motorway or A road in the Manchester Network.
- The A-road consists of several consecutive segments, which comprise of either two or three lanes. It is always assumed that one of these lanes is a dedicated lane, except in intersections when one cannot define a dedicated lane due to AIMSUN limitations.

Scenarios

In order to identify the most optimal strategy for providing dedicated lane which can potentially be most beneficial, the placement of dedicated lane was investigated under various scenarios including:

- Baseline scenario – AV implementation without a dedicated lane
- Scenario 1 – CAVs use a dedicated (innermost) lane in the motorway
- Scenario 2 – CAVs use a dedicated (innermost) lane in the motorway and the A-road
- Scenario 3 – CAVs use a dedicated (innermost) lane in the A-road.
- Scenario 4 – CAVs use a dedicated (outermost) lane in the A-road.

These scenarios were formulated in order to address the research questions, outlined under 2.2.

In order to address the question of what is the minimum required market penetration rate for dedicated lanes to be a viable option, several mixed fleet combinations including human driven vehicles (HDVs) and CAVs with different market penetration rates were tested in each of the aforementioned scenario.

3.1.2.2 *Parking price policies*

A microsimulation model of Santander City was employed for this sub-use case (Figure 3.2). This city centre area model served the purpose of analysing the impact of various possible AV parking behaviours due to different parking price policies. The used network model contains 108 nodes (intersections) and 382 sections (one-way links). The study considers the evening peak hours (1900 - 2200) for analysis with an estimated traffic flow of 42337 private car trips.

Figure 3.2: The modelling area in Santander city (a) and in AIMSUN software (b)

This sub-use case refers to enforcing parking behaviour through different parking price policies. However, these behaviours can also be influenced by limiting parking spaces within a particular area. With automated vehicles, the widespread belief is that one would be able to command their highly automated vehicles to drive around with no occupants in them to avoid parking for a short duration. Four parking behaviours were considered for this sub-use case (Figure 3.3):

- Enter and park inside the area (baseline – consistent with the current situation),
- Enter, drop off passengers and return to origin to park (outside and inside included),
- Enter, drop off passengers and return to outside parking restriction area to park, and
- Enter and drive around (short stay)- the vehicle drops the passenger and drive around while waiting for the passenger to ride again

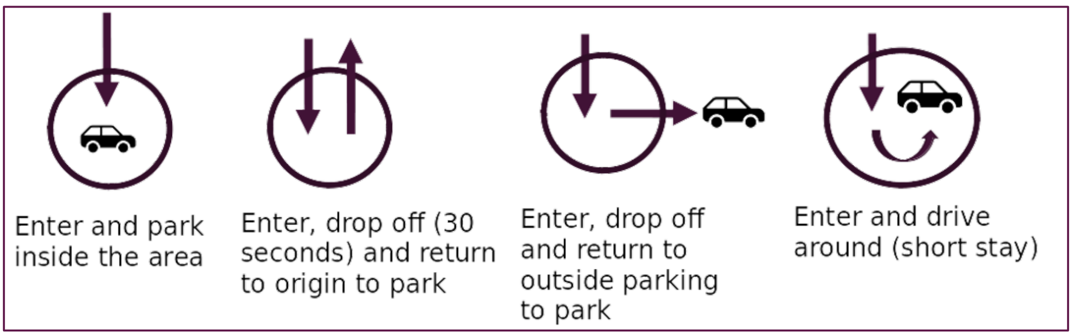


Figure 3.3: CAVs Parking behaviours

Different scenarios were considered based on the proportions of vehicles choosing these parking options (see Table 3.3).

Table 3.3: Scenarios relating to the prevailing parking behaviors.

	Return to Origin %	Park Outside %	Drive around %	Park Inside %
Baseline	0%	0%	0%	100%
Case 1 (balanced)	22%	45%	20%	13%
Case 2 (Heavy drive around)	0%	0%	100%	0%
Case 3 (Heavy Return to origin and Park outside)	33%	67%	0%	0%

Assumptions

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

- In the baseline scenario, it is assumed that sufficient spaces are available, and vehicles can park themselves inside without causing any disturbance to the traffic
- In the 'heavy drive around scenario', vehicles drop the passenger and drive around nearby
- In the case of 'heavy Return to origin and Park outside' vehicles do a mixed activity of parking outside and return origin
- The 'Balanced' scenario consists of a combination of all the parking choices available
- All CAVs are EVs
- All human driven vehicles are non-electric vehicles.
- CAVs and classic vehicles can travel together without any requirement of dedicated lanes
- HGVs and LGVs are not present
- There exist only given parking options

Several possible compositions of modes (Human driven car, first generation AVs and second-generation AV) were considered for all scenarios for analysis (Table 3.2).

3.1.2.3 Parking space regulations

The study network used for this sub-use case is a traffic microsimulation model (developed using AIMSUN software) of the city of Leicester. Due to having the city centre area, this model served the purpose of analysing various on-street parking space regulations. The Leicester city centre network is around 10.2km² and consists of 788 nodes and 1,988 sections. The traffic demand for passenger cars, LGVs and HGVs are 23,391 trips, 3,141 trips and 16 trips, respectively. The network is presented in Figure 3.4.

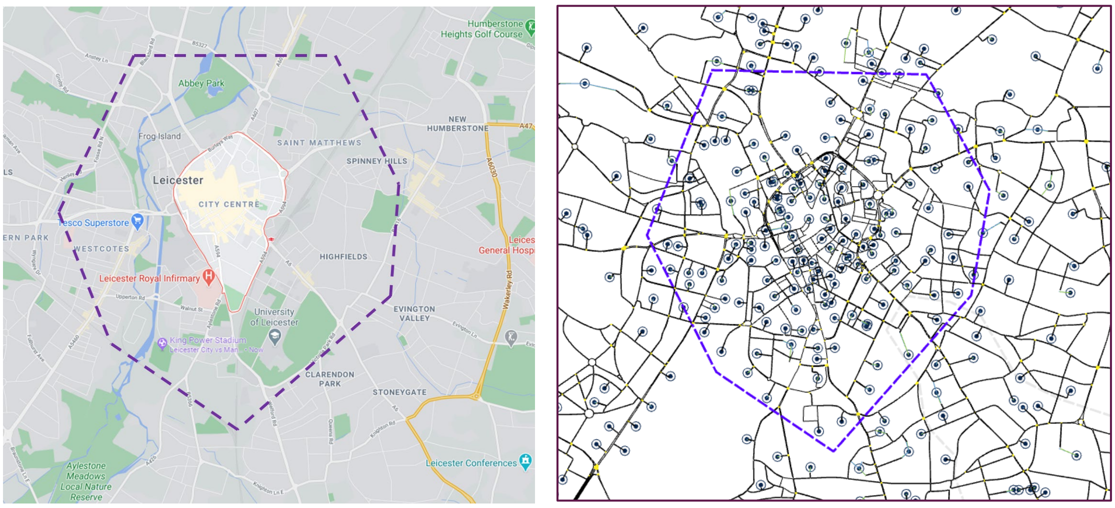


Figure 3.4: The Leicester city centre network in AIMSUN software

Scenarios

This specific network includes the city centre area only. For practical purposes to be more effective using simulation, on-street parking in the city centre has been divided into 4 parking zones, including a total of 52 streets with 138 parking bays as showed in Figure 3.5.

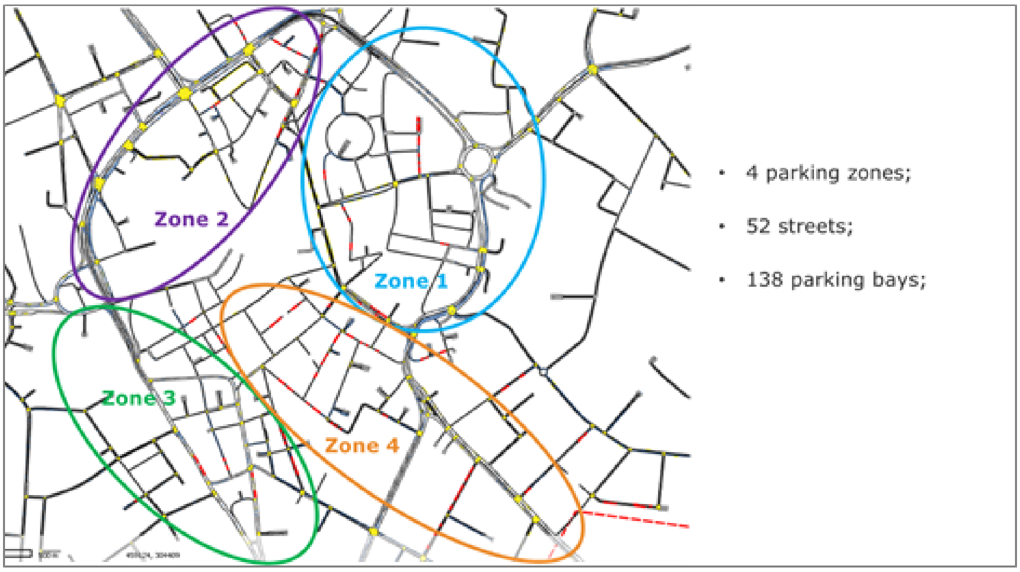


Figure 3.5: On-street parking zones in AIMSUN software

Within this SUC, six scenarios will be studied using microscopic simulation:

- Baseline scenario - CAV implementations without replacing the on-street parking intervention, CAV market penetration from 0% to 100% at 20% increments. Including a total of 52 streets with 138 parking bays for all 4 parking zones.

- Removing half of the on-street parking spaces - Scenarios based on the reduction of parking capacity, i.e., 50%. As described in the literature review section, the introduction of AVs offers the potential to reduce the urban spaces requirements for parking, the on-street parking spaces for 4 parking zones have been reduced to 28 streets and 79 parking bays, respectively.

- Replacing on-street parking spaces with driving lanes. In this scenario, on-street parking spaces will convert to driving lanes (shown in Figure 3.6).

- Replacing on-street parking spaces with cycling lanes. In this scenario, on-street parking spaces will convert to a dedicated cycle lane (shown in Figure 3.6), which means other vehicle types are not allowed to use the cycle lane. It should be noted that the cyclist behaviour has not been simulated in the modelling due to the limitation of the software.

- Replacing on-street parking spaces with pick-up and/or drop-off points (shown in Figure 3.7). The scenario assumes the AVs are shared AVs. As a result, after the vehicle pick-up or drop-off the passenger, the vehicle will exit the study area to return home or serve another customer. More detail of shared AVs can be found in automated ridesharing SUC.

- Replacing on-street parking spaces with public spaces. In this scenario, on-street parking spaces will convert to public spaces, e.g., green, and recreational spaces (shown in Figure 3.6).

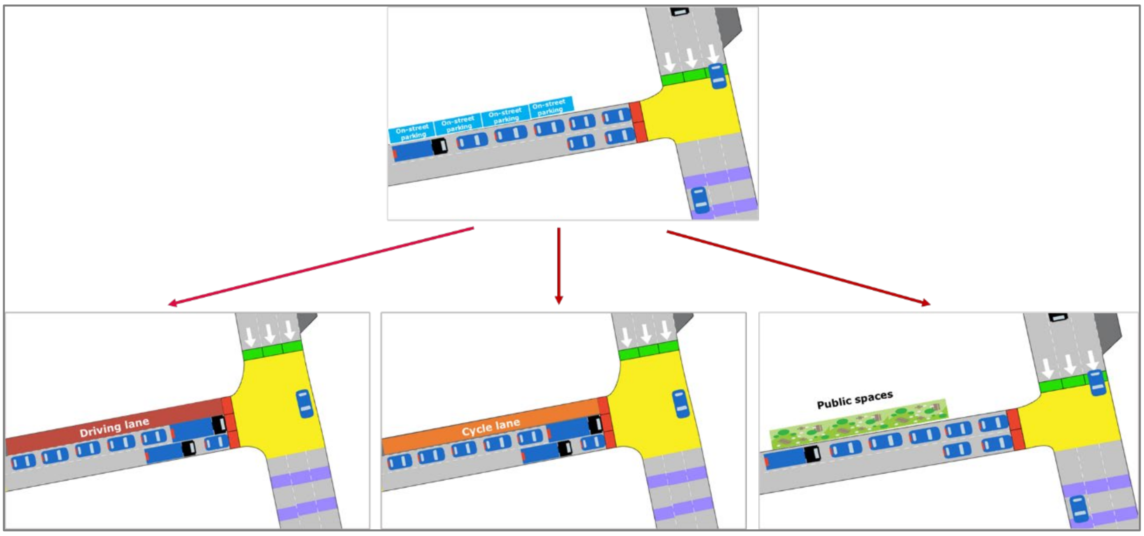


Figure 3.6: Replacing on-street parking with driving lane, cycle lane and public spaces

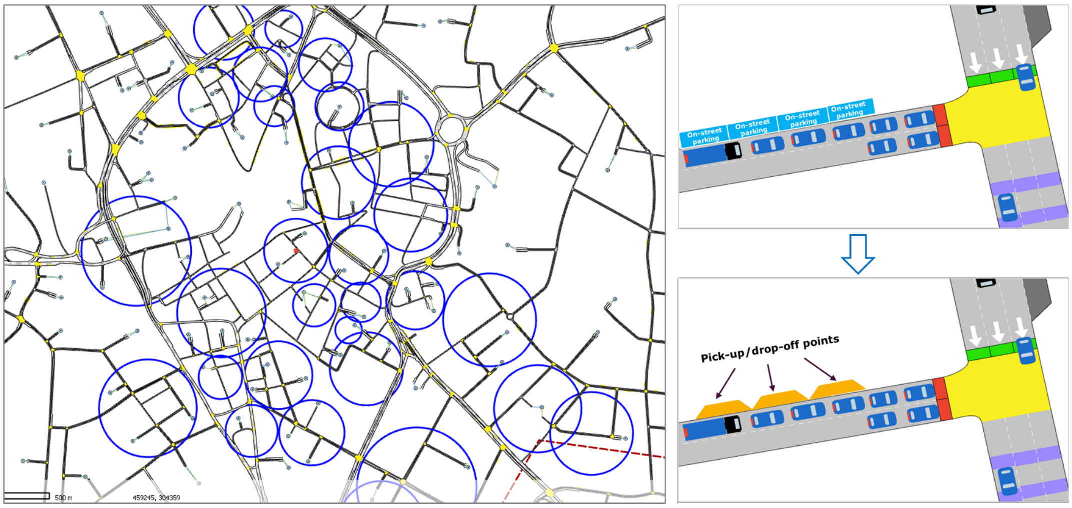


Figure 3.7: Replacing on-street parking with pick-up/drop-off points and the pick-up/drop-off locations in AIMSUN software

Assumptions

The following assumptions and limitations exist in this sub-use case implementation:

- All CAVs are assumed to be EVs,
- All human driven vehicles are assumed to be non-electric vehicles,
- Simulations are run for lunchtime rush hour, considering it to be the most critical time period for this sub-use case'
- No residential parking is considered in the model,
- No changes have been considered in the disabled on-street parking bay,
- The pick-up/drop-off scenario was assumed to follow SAVs concept,
- On-street parking manoeuvre duration (blockage time) is assumed to be 30s with 20s deviation based on the previous literature (Chai et al., 2020; Chow, Rath, Yoon, Scalise, & Saenz, 2020; Fehr & Peers, 2018; Wijayaratna, 2015; Portilla*, Oreña, Berodia, & Díaz*, 2009),
- Cyclists are not modelled in the replacing on-street parking spaces with cycling lanes scenario due to the software limitation.

Modelling on-street parking manoeuvres

Within this sub-use case, the function of the periodic section incident has been applied to simulate the on-street parking manoeuvres (shown in Figure 3.8). It's a traffic incident that causes a lane blockage over a certain time period. This action creates random incidents and are placed randomly throughout the area i.e., street, parking bay (Transport Simulation Systems [TSS], 2021).

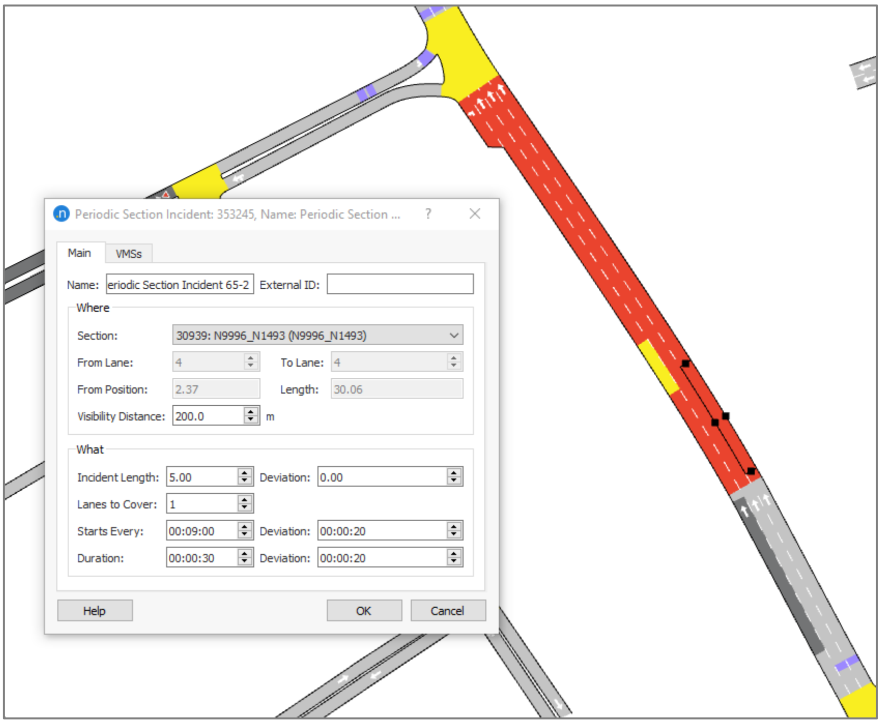


Figure 3.8: Screenshot of periodic section incident in AIMSUN Next

Figure 3.9 illustrates examples of the periodic section incident representing on-street parking on a single lane and a multi-lane road in the model using the AIMSUN Next simulation platform. The left image demonstrates the incident (on-street parking) happening on a single lane blocking the traffic over a certain time. The right image shows the incident happening on a multi-lane road where the following vehicle decides to change lane because of the leading vehicle making an on-street parking manoeuvre.

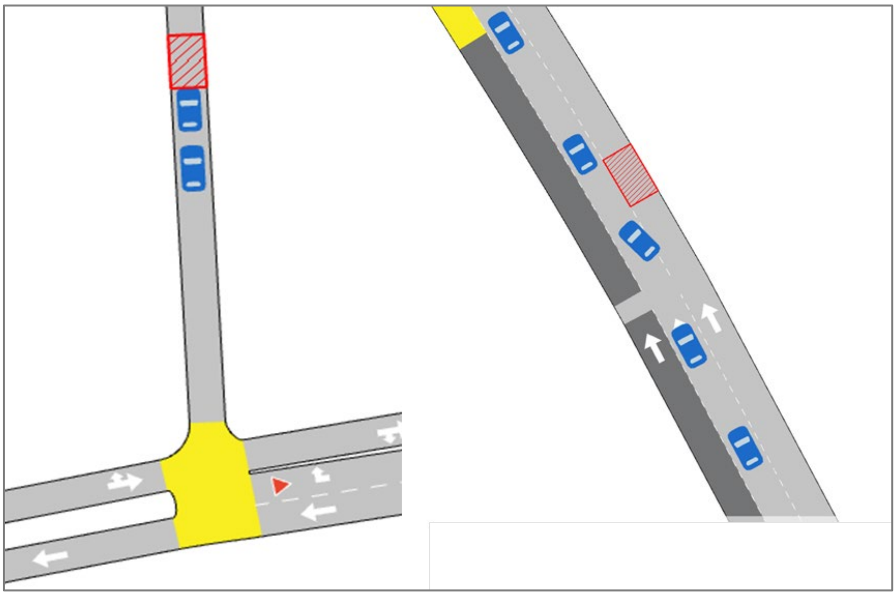


Figure 3.9: Periodic section incident on a single lane and multi-lane road in the model using in AIMSUN Next

3.1.2.4 Automated ride sharing

This sub-use case investigates the impacts of introducing autonomous shared vehicles (SAV) on the efficiency of transport systems. The proposed service combines free-floating car-sharing, ridesharing, and fully autonomous vehicles operating in Manchester (UK). With respect to operation, the proposed service is considered to provide on-demand trips where SAVs pick up passengers from their origins and drop them off at their destinations under time constraints.

In addition to passengers' origin, destination, departure, and arrival time, the SAV assignment in this sub-use case also considers the passengers' willingness to share (WTS) their rides with others which could depend on several factors such as increased travel and detour time (König & Grippenkoven, 2020), and the acceptance of sharing same vehicle with strangers (Lavieri & Bhatb, 2019). The passengers' WTS has a significant impact on the efficiency of SAV service. For this reason, the impact due to this aspect is also investigated within this sub-use case.

The service introduced in this study is modelled by one of the well-known optimisation problems: the **Vehicle Routing Problem with Pickup and Delivery with Time Window (VRPPDTW)** (Mahmoudi & Zhou, 2016). With this optimisation process, trip-requests are matched to a SAV fleet (that was determined within the process), and optimised routes for SAVs are provided. The optimisation output served as an input for the AIMSUN Next Microsimulation tool to generate different KPIs to assess the impact of this service on mobility, safety, and environment. An overview of the modelling and implementation of this SUC is shown in Figure 3.10.

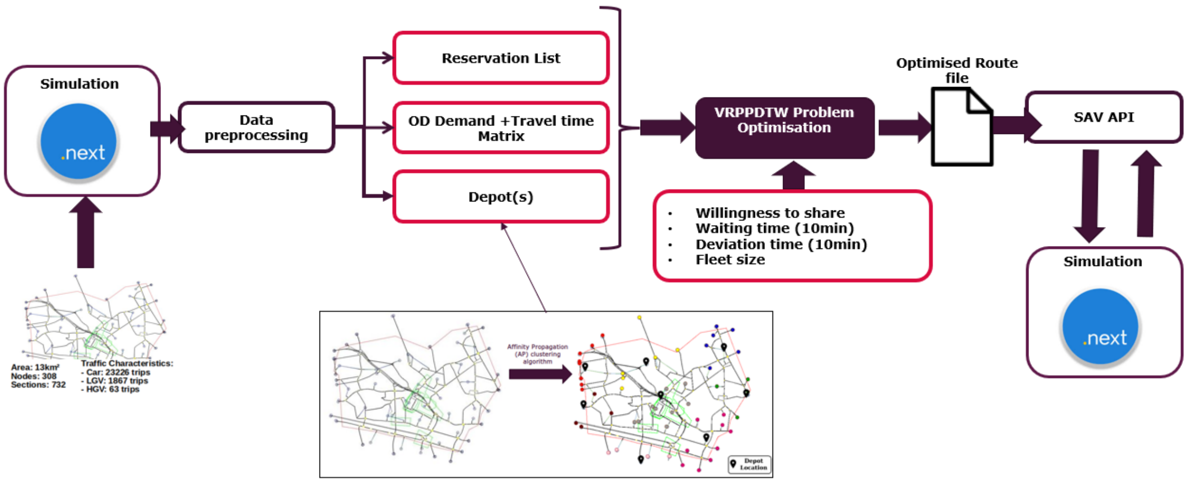


Figure 3.10: Overview of the modelling process of automate ridesharing SUC

Network Model & Data Preparation
To illustrate the potential benefits of the proposed ride-sharing service, a calibrated and validated microsimulation model (developed using AIMSUN simulation platform) was used consisting of a 13km² area from the Great Manchester Area (UK) that contains 308 nodes and 732 road sections (Figure 3.11), and OD matrix of 58x58 centroids from the network. Traffic data of evening peak hours (1700 – 1800) was used, with an estimated traffic demand of 23226 car trips, 1867 large goods vehicles (LGV) trips, and 63 heavy goods vehicle (HGV) trips.

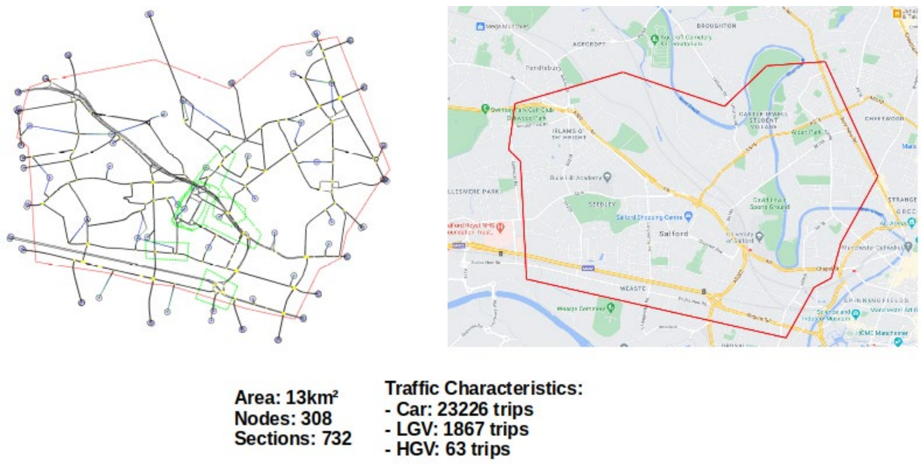


Figure 3.11: The Manchester network in AIMSUN software

As mentioned above, the proposed service is modelled as VRPPDTW problem, and to perform the optimisation process to solve this problem, a set of files have been extracted from the micro-simulation model of the study area:

- The Origin-Destination (OD) traffic demand matrix for personal car trips in the study area,
- A GIS file that contains the exact coordinates of the study area's centroids,

- Travel Time matrix with values derived from the simulation of the original OD demand,
- A list of personal vehicle trips (trip ID, pickup centroid, drop off centroid, departure time, and arrival time) was also obtained from the simulation of the original OD demand.

These files hold data that will be used to generate input to the optimisation process, such as depots' locations, trip requests, pick up and drop off time windows, etc.

It was assumed that demand for this new service will replace a share of personal vehicle demand. Through the simulation of the original OD demand matrix provided with the network model, a list of trips corresponding to the personal vehicles was obtained and used to select random candidate trips that this service will perform.

Google's OR-Tools will be used to solve the VRPPDTW problem to assign routes for SAVs pickup and drop-off passengers. Each centroid in the network can be a pickup or drop-off location for several trips, which is not suitable for the OR-Tool solver that assumes each node can be visited only once and can be either a pickup or drop-off site. Therefore, to respond to this constraint, a dummy node was created for every passenger origin or destination with zero distance from the original location to distinguish pickup and drop-off nodes.

Every user of this new service has a preferred time window to be picked up from his/her origin and the desired time window for arrival at his/her destination. The departure and arrival times from the list of trip requests extracted from the simulation are used as lower bounds of pickup and arrival time windows. The upper bounds values are related to the passenger's acceptable waiting time and detour from its original route (caused by ridesharing with others), and within this project, it was assumed that a passenger could tolerate waiting and detour time range from 5 min to 10 min. Instead of having fixed waiting and detour time values for all passengers, we applied a normal distribution to generate a set of values assigned to all passengers' trip requests.

Trip requests can be classified into individual or shared trips, depending on the passenger WTS. According to the literature, the acceptance of the shared trip option could be related to the user's approval of extra travel time associated with the pickup/drop-off of other passengers (König & Grippenkoven, 2020) and to his/her sensitivity toward sharing the same vehicle with other strangers (Lavieri & Bhatb, 2019). To study the impact of the user's disposition to shared rides on the overall performances of the service and the network, we developed scenarios based on different aggregated levels of WTS. To facilitate the integration of this notation into the optimisation problem, it was assumed that a passenger is either willing or unwilling to share his/her ride. In other words, the passenger's decision will not be related to the value of time or money or even the number of other passengers sharing his ride. Passengers' preference for a shared ride was assigned randomly based on a predefined level of WTS. These preferences will be given as an input to Google's OR-Tools solver through a 1D array containing the demand corresponding to the number of passengers to be picked up or dropped off in each location. A positive value represents the demand at the pickup location, and a negative value represents the demand at drop-off location. If a passenger is willing to share his/her ride, the demand will be equal to the capacity of the SAV, which is assumed to be equal to regular 4-seater car; otherwise, the demand will be equal to one.

Depots Allocation

Depots and charging station locations are critical factors in deploying a ride-sharing service. In this study, the Affinity Propagation clustering algorithm (Frey & Dueck,2007) is used to determine the depots' locations. In contrast to other traditional clustering algorithms, such as K-means, the AP algorithm does not require inputting the number of clusters in advance. It determines the optimal number of clusters and their exemplars (clusters' centres) based on a message-passing procedure where all data points are considered as exemplars and exchange messages between them concerning their attractiveness and their availability to associate with other data points until an optimal set of exemplars and clusters emerges (Givoni & Frey,2009).

The affinity propagation algorithm was implemented using python's Scikit-learn package and executed with 1000 maximum iterations taking the exact centroids' location in the Manchester network model and their corresponding total trip demand from the original OD matrix. As shown in Figure 3.12 eight clusters were determined by the algorithm, i.e., eight depots assigned to the nearest centroid from the exemplar of each cluster.

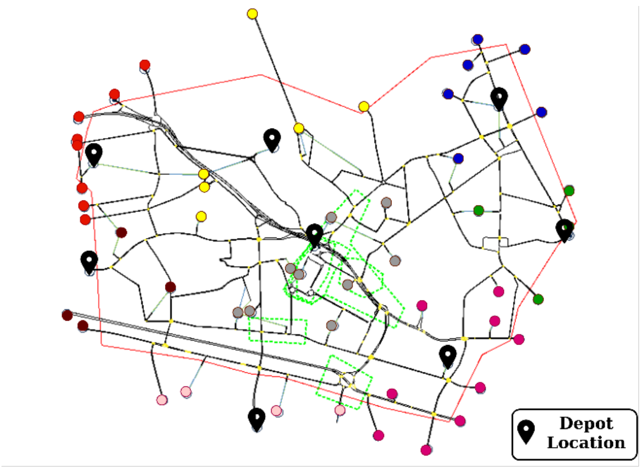


Figure 3.12: Allocation of SAV service depots based on Affinity Propagation clustering algorithm

Optimisation process

The following input data was given to Google’s OR-Tools solver to solve the modelled VRPPDTW:

- The travel time matrix with values derived from the simulation of the original OD demand,
- The initial fleet size,
- The 1D demand array,
- The capacity of a SAV (4-seater car),
- The list of pick-up and drop-off pairs,
- The list of pick-up and arrival time windows, and
- The depots’ locations

The analysis was performed for the afternoon peak hour period (1700-1800). It was assumed that the SAVs were not required to return to their depots, but instead, they ended their routes at their last drop-off location, which was represented by the arbitrary ending depot location, which had zero distance from every other centroid. Regarding the initial fleet size, a SAV fleet equal to the served demand was assumed to be parked at each depot to ensure that every trip request is assigned to a SAV.

The maximum travel time for each SAV was set to one hour to ensure that SAVs finished their optimised routes within the simulation period. Moreover, a limit of 1000 solutions was set for every scenario to prevent the solver from running indefinitely due to the size of the optimised problem, while sufficient investigation of the solution space will take place.

Scenarios & Assumptions

Within this sub-use case, the impact of automated ride sharing is studied under the scenarios resulting from the combination of different rates of demand that will be served by SAVs (5%, 10%, 20%) and the percentage of travellers willing to share their rides (WTS):

1. No policy intervention: baseline scenario of increasing penetration of automated vehicles without an automated ridesharing system
2. 5% demand for SAVs: 5% of the total private vehicle travel demand (trips) is replaced by SAV trips, with a variable WTS (20%, 50%, 80%, 100%)
3. 10% demand for SAVs: 10% of the total private vehicle travel demand (trips) is replaced by SAV trips, with a variable WTS (20%, 50%, 80%, 100%)
4. 20% demand for SAVs: 20% of the total private vehicle travel demand (trips) is replaced by SAV trips, with a variable WTS (20%, 50%, 80%, 100%)

For all scenarios, deployment of CAVs in the network was tested from 0% to 100% in 20% increments with the two types of CAVs presented in section 3.1.1.

The SAV capacity considered in this SUC 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 2.1.

The following assumptions have been made for this sub-use case implementation:
- All CAVs and SAVs are EVs.
- The battery capacity can support full-day operations for each SAV.
- Parking spaces are enough 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 parameter with two statuses (Yes, No)
- Cancellation of assigned SAV is not allowed.
- An SAV request refers to one traveller.

Optimisation Results

Table 3.4 shows the optimisation results for the different scenarios studied within this SUC. The results indicate that the fleet size required to replace conventional personal vehicle trips gradually decrease 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 vehicles conventional that one SAV can replace.

Table 3.4: Optimisation results for automated ride sharing service

Demand to be served	Trips to be served	Willingness to share	Optimal SAV Fleet size	SAV Replacement Rate *
5%	1134	20%	645	1,8
		50%	570	2,0
		80%	490	2,3
		100%	435	2,6
10%	2239	20%	1154	1,9
		50%	1009	2,2
		80%	839	2,7
		100%	720	3,1
20%	5070	20%	2391	2,1
		50%	2067	2,5
		80%	1694	3,0
		100%	1436	3,5
(*) : Number of personal vehicles replaced by one shared AV (SAV)				

Regarding travelled distance, Figure 3.13 shows that a higher willingness to share reduced the total and empty travelled distance covered by the SAV fleet in all scenarios. The results also revealed that with higher demand, the distance will be gradually increased. This increase is obtained not just because of serving more passengers but also because of the empty repositioning trips that SAVs need to perform to pick up passengers that represent a significant share of the overall trips, as seen in Figure 3.14.

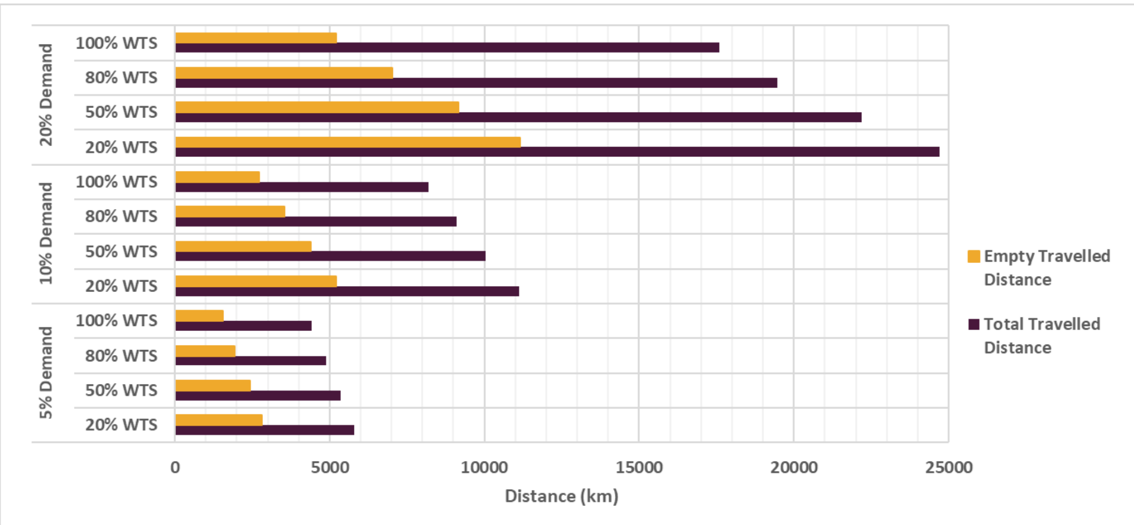


Figure 3.13: Total distance travelled by the shared autonomous vehicle (SAV) fleet in kilometres with different served demand and passengers willingness to share (WTS) percentages

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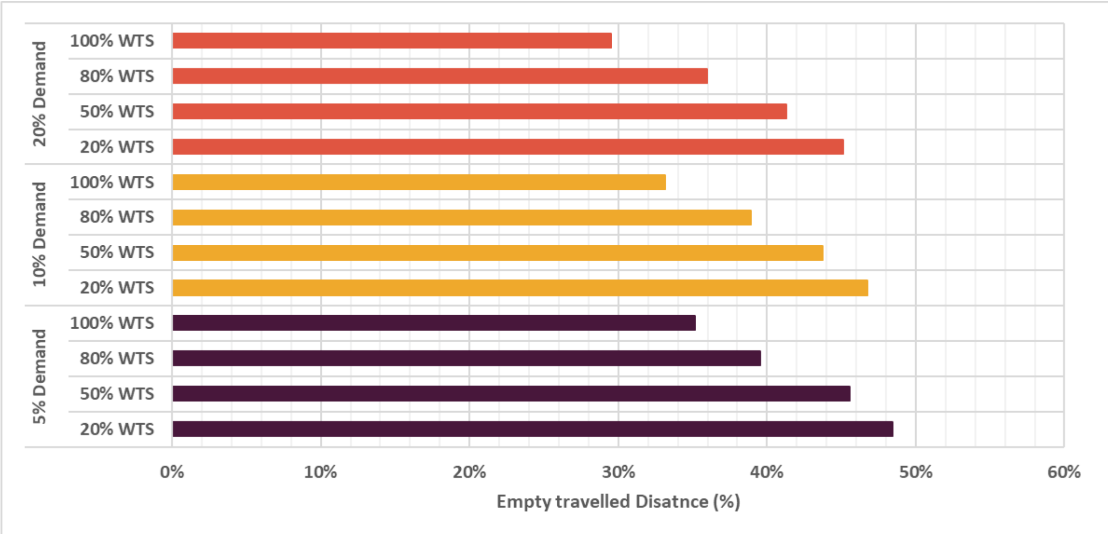


Figure 3.14: Percentage of empty distance travelled by the entire SAV fleet

3.1.2.5 Green Light Optimal Speed Advisory (GLOSA)

The traffic microsimulation model that is used for this sub-use case was provided by Transport for Greater Manchester. The model of Greater Manchester provides a sufficiently large and complex transport network with signalised intersections and other various road sections, rendering it suitable for the specific experiment. For implementing GLOSA, a corridor near the Salford area (Figure 3.15) was selected in the Manchester with three signalized intersections sufficiently distant from each other. The impact of GLOSA was analysed under fixed time coordinated traffic control at these study locations signals.

Figure 3.15: Test corridor in Manchester network for GLOSA application

The test scenarios on GLOSA implementation and CAV deployment are as follows:

- Baseline scenario – No GLOSA, CAV market penetration from 0% to 100% in 20% increments.
- Scenario 1 – GLOSA on intersection 1;
- Scenario 2 – GLOSA on intersections 1 and 2; and
- Scenario 3 – GLOSA on intersection 1, 2 and, 3.

Simulations were performed for the peak hours on baseline and all three analysis scenarios with CAV deployment as shown in Table 3.2. The analysed impacts included:

- Travel Time
- Delays
- Number of Stops
- Emissions
- Total Conflicts (Safety Impacts)

The following assumptions were made in the frame of GLOSA application.

1) The quality of communication between signals and vehicles is ideal and all messages are delivered successfully and without delay.
1) All the drivers accept and comply with the recommended speed.
2) GLOSA is applied at each simulation step.
3) All CAVs will have the capability to communicate with traffic controllers.
4) All CAVs are electric whereas human-driven vehicles are non-electric

Simulations were run for the peak hours performing 10 replications under each scenario.

GLOSA Algorithm

GLOSA Algorithm was developed based on reviewing some of the previously developed algorithms in literature (Stevanovic et al, 2013) with modifications as deemed adequate for the test network. The key steps describing the functionality are shown in Table 3.5.

Table 3.5: Steps involved in GLOSA system operation

Step 1. GLOSA system in vehicle searches for a traffic signal controller downstream **Step 2.** If a traffic signal controller downstream is detected, go to step 3, else go to step 1 **Step 3.** GLOSA system in vehicle collects data on vehicle position and speed **Step 4.** Get Map Data Message (MAP) information about the lane and turning restrictions. (GLOSA application generates geometry from MAP message to determine the vehicular position and determine the corresponding lane number) **Step 5.** Calculate vehicle's distance to stop bar at the intersection approach **Step 6**. Determine the existing queue length at the current moment **Step 7**. Collect current signal phase and timing information (SPAT) from the controller at the current moment for corresponding lane of the approach at the intersection. **Step 8.** Calculate the time required to arrive at the intersection **Step 9.** Determine the phase at the arrival time -If the current phase is Green, check if vehicle is arriving at Green? If yes, go to step 10, If not go to step 11. -If the current phase is Red check if vehicle is arriving at Green. If yes, go to step 10, if not go to step 14. **Step 10.** Vehicle is arriving at Green. Send advisory message to maintain current speed **Step 11.** Vehicle is not arriving at green. Calculate advisory speed to arrive at current green phase **Step 12.** Is advisory speed ≤ speedMax and advisory speed ≥speed Min, If yes go to step 13, else go to step 14 **Step 13.** speed upto advisory speed **Step 14.** Calculate the advisory speed to arrive at junction on next green phase by using current queue length and queue dissipation time. **Step 15.** If the advisory speed ≥speed Min and advisory speed ≤ speedMax (where speedMin=50% speed limit), If yes go to step 16, else go to step 17

Step 16. Slow down to speedMin	
Step 17. Exit (vehicle will have to stop	

Before applying the GLOSA algorithm on the test network, the impact of activation distance and frequency of GLOSA was analysed. The activation distance was kept to 400m while GLOSA was applied on each time step. Minimum speed threshold was kept as 50% of speed limit following the suggestions provided in some previous studies (Katsaros, Kernchen, Dianati, & Rieck,2011, Masera et al.,2019) while upper limit was kept as speed limit +5mph.

3.2 Mesoscopic simulation of activity chains

The mesoscopic mobility simulation of agents and their plans of activities is used as a method to estimate the impacts of RUP on the travel time (section 4.1.1) and other medium-term impacts described in Deliverable D6.3 (Sha et al., 2021). The model is based on calibrated choice behaviours of the simulated population, and its methods provide the means to draw direct, data-supported conclusions on the altered choices of agents regarding the use of transport modes under changing circumstances of transportation availability.

All investigated scenarios were developed for a model of Vienna and its wider surrounding area shown in Figure 3.16 to serve as a prototypical example for a historically grown ("old" European) city. The segmentation of the city into roughly ring-shaped domains that lie concentric around the city centre was made to enable analyses in accord with the defined impact requirements. Borders between these domains are formed by major arterial (ring-)roads which are used to circumvent crossing through more densely populated areas towards the city centre.

Each agent within the mesoscopic simulation uses a decision model, which is based on the best available statistical knowledge of such an agent's characteristics regarding geographical locations, daily activity patterns and sociodemographic variables. Being a central component of the activity chain simulation model, it allows individual agents to react to changes in model conditions by adapting their daily activity plans and utilized modes of transportation. Adaptions are gauged with respect to their "goodness" by using a *utility function* that summarizes the timeliness of activities reached as well as how costly it was to access those places of activity considering both time and money. The attributed weights of these last two cost factors are described by the parameters "value of travel time saved" (VTTS) and "marginal utility of money" (mUoM), respectively. On the one hand, a dominating high value of VTTS for a specific agent will result in behaviour that tries to greatly reduce the time-costs of traveling. A dominating high value of mUoM on the other hand will encourage behaviour that strives for monetary cost reduction.

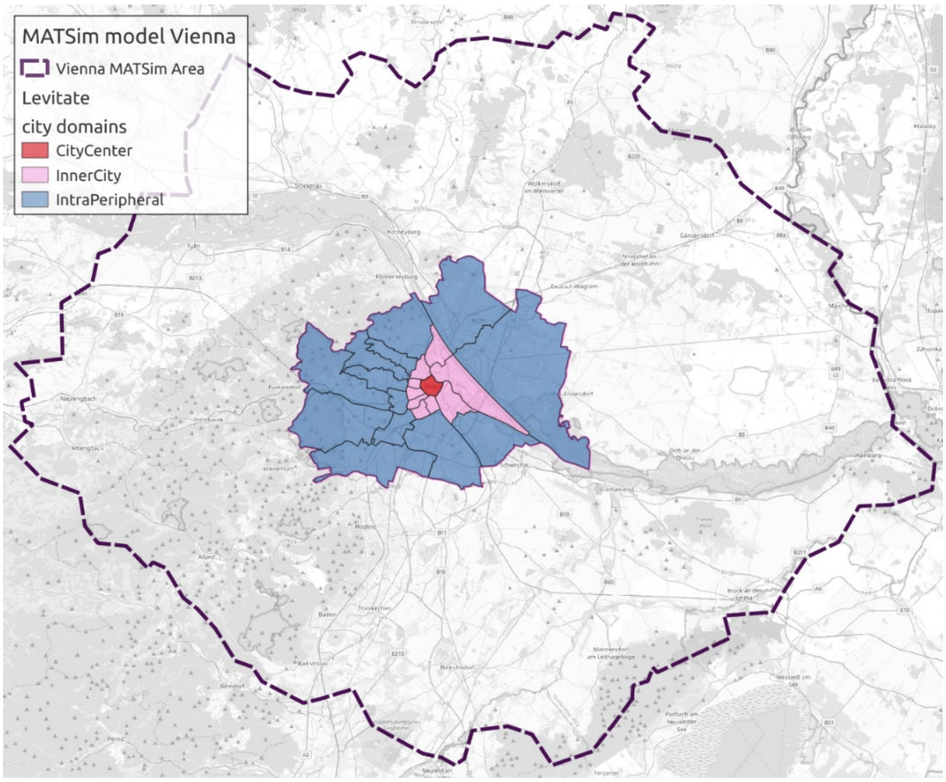


Figure 3.16: MATSim model Vienna total area overview. The color-shaded domains within the model area cover the actual extent of the city of Vienna. The dashed line marks the wider model region surrounding the city.

A major assumption of the employed model is that such domain structures can be defined for most cities with a comparable structure and evolution.

The four defined domains are:

1. **City centre (CC)**: mostly reduced vehicle traffic areas, restricted entry is common
2. **Inner city (IC)**: containing a densely populated belt around CC with lots of habitation areas
3. **Intra peripheral (IP)**: domain outwards from IC up to the city limits which enclose the actual investigation area; habitation regions, some commercial, light industrial areas, larger recreational zones
4. **Extra peripheral (XP)**: the remainder of the model area, defining the outer boundary and conditions for the inner investigation area

3.2.1 Model description

The **mesoscopic MATSim simulation model for Vienna** is described in detail in (Müller et al., 2021). In short, the simulation area (see Figure 3.16) covers about 4,100 square kilometres with a population of about 2.3 million including the 1.7 million inhabitants of Vienna (Eurostat, 2019). We used a 12.5% sample of the mobile population which corresponds to around 200,000 agents in the whole simulation area. By simulating traffic in the vicinity of at minimum 30 kilometres from the city centre, large parts of the Vienna metropolitan area are covered. The road network for the simulations comprises of 156,000 links, and various facilities like workplaces, schools, shopping and leisure areas.

MATSim requires an initial set of travel diaries of the agent plans representing a set of activity locations for a given sequence of activities. These parameters do not change over simulation iterations and in the scenario simulations. To simulate traffic on the road network, two main data sources are utilized. The first are travel diaries with detailed origin-destination matrices, choice of transport mode, and various socioeconomic indicators of the surveyed mobile population. This information is provided by the Austrian national mobility survey "Österreich Unterwegs 2013-2014" (Tomschy et al., 2016) which is representative at the municipality level throughout the modeled region. The second input dataset are the locations of facilities or points of interest extracted from OpenStreetMap. They are used to provide distinct activity locations (facilities) by disaggregating the available coarse spatial information of municipality. This is done for travel origins and destinations and categorized by housing, work, education, shopping, recreation, and errands. These data are supplemented with population density maps derived from (Eurostat, 2019) to spatially map the facilities along with the potential places of residence and work for the simulated agents.

Thus, disaggregating the activity location survey information means selecting appropriate points of interest from the specified community area code. This selection is done by applying an optimization algorithm based on the travel times and travel distances specified in the travel survey data. As a result, we obtain optimal matching locations for each agent's activity sequence within the set of possible locations for each activity type.

After the synthetic population is generated, these plans are fed into an inter-modal routing algorithm to generate several likely paths a trip will take. This is done using Austrian Institute of Technology's (AIT) proprietary inter-modal routing algorithm *Ariadne* (Prandtstetter, Straub & Puchinger, 2013)

MATSim works with a scoring function to evaluate the success of an agent's travel diary at the end of the day. The basic logic behind this utility function is to reward times spent at a planned activity location and penalize all travel times according to the mode. The scoring parameters for each mode are estimated from a stated and revealed preference survey (Hössinger, et al., 2020; Jokubauskaitė, et al., 2019). The model is calibrated by the modal split for each trip according to the travel diaries given in the "Österreich Unterwegs 2013-2014" survey. After adjusting the constant of the mode utility functions, a deviation from the observed data of less than 1% for each mode was achieved.

Consistent with overall project goals to describe likely automation scenarios of the future, the modeling of different car fleet partitions of CAV of the 1st generation ("cautious" CAV1) and CAV of the 2nd generation ("aggressive" CAV2) is indicated in Table 3.6. The vehicles' characteristics are represented in the model by assigning different utility functions (see section 3.2) for private cars to randomly distributed shares of the population. For a definition of these generations also see section 3.1.1. Using an AV1 will therefore be attributed with 80% of the VTTS of a private car, while an AV2 with 75% of a car's VTTS, which accounts for the possibility of the attention or time in the vehicles to be spent on other things but driving. The rationale behind setting the parameters for CAV1, CAV2 is based on studies on the estimation of the VTTS for automated vehicles and shuttles. Whereas Lu, Rohr, Patruni, Hess, & Paag (2018) found no differences in the VTTS between drivers and passengers of a car, Fosgerau (2019) and Ho, Mulley, Shiftan, & Hensher

(2015) come to the conclusion that the VTTS for a passenger can be regarded as about 75 % of the rate for car drivers. We follow in our model these latter findings and slightly increase the VTTS for CAV1 as the driving experience is assumed to be not as convenient as with an CAV2.

As the throughput of roads will increase with a higher automation rate due to more densely packed moving vehicles, the simulation model parameter "flow capacity factor" of the road network was adapted to account for this effect. The flow capacity factor is generally set to the percentage of population that is simulated (in our case 12.5%) as it represents the relative number of vehicles that can pass a link (Llorca & Moeckel, 2019). This was done in accordance with earlier project results on the passenger car unit (PCU) dependency obtained by microscopic simulations (Tympakianaki et al., 2020) and is also shown in Table 3.6. The private cars' behavior will remain the same in any other respect.

In addition, three different scenarios of the economic situation of agents are considered by variation of the marginal utility of money (mUoM), which was either left at the baseline settings (no economic change) or set to an increase/decrease of 5% resembling correlation to the ratio of inflation rate by average available income.

For each of the common eight different car fleet partitions of CV, AV1 and AV2, every combination of RUP implementation and marginal utility of money was simulated.

Table 3.6 The CAV market penetration rate scenarios and the respective shares of AV generations and the anticipated increasing road network throughputs given as flow-capacity-rate.

Type of Vehicle	**A**	**B**	**C**	**D**	**E**	**H**	**F**	**G**
Conventional Car	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation CAV	0%	20%	40%	40%	40%	0%	40%	20%
2nd Generation CAV	0%	0%	0%	20%	40%	100%	60%	80%
Flow capacity rate	0.1150	0.1205	0.1262	0.1317	0.1368	0.1413		

3.2.2 Implementation assumptions

A simplified schematic view of the full model region (as in Figure 3.16) is depicted in Figure 3.17. The investigation area is defined as inside the city limits (everything including domain intra-peripheral and inwards) which is delineated by the investigation perimeter.
As was defined in the project goals, the relevant area for implementing RUP scenarios should comprise everything within IC (i.e., tolling should happen on crossing into or traveling within IC).

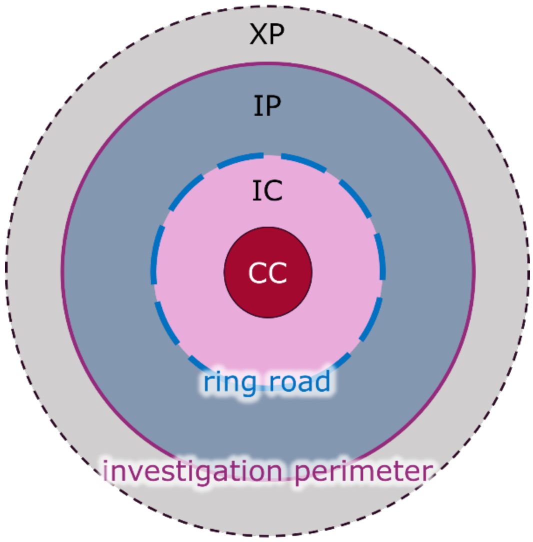


Figure 3.17 Schematic view of the four city domains used for mobility investigations. The domains are city center (CC), inner city (IC), intra peripheral (IP) and extra peripheral (XP).

To analyse the implementation measure of RUP, deployment of automated passenger cars considers each vehicle as a privately owned car. These vehicles are not capable to relocate or carry out rides on their own, thus providing autonomy and driving capabilities only when the owner is aboard.

The indicators derivable from the developed scenarios as specified within the project are:

- travel time of an average 5 km trip within the inner city,
- modal splits and modal shifts (i.e., changes in modal split) of active (walking or cycling) and public transport modes of travel,
- total distance travelled within the city.

Regarding the definition of these indicators, some details need to be given:

- The modes available in the simulation model to sufficiently describe the diverse travel activities are car (conventional), av1 (automated car "cautious"), av2 (automated car "aggressive"), pt (public transport), bike (cycling), walk. To consider the main transport mode of a trip, the longest-distance-mode of any given locomotion between two places of agent activity was chosen, with these activities resembling the fixed intermediary stops along a daily plan or journey.

- The travel time was defined for trips within the tolled area (IC), as an inverse speed of minutes per 5 km distance (1/5 [min / km]). Additionally, an upper quantile of 0.15 % of the inverse speed for each of the separate modes of transport was removed to reduce the influence of outliers (that took unreasonably long to complete their trips) on the mean-value statistics, therefore improving statistical robustness of the travel time indicator.

- The total distance travelled was defined as the sum over all those parts of any trip that lie within the limits of the whole city.

3.2.3 Scenarios

Static RUP

Definition: The term static toll refers to the payment of a fixed amount due whenever a vehicle enters a defined tolling area. For the presented SUC this means that no distinction is made regarding the type of passenger car, thus including conventional vehicles (CV), "cautious" automated vehicles (AV1) and "aggressive" automated vehicles (AV2).

The tolling fees were implemented in several pricing levels with corresponding rationales:

- 0 €: resembling **un**implemented policy
- 5 €: as moderate policy level of discernible effects
- 10 €: as elevated policy level of larger effects
- 100 €: as "full-force" prohibitive policy level, exerting the maximum policy effect expectable

Dynamic RUP

Definition: The term dynamic toll refers to the payment of a fixed amount due for each unit of distance (i.e., 1 [km]) a vehicle travels within a defined tolling area. For the presented SUC this means that no distinction is made regarding the type of passenger car, thus including conventional vehicles (CV), "cautious" automated vehicles (AV1) and "aggressive" automated vehicles (AV2).

In accordance with the SUC of static RUP, the dynamic tolling fees per unit distance were chosen comparably for the IC area, where the approximate diameter of this area is set to 7 km. In the dynamic RUP tolling scheme, the full crossing of the diameter distance of 7 km results in the same tolling fee levels as given for the static RUP. Presupposing equivalent intentions regarding the implementation of measures, tolling fees therefore calculate to 0, 5/7, 10/7 and 100/7 [€/km], respectively.

3.3 Delphi

3.3.1 Background of the Delphi method

The Delphi method is a process used to arrive at a collective, aggregate group opinion or decision by surveying a panel of experts. This concept was developed by the RAND Corporation for the military in order to forecast the effects of new military technology on the future of warfare, and then continued to make multiple practical applications of this method (Dalkey & Helmer, 1963). The Delphi methodology is based on a repetitive interview process in which the respondent can review his or her initial answers and thus change the overall information on each topic (Hsu & Sandford, 2007). This presupposes that the participants will be willing to not only give answers on the topics but also to repeat the interview in possibly more than two cycles. The Delphi method has three different dimensions: the exploratory Delphi aiming at the forecast of future events, the normative Delphi, in order to achieve policy consensus on goals and objectives within organisations or groups and the focus Delphi in order to gain feedback from stakeholders in some policy outcome (Garson., 2012). The Delphi method presents the following characteristics and features: anonymity of experts which assures free expression of opinions provided by the experts. This method helps to avoid social pressure from dominant or dogmatic individuals or even from the majority or minorities. At any point, experts can change their opinions or judgments without fear of being exposed to public criticism, providing controlled feedback as experts are informed about views of other experts who participate in the study (Profillidis & Botzoris, 2018).

3.3.2 The Delphi method within LEVITATE

Within LEVITATE, the Delphi method is used to determine all impacts that cannot be defined by the other aforementioned quantitative methods (traffic simulation, system dynamics, etc.). Initially, a long list of experts was identified for each use case (i.e., urban transport, passenger cars and freight transport), and contacted via an introductory mail asking them to express the willingness of participation. Those who responded positively participated in the main Delphi process, amounting to 70 experts in total (5 experts accepted to answer to 2 questionnaires). Experts come from various organisations such as research institutes, companies and universities (presented in Figure 3.18), where they have different job positions, such as directors, professors and managers (presented in Figure 3.19) and they come from different countries (presented in Figure 3.20).

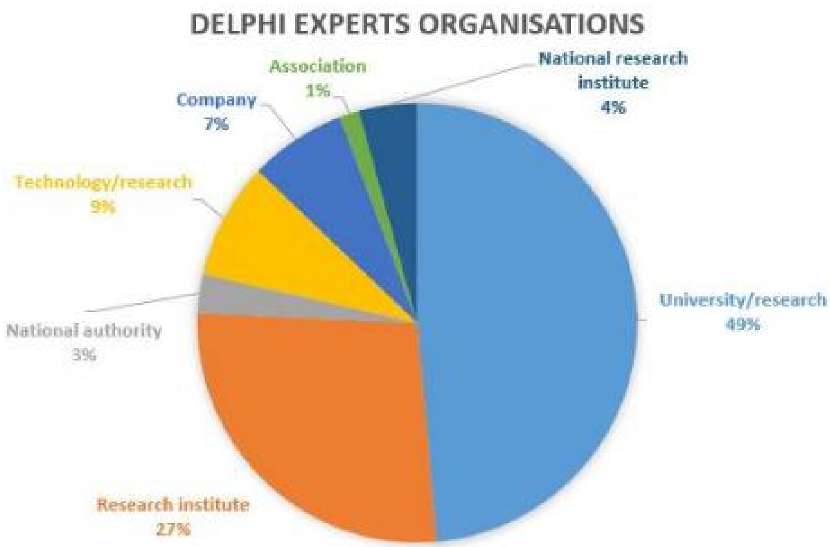


Figure 3.18: Delphi experts' organisations

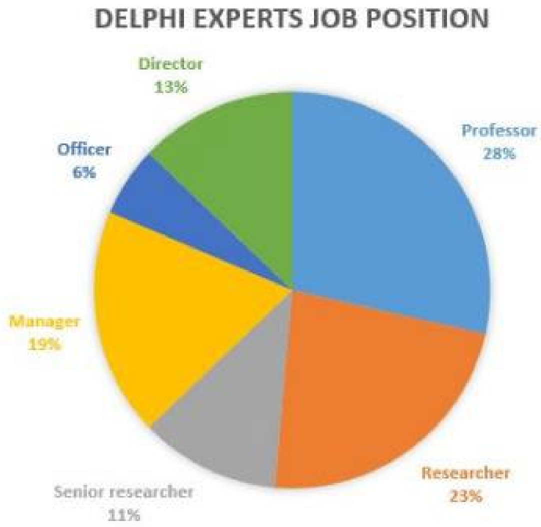


Figure 3.19: Delphi experts' job positions

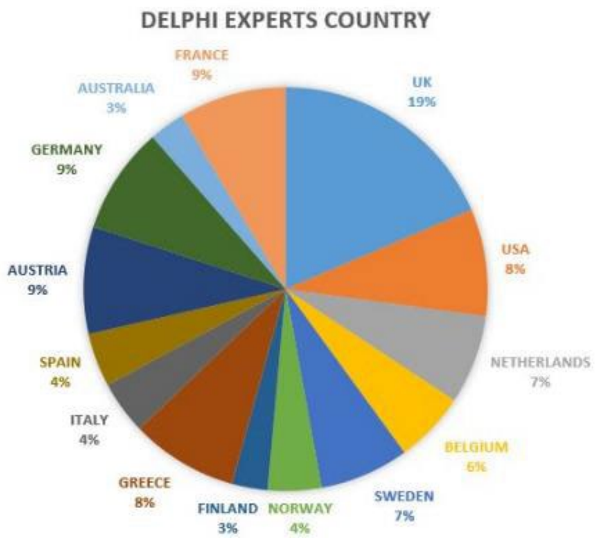
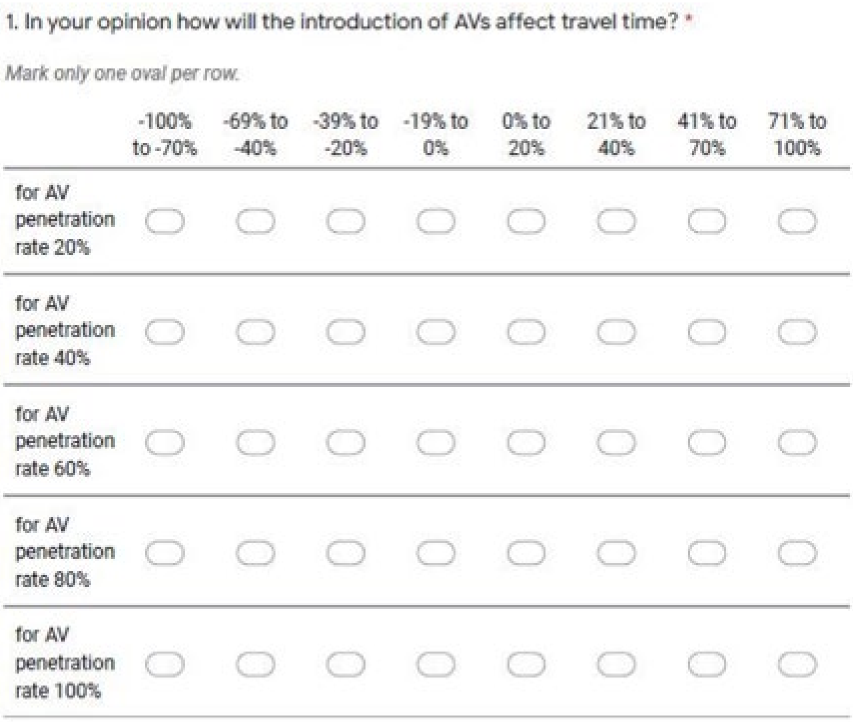


Figure 3.20: Delphi experts' countries

The Delphi method consisted of two rounds of e-mails. During the first round, experts received a questionnaire (30-45min duration) regarding a few (2-4) automation interventions related to automated urban transport, automated passenger cars or automated freight transport, as per their specific expertise. Before starting the questionnaire, they were asked to reply to the consent form accepting the use of the information they will add in the questionnaire. Then they were asked to evaluate the potential influence of the proposed interventions on different impact areas. Their answers were then analysed in order to create (anonymous) summary data for the different CCAM related interventions. These results were distributed with the second-round questionnaire and gave respondents the opportunity to reflect on the first-round outcomes before providing their answers again. In some cases, it led to respondents changing their first-round responses to something conforming more to the answers provided by other respondents

In each first round questionnaire, experts were asked about the influence of automation related interventions on the proposed impacts for different connected & automated vehicle (CAV) market penetration rates. The CAV market penetration rates used are 0% (the baseline scenario), 20%, 40%, 60%, 80% and 100%, as defined by micro-simulation scenarios at the corresponding stage in the project; all methods have been using the same scenarios to achieve uniformity of the different results. The impacts included in the Delphi method are: travel time, vehicle operating cost, amount of travel, access to travel, modal split of travel using public transport, modal split of travel using active travel, shared mobility rate, vehicle utilization rate, vehicle occupancy, parking space, energy efficiency, public health and inequality in transport.

For each impact and each automation related scenario the participants were asked to indicate the percentage of change that the intervention would have for the mentioned CAV market penetration rates (Figure 3.21). The percentages varied from -100% to +100% where the negative (minus sign) was either an improvement or a deterioration depending on the type of impact. For example, a negative effect on travel time would mean a reduction and thus an improvement, while on the other hand a negative percentage of change on public health would mean a deterioration.


1. In your opinion how will the introduction of AVs affect travel time? *

Mark only one oval per row.

	-100% to -70%	-69% to -40%	-39% to -20%	-19% to 0%	0% to 20%	21% to 40%	41% to 70%	71% to 100%
for AV penetration rate 20%								
for AV penetration rate 40%								
for AV penetration rate 60%								
for AV penetration rate 80%								
for AV penetration rate 100%								

Figure 3.21: Example Delphi question

Participants were divided in seven groups. Each group had a different questionnaire related to a specific type of interventions based on their expertise. Each questionnaire concerned 2-4 automation related interventions, including the baseline scenario where no policy intervention is applied except the introduction of CAVs in the urban environment. The questionnaire was also separated with size limitations in mind, as passenger cars would constitute an immense single questionnaire if their sub-use cases were considered all at once. For LEVITATE WP6:

- 10 experts participated in the first Delphi round for the parking regulations sub-use cases and 5 continued to the 2nd round.
- 10 experts participated in the 1st Delphi round for the parking behaviours sub-use cases and 6 continued to the 2nd round.
- 10 experts participated in the 1st Delphi round for the ridesharing and GLOSA sub-use cases and 6 continued to the 2nd round.
- 10 experts participated in the 1st Delphi round for the AV dedicated lanes sub-use cases and 6 continued to the 2nd round.
- 10 experts participated in the 1st Delphi round for the city toll sub-use cases and 7 continued to the 2nd round.

After the reception of the answers of the 1st Delphi round questionnaires, subsequent aggregation coding and analysis followed. For each intervention and each impact, a table was created: its rows represented the CAVs market penetration rates and the columns the different percentages of change (Table 3.7). All experts' answers were introduced in the table and then for each row (each CAVs market penetration rate) the percentage equal with the average of all answers was extracted.

Table 3.7: Example 1st round Delphi answers analysis

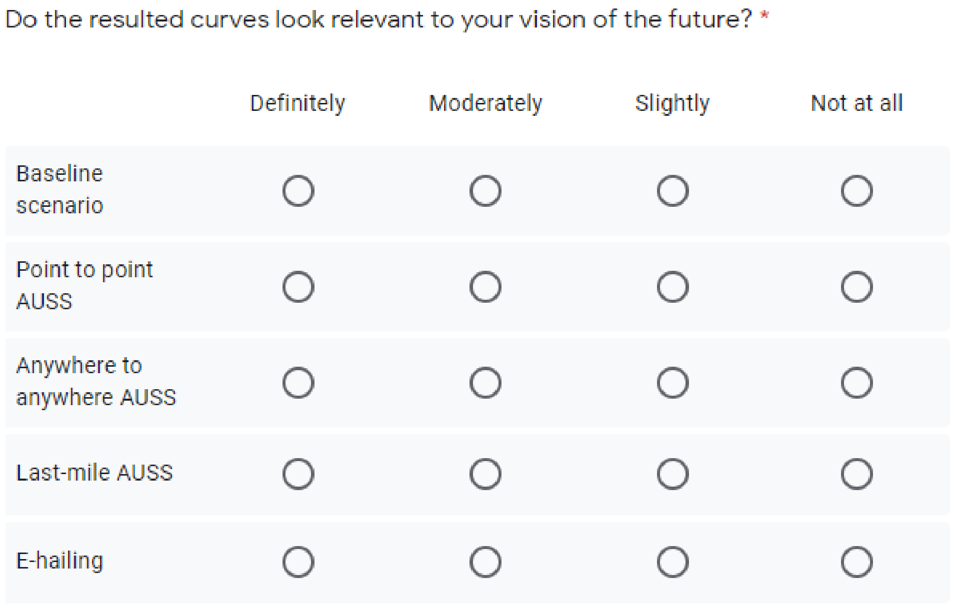
Centroids	**-85%**	**-55%**	**-30%**	**-10%**	**10%**	**30%**	**55%**	**85%**
AV MPR	-100% to -70%	-69% to -40%	-39% to -20%	-19% to 0%	0% to 20%	21% to 40%	41% to 70%	71% to 100%
20%	0	0	1	3	6	4	0	0
40%	0	0	0	3	6	2	3	0
60%	0	0	1	3	3	6	1	1
80%	0	0	3	4	1	2	4	0
100%	0	2	4	1	4	0	2	0

This percentage is the coefficient that will be used in the PST (Table 3.8). The conversion to percentage fluctuations ensures that the PST operates with different starting values provided either by default or by the user, to increase the flexibility and applicability of the tool.

Table 3.8: Example table PST coefficients

AV MPR	**Aggregate change**	**PST coefficients**
20%	2.75%	1.028
40%	-1.50%	0.985
60%	19.68%	1.197
80%	32.61%	1.326
100%	35.43%	1.354

Additionally, for each impact, a curve was created representing the values of the percentages for the different CAV market penetration rates. The resulting curves for all interventions and impacts were presented to the experts for the 2nd round of the Delphi, who were then asked whether they agreed with the 1st round results (Figure 3.22). They were given the opportunity to propose different percentages in case they disagreed. These suggestions were then incorporated in the final coefficients introduced in the LEVITATE PST through a weighted average scheme to make sure that each expert contributes equally.


Do the resulted curves look relevant to your vision of the future? *

	Definitely	Moderately	Slightly	Not at all
Baseline scenario	○	○	○	○
Point to point AUSS	○	○	○	○
Anywhere to anywhere AUSS	○	○	○	○
Last-mile AUSS	○	○	○	○
E-hailing	○	○	○	○

Figure 3.22: Example round 2 question

4 Short-term impacts

In order to provide a structure to assist in understanding how CCAM impacts will emerge in the short, medium and long-term, a preliminary taxonomy of the potential impacts of CATS was developed by Elvik et al. (2019). This process involved identifying an extensive range of potential impacts which may occur from the future expansion of CCAM. A range of impacts were classified into three categories, direct impacts, systemic impacts, and wider impacts. Direct impacts are changes that are noticed by each road user on each trip. These impacts are relatively short-term in nature and can be measured directly after the introduction of intervention or technology.

The short-term impacts of CCAM developed in the present report are those described as direct impacts focusing on travel time, vehicle operating cost and access to travel. These short-term impacts within each sub-use case in WP6 are described in the following sub-sections.

4.1 Travel time

The estimation of the impact of CCAM services on travel time was conducted using variety of suitable methods (based on the nature of policy intervention), including mesoscopic simulation (section 3.2), microscopic simulation (section 3.1), and the Delphi method (section 3.3). Due to differences in the methods used to investigate this impact, some specific differences in the accessible data need to be mentioned:

- For the mesoscopic activity chain simulation: The indicator of the average travel time (min) for a 5km trip within the inner city was chosen to measure the impact on travel time.
- For the microsimulation approach: the indicator of average travel time (sec/km) was chosen to measure the impact on travel time.

4.1.1 Results from mesoscopic simulation

The intent of implementing RUP for a chosen area is regional reduction of use of the tolled modes of transport, which, in the presented scenarios are the conventional and automated passenger cars. Due to the nature of the employed mesoscopic simulation models – both in terms of pricing scope and granularity - only one of the impacts studied within the project can be expected to indicate significant short-term consequences for different road pricing schemes. Reduction in the use of tolled modes impacts the overall characteristics of the changed population of mobile agents (representing traveling persons within the simulated area) and their trips between locations of activity.

Trips are classified according to their longest distance mode (ldm), meaning the largest part of the overall distance has been covered by using a car, for example. No matter what the ldm of one specific trip may be, they mostly are composed of stages of different modes, including at least access and egress walking to and from other modes of transport.

4.1.1.1 Road use pricing

The impact of travel times of the simulated agents is derived by considering all the trips taking place within the inner-city boundaries (compare Figure 3.16 and Figure 3.17) and rescaling their durations to reflect full 5 km trip distances, consequently.

Static RUP

Impact results of examining the effects on the average travel time for different static road use pricing schemes (as defined in section 3.2.3) are displayed in Figure 4.1. They show the simulated mobility behaviour when the entrance fee into the tolling area of the inner city (IC) is increased. The average travel time also increases with higher fees because the simulation agents decide to switch to a toll-free mode of transport (e.g., public transport) when entering the tolling area. Interestingly, increasing the toll from 5 to 10 € seems to have an effect almost as big as the step from 0 to 5 €. Raising the toll to 100 € yields another larger increase in average travel time, by deterring the remaining agents from using their car to enter the IC area. Throughout all automation levels the maximum increase in average travel time amounts to an approximate 3 minutes (+ 5 %) when comparing no tolling (0 €) to the prohibitive tolling (100 €). With increased automation, a trend of slight reduction of average travel time (by a total of 0.5 minutes or 0.82 %) is visible and consistent for all investigated pricing levels above 0 €. For the unimplemented RUP (toll of 0 €) this trend appears even smaller. This means that the increase in vehicle automation shows very little effect on the defined impact of travel time.

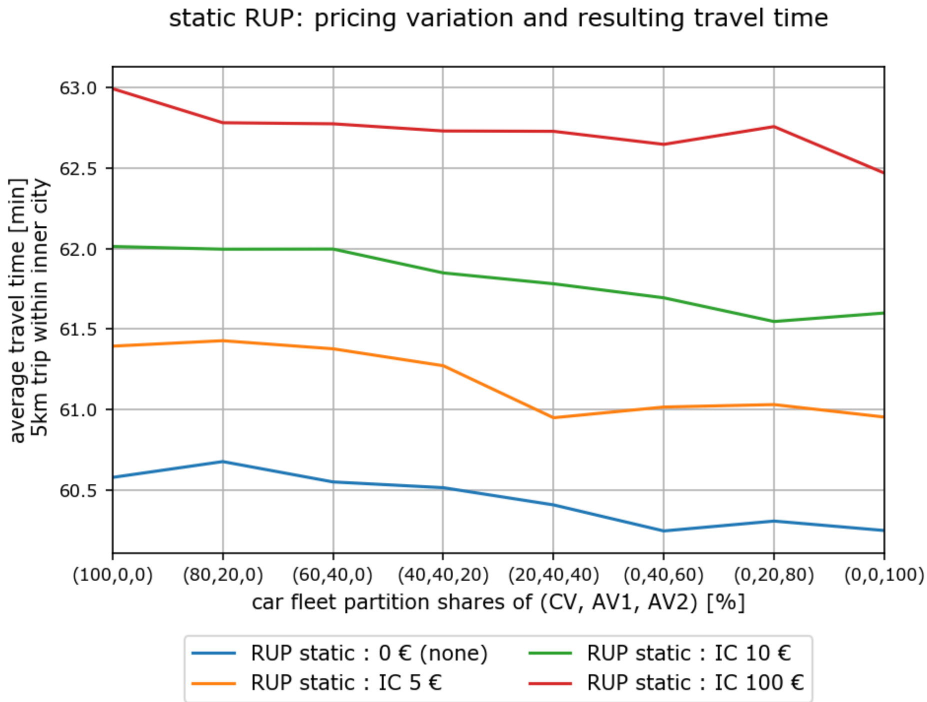


Figure 4.1: Static RUP average travel time of a 5 km trip within the inner city for the static RUP scenarios at increasing pricing levels, shown along an assumed evolution of increasing car fleet automation along the horizontal axis.

Dynamic RUP

Effects on the average travel time for different dynamic road use pricing schemes (as defined in section 3.2.3) are shown in Figure 4.2. The simulated mobility behaviour

describes the situations when the fee per 7 km of distance driven inside the tolling area of the inner city (IC) is increased in steps equivalent to the prices defined before.
In these scenarios not all vehicles entering the tolling area will be charged equally high fees, as some of the agents only cross into the IC briefly to soon leave again, therefore only amounting to low tolling costs.

When comparing these results to the static RUP case, a minor trend in reduction of average trip times by 0.3 minutes for increasing automation scenarios. Similar to static RUP, the effect on the defined impact is very small. The maximum tolling case (100 €) does not show a decrease in travel time at all.
Changing the toll from 0 to 5 € is the pricing step that has the largest increasing effect on the travel time. Prohibitive tolling (of 100 €) causes average trip time to increase by more than 3 minutes (+ 5 %), when compared to the toll-free case (0 €). The high price of car use caused by tolling enables greater tolerance for longer travel times when using alternative modes of transport.

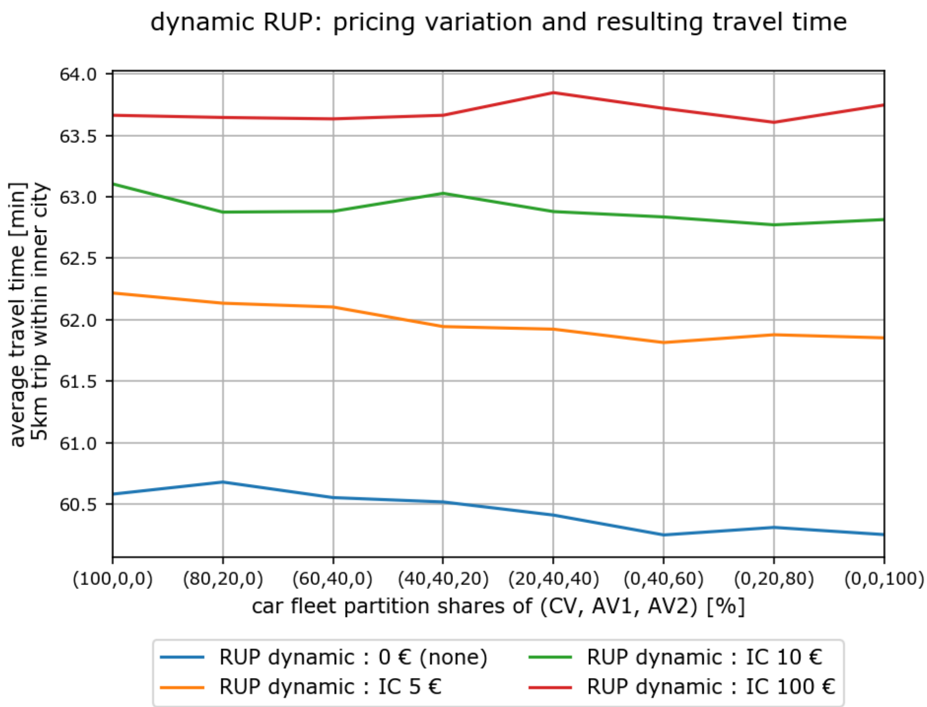


Figure 4.2: Dynamic RUP average travel time of a 5 km trip within the inner city for the dynamic RUP scenarios at increasing pricing levels, shown along an assumed evolution of increasing car fleet automation along the horizontal axis.

Marginal utility of money (mUoM)

To investigate effects on the average travel time under the assumption of changed economic circumstances for the simulated population (e.g., due to altered inflation), the model parameter of monetary value was chosen to reflect these changes. Simulations were made to assume monetary value shifts of +/- 5%, which cause the simulated agents to reconsider their mobility behaviour with respect to the monetary cost shares (as opposed to time-costs - see section 3.2). Again, in Figure 4.3 a basic trend of slight reduction in average travel time is visible with increased automation. Considering the full span from mUoM = 0.95 to mUoM = 1.05 shows that the difference in the average travel time amounts to approximately + 0.4 minutes (+ 0.65 %) for any given level of automation. This clearly reflects the behaviour of people willing to accept longer travel times when perceived traveling costs increase, while faster traveling choices are made available with decreasing costs.

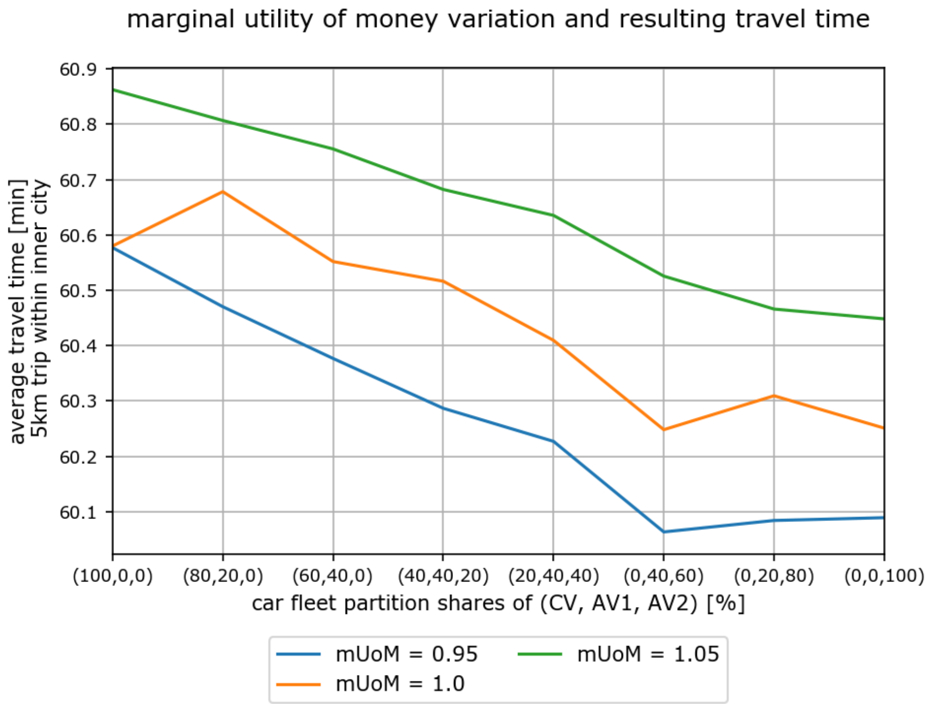


Figure 4.3: No RUP scenarios (0 € toll) average travel time of a trip within the inner city for the no RUP scenarios (0 € toll) and varied levels of the marginal utility of money, shown along an assumed evolution of increasing car fleet automation along the x-axis.

As a more detailed observation, the kink in the travel time for the nominal value of mUoM = 1 in the no-automation scenario ((100,0,0) in Figure 4.3) can be considered: The leftmost data point for this scenario is the result of an exceptionally long optimization process, as it resembles the foundational baseline for all further simulations. It reflects the stock case of reality ("baseline 0") with respect to mobility behaviour as well as it could be modelled. Therefore, the simulated agents in that case were given many opportunities to optimize their behaviour to collectively arrive at a very stable optimum. All other shown data points result from scenario simulations that start from this "baseline 0" after having their conditions adapted to the specific situations under investigation. A decrease of the relative value of money by 5 % (with mUoM = 0.95), would make more expensive trips more probable, but the no-automation case by itself does not exert a cost pressure strong enough to trigger a change in the mode choice of the agents that would show in the average travel times. A conclusion to be drawn from this is that people who have arrived at mobility habits over the course of a long time and thus perceive them as optimal choices, likely will require a disruptive incentive to change these habits.

While the indicator results are in part also affected by random fluctuations, the overall outcomes show consistent development towards more automation for all considered scenarios in Figure 4.3.

4.1.2 Results from microscopic simulation

4.1.2.1 Provision of dedicated lanes on urban highways

The impact of CAVs dedicated lane on travel time was analysed through microsimulation method. Simulations were run for the relevant scenarios where the provision of a dedicated lane is applicable, i.e., mixed fleet scenarios only. Needless to say, full MPR scenarios do not require dedicated lanes.

According to the results obtained from microsimulation, establishing CAV dedicated lane at low MPR can degrade the network performance, increasing the travel time as compared to the baseline scenario (without dedicated lane). When CAVs become a significant part of the mixed traffic (higher MPR scenarios, the benefits of setting dedicated lanes diminish as well. At low MPR, the predominant part of the impact will be on non-dedicated lanes, while at higher MPR, the negative impact on traffic flow would likely be transferred to the CAV dedicated lane, unless the number of dedicated lanes for CAVs is increased. Since only one dedicated lane scenario was tested under this SUC, the results indicated that the potential for travel time saving could be achieved at moderate penetration rates scenario such as indicated in Figure 4.4 at 60-40-0. These findings are also in line with those reported by Vander Laan and Sadabadi (2017), Ye and Yamamoto (2018), and also with the findings of Ma and Wang (2019) study. Under the test network, the results clearly indicated more travel time savings when dedicated lane is provided on both Motorway and A-Road as compared to Motorway only. However, A-Road only case showed additional benefits, where A-Road innermost lane placement strategy indicated the maximum travel time saving as compared to the outermost one as well as other tested scenarios and baseline (Figure 4.4). This reflects lesser interruptions in flow, lesser delays, and increased flow in case of A-Road innermost (left-most lane) lane scenario. The performance of CAV dedicated lane can potentially be further increased by requiring CAVs to go at a faster speed than vehicles on other conventional lanes, as also suggested by Ye and Yamamoto (2018).

It is important to note that Figure 4.4 presents network level results where dedicated lane configurations were tested on a major arterial and motorway in the study network of Manchester area. The penetration rate of CAVs and the assumptions used to model them indicating their individual performance are critical elements in determining the impacts due to provision of a CAV dedicated lane. Also, the trend in the following figure represents the combined impact of automation and the intervention (dedicated lane).

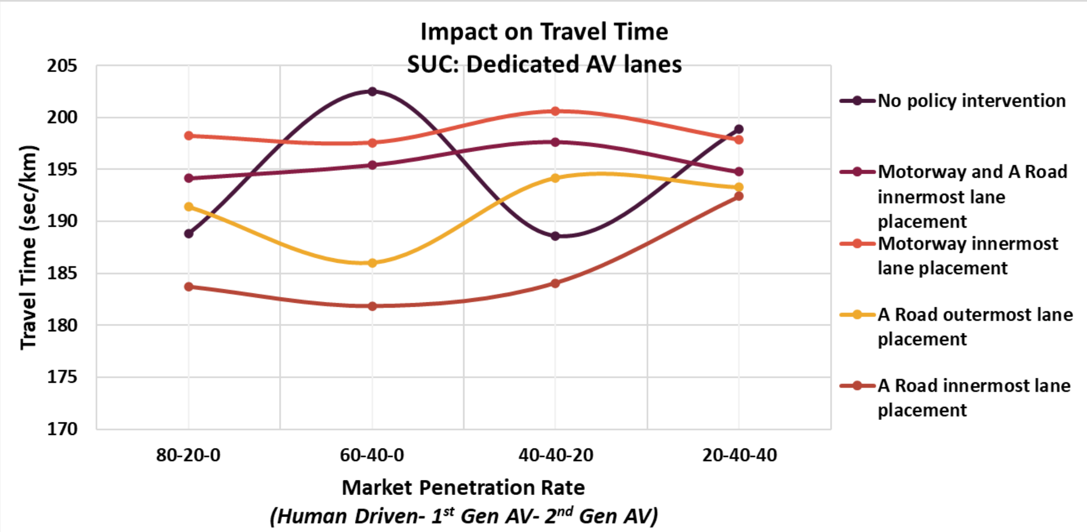


Figure 4.4: Impact on Travel Time due to MPR of CAVs and provision of Dedicated Lane

In order to determine the impact of the dedicated lane exclusively, percentage change at a certain MPR in travel time is calculated comparing to the value in the corresponding baseline MPR scenario, as shown in Table 4.1. The impact due to the intervention (provision of dedicated lane) can be now more clearly seen through the figures presented in Table 4.1. The percentage reduction in travel time is maximum at moderate MPR scenario i.e., 60-40-0 across all cases with further decrease under A Road innermost lane case reaching slightly more than 10%.

Table 4.1: Percent Change in Travel Time w.r.t to Baseline for Dedicated Lane SUC

Market Penetration Rate	Motorway and A Road innermost lane placement	Motorway innermost lane placement	A Road outermost lane placement	A Road innermost lane placement
80-20-0	2.83%	4.99%	1.38%	-2.70%
60-40-0	-3.48%	-2.43%	-8.13%	-10.20%
40-40-20	4.81%	6.37%	2.96%	-2.40%
20-40-40	-2.06%	-0.51%	-2.81%	-3.23%

4.1.2.2 Parking price policies

The microsimulation results of travel time under different parking price strategies tested on the Santander model are presented in Figure 4.5. Under the baseline or no policy intervention scenario, it can be seen that the travel time randomly varies with the penetration rate of CAVs. This trend is similar to the one observed in the dedicated lane results discussed above (Figure 4.4). The reduction in travel time can be observed at higher MPR scenarios. The non-uniform trend of travel time under baseline is primarily due to the assumptions used to model 1st and 2nd Generation CAVs behaviours and their resulting interactions with HDVs and each other.

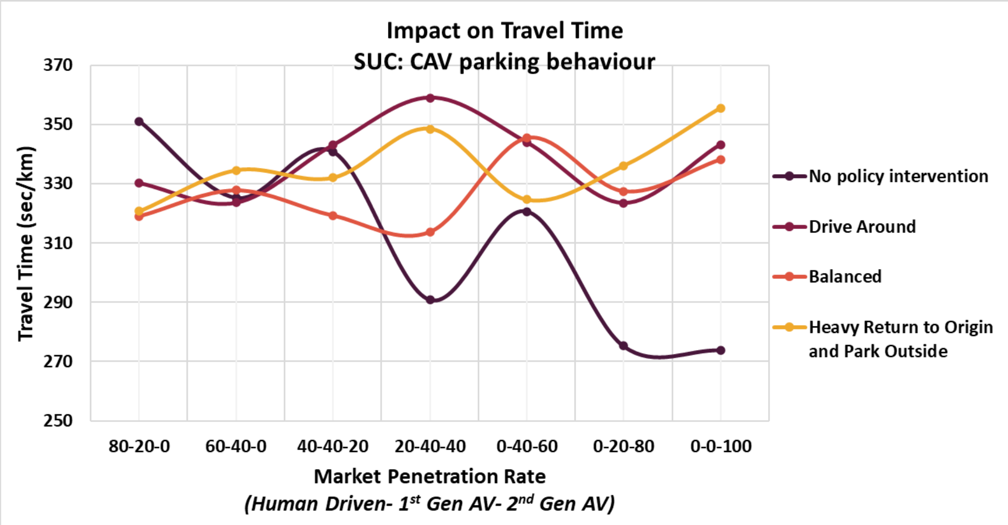


Figure 4.5: Impact on Travel Time due to MPR of CAVs and interventions for CAV parking price policies SUC

In terms of impact on travel time under different parking behaviours emerging due to different parking pricing, on average the travel time was found to increase under all pricing strategies as compared to the no policy intervention (baseline) scenario (Table 4.2). At full MPR, the highest travel time can be observed in the case of heavy return to origin and park outside case whereas the minimum travel time is observed under the balanced case as compared to other scenarios including drive around and heavy return to origin and park outside. This trend can be expected as under the drive around scenario vehicles are never parked increasing the traffic volume on the road and hence the travel time is increased. Similarly in the case of heavy return to origin and park outside most of the vehicles use the road and return the parking space which leads to increased vehicles on road and causes increased travel time.

Table 4.2: Percent Change in Travel Time w.r.t to Baseline for parking price policies SUC

Penetration Rate	Drive Around	Balanced	Heavy Return to Origin and Park Outside
80-20-0	-6,0%	-9,1%	-8,7%
60-40-0	-0,5%	0,8%	2,9%
40-40-20	0,7%	-6,3%	-2,6%
20-40-40	23,4%	7,9%	19,8%
0-40-60	7,3%	7,7%	1,2%
0-20-80	17,5%	19,0%	22,1%
0-0-100	25,3%	23,5%	29,8%

4.1.2.3 Parking space regulations

This section presents the microsimulation results of travel time for replacing on-street parking with different interventions on the Leicester network. It is noted that the travel time is the average time that vehicle needs to travel one kilometre inside the network (measured in sec/km) (Transport Simulation Systems, 2021).

In this sub-use case, on-street parking spaces have been replaced with various interventions i.e., removing half of the on-street parking, replaced with driving lane, cycle lane, pick-up/drop-off points and public spaces. Details on each of the intervention have been described in section 3.1.2. Travel time is one of the most common indicators to measure the network mobility performance and efficiency, and in practice the smaller value of travel time represents better network performance (Rao & Rao, 2015). The results with an absolute numerical value of travel time for each of the tested intervention based on CAVs fleet market penetration level are presented in Figure 4.6.

As shown in Figure 4.6, under no policy intervention, with increasing CAVs in the network some irregular pattern can be identified with regard to impact on travel time however, at higher MPRs, in general, the travel time was found to decrease as the CAVs market penetration rate increases both in baseline and under all tested interventions . In other words, less journey time is needed for higher CAVs market penetration rates. This is in line with the finding of some previous studies showing that autonomous vehicle has an omniscient capability such as keeping consistent speed and allowing vehicles to accept much short gaps to achieve the best performance in the traffic stream (Almobayedh, 2019; Li et al., 2019; Stogios et al., 2019; Stogios, 2018). The results also show significant decrease in travel time due to various parking space regulations as compared the no policy (baseline) intervention scenario.

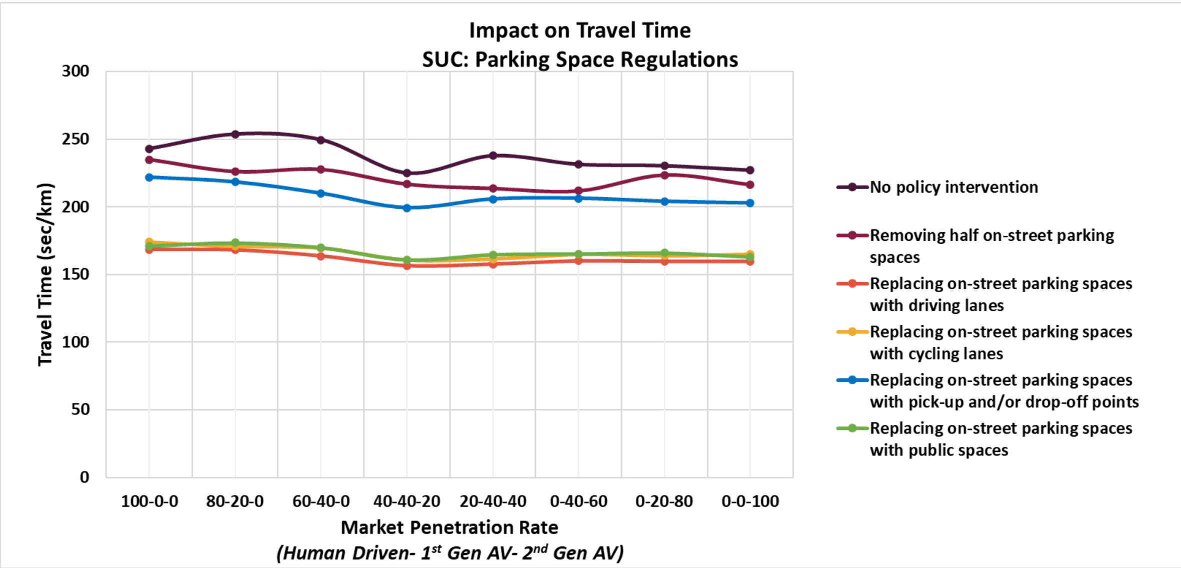


Figure 4.6: Impact on Travel Time due to MPR of CAVs and interventions for parking space regulations SUC

The impact from each of the individual interventions can be clearly seen in Table 4.3, where travel time is calculated as a percentage change compared to the value in the corresponding baseline MPR scenario. The interventions of replacing on-street parking with driving lane, cycle lane and public spaces have shown a significant improvement in reducing the travel time compared to the baseline scenario. For example, at a 100% market penetration rate, the travel time reduces from 227.2s to 159.5s for replacing with driving lane, 164.9s for replacing with cycle lane, and 163.0s for replacing with public spaces, respectively. In other words, between 27% to 30% reduction can be achieved for these three scenarios. The results also show that the impact due to removing half of the on-street parking spaces and replacing on-street parking spaces with pick-up/drop-off areas have relatively less impact on travel time compared to the other policy interventions. One of the most important potential reasons is that the interventions of removing half of the on-street parking spaces and replacing them with pick-up/drop-off points may cause queues built-up near those areas due to frequent parking manoeuvres or while vehicles picking up and dropping off passengers, resulting in an increased congestion, delays and increased travel time. This finding is consistent with the observations by other studies (Chai et al., 2020; Winter, Cats, Martens, & van Arem, 2021; ITF, 2018). The results also suggest that by replacing half of the on-street parking spaces may not provide the expected improvement in the city centre, especially with a congested network.

Table 4.3: Percent Change in Travel Time w.r.t to Baseline for parking space regulations SUC

CAVs Penetration Rate	Baseline	Removing half on-street parking spaces	Replacing with driving lanes	Replacing with cycling lanes	Replacing with pick-up and/or drop-off points	Replacing with public spaces
100-0-0	-3%	-31%	-28%	-9%	-30%	-3%
80-20-0	-11%	-34%	-33%	-14%	-32%	-11%
60-40-0	-9%	-34%	-32%	-16%	-32%	-9%
40-40-20	-4%	-31%	-29%	-12%	-29%	-4%
20-40-40	-10%	-34%	-32%	-13%	-31%	-10%
0-40-60	-8%	-31%	-29%	-11%	-29%	-8%
0-20-80	-3%	-31%	-29%	-12%	-28%	-3%
0-0-100	-5%	-30%	-27%	-11%	-28%	-5%

4.1.2.4 Automated ride sharing

The impact of an automated ridesharing system on travel time was quantified through microsimulation method under no policy intervention (baseline) scenario and the automated ridesharing scenarios (defined in section 3.1.2). According to Figure 4.7, introducing an automated ridesharing service triggered an increase in travel time for all market penetration rates compared to no policy intervention baseline scenario, regardless of the percentage of the demand served by the introduced service. The results also indicate that the increase in travel time is strongly related to the rate of travellers willing to share their trips. In terms of the results of the maximum percentage of served demand 20% (Table 4.4), with low willingness to share (20%), the average travel time increases by +9% at lower MPR (80-20-0 and 60-40-0) and up to +17% at higher MPR with respect to the baseline scenario (Table 4.14). For 100% willingness to share, at lower and medium MPR, travel time increases to +11%, while at high MPR, the values were close to baseline results with a slight increase up to +5%.

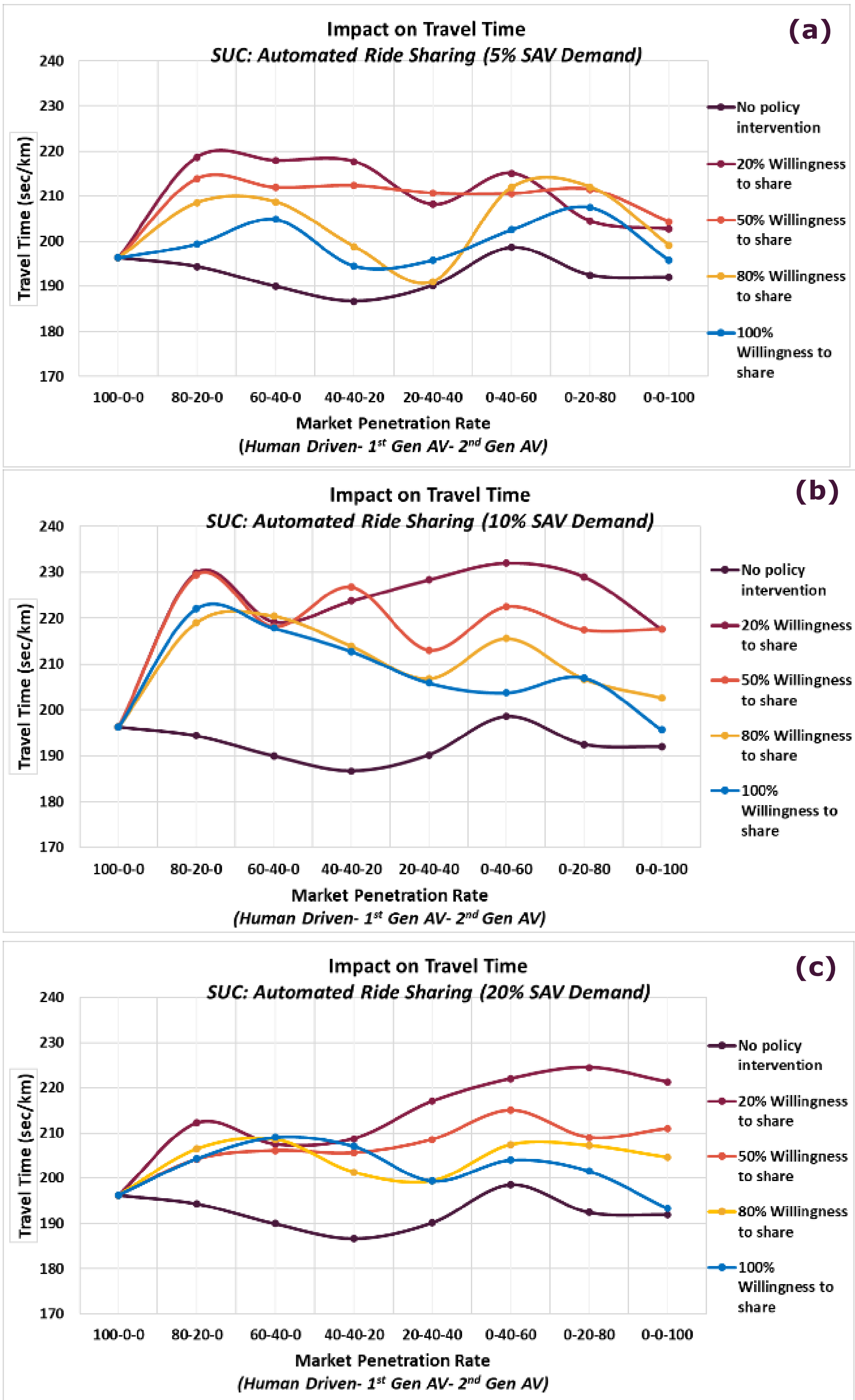


Figure 4.7: Impact on Travel time due to MPR of CAVs and Automated Ride Sharing service

Table 4.4: Percentage change of travel time with respect baseline scenario for automated ride sharing SUC (20% served demand)

Market Penetration Rate	20% Willingness to share	50% Willingness to share	80% Willingness to share	100% Willingness to share
80-20-0	9%	5%	6%	5%
60-40-0	9%	9%	10%	10%
40-40-20	12%	10%	8%	11%
20-40-40	14%	10%	5%	5%
0-40-60	12%	8%	4%	3%
0-20-80	17%	9%	8%	5%
0-0-100	15%	10%	7%	1%

The increase in travel time is mainly caused by additional empty trips due to SAVs causing negative impact on traffic flow. Another contributory factor is the circulating behaviour of SAVs that tend to use low capacity and/or secondary roads to reach their destinations impacting the overall network performance. These results are in line with the findings of Overtoom et al. (2020).

4.1.2.5 Green Light Optimal Speed Advisory (GLOSA)

Considering GLOSA advisory speeds sent by GLOSA are accurate and the drivers comply with them, the expectation is that it will generate smoother traffic flow, reducing the number of stops. However, at low penetration of GLOSA equipped vehicles, these benefits can be expected to be much lower due to lesser homogeneity and more speed variations in traffic flow. However, previous studies exploring impacts of GLOSA have reported benefits under fixed time controllers and not under actuated signals (Stevanovic et al, 2013). With regard to travel time savings, Gajananan et al (2013) used an integrated traffic, driving and communication simulator to investigate the effects of GLOSA on emissions, travel times and stopped times. GLOSA introduction led to a reduction in all 3 of these areas with 40-68% reduced stopped times and 10-16% reduced travel times.

The simulation results from testing GLOSA system on one (case 1), two (case 2), and all three intersections (case 3) on the study network clearly showed travel time savings with respect to no policy intervention (without GLOSA) (Figure 4.8). Further travel time savings were observed when the system was applied to all three intersections as compared to case 1 and case 2. It is important to note that the increase in travel time with respect to increasing MPR is inherent due to the baseline trend (as shown by the dark coloured line).

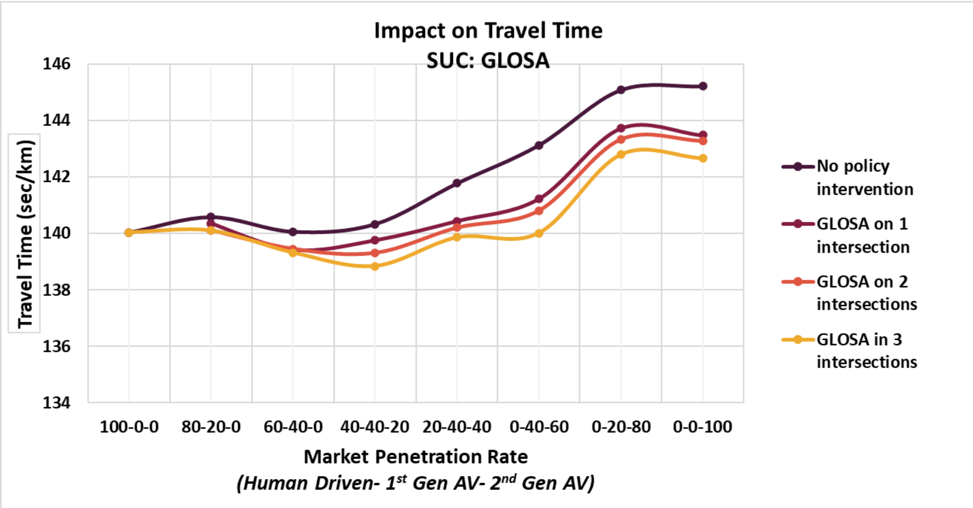


Figure 4.8: Impact on Travel Time with GLOSA application per MPR of CAVs

In terms of percentage change in travel time (due to GLOSA) with respect to respective MPR baseline scenario (Table 4.5), a maximum of 5.4% travel time reduction was obtained under case 3 at 0-40-60 MPR scenario while almost 4.2% reduction in travel time was observed at 100% MPR.

Table 4.5: Percentage change of travel time with respect to no intervention baseline scenario for GLOSA

Market Penetration Rate	GLOSA on 1 intersection	GLOSA on 2 intersections	GLOSA on 3 intersections
80-20-0	-0,4%	-0,8%	-0,8%
60-40-0	-1,1%	-1,0%	-1,3%
40-40-20	-0,9%	-1,8%	-2,6%
20-40-40	-2,2%	-2,7%	-3,3%
0-40-60	-3,2%	-4,0%	-5,4%
0-20-80	-2,1%	-2,8%	-3,7%
0-0-100	-2,8%	-3,1%	-4,2%

To supplement the findings on travel time savings, number of stops (average number of stops per vehicle while travelling in the section) are plotted against MPR under 3 cases where GLOSA system was applied (Figure 4.9). Results show a reduction (almost 3.2%) in number of stops when GLOSA was applied to all three intersections.

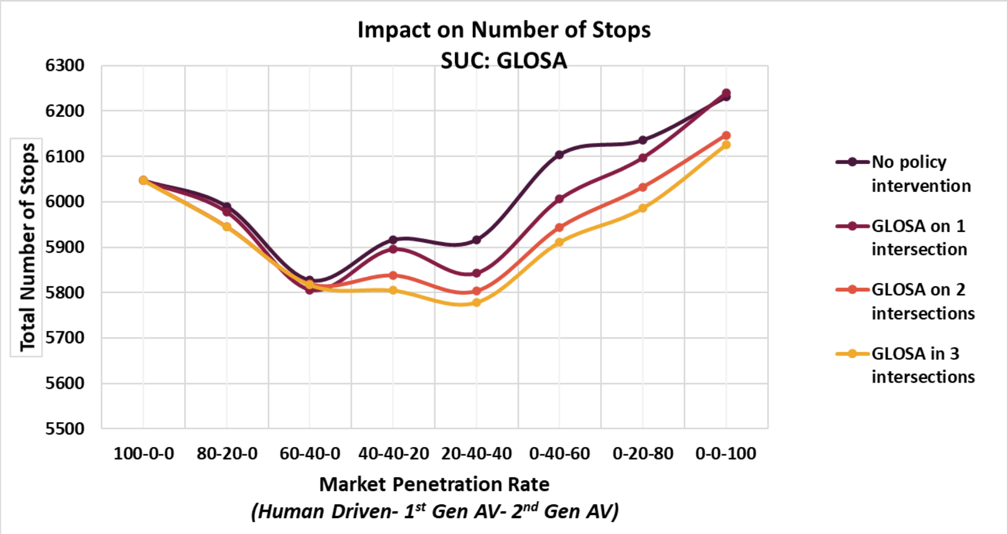


Figure 4.9: Impact on No. Of Stops with GLOSA application per MPR of CAVs

The reduction in travel time and no. of stops with GLOSA vs. no GLOSA shown in the results are consistent with the expectations from GLOSA system and findings of other literature; however, percentage reduction is found to vary across the previous studies (Stevanovic et al 2013, Eckhoff et al, 2013). Potential reasons can be the differences in the network and traffic characteristics, fleet compositions, and assumptions on the vehicle characteristics.

4.1.3 Results from Delphi

4.1.3.1 Road use pricing

According to the experts' answers in the first round of the Delphi, the introduction of AVs in the baseline scenario will lead in the short term to a slight increase (6,1%) in travel time but with the increase of AVs market penetration rate this scenario will progressively reduce travel time reaching in the long term a maximal percentage of -22,5%. The introduction of city tolls will generally reduce travel time. More precisely, after the empty km pricing scenario will affect the most travel time among the other city toll scenarios, leading to a maximal reduction of -18 % in the long term. Static and dynamic city tolls will also positively affect travel time leading to a reduction of -7,6% and -13,5% respectively.

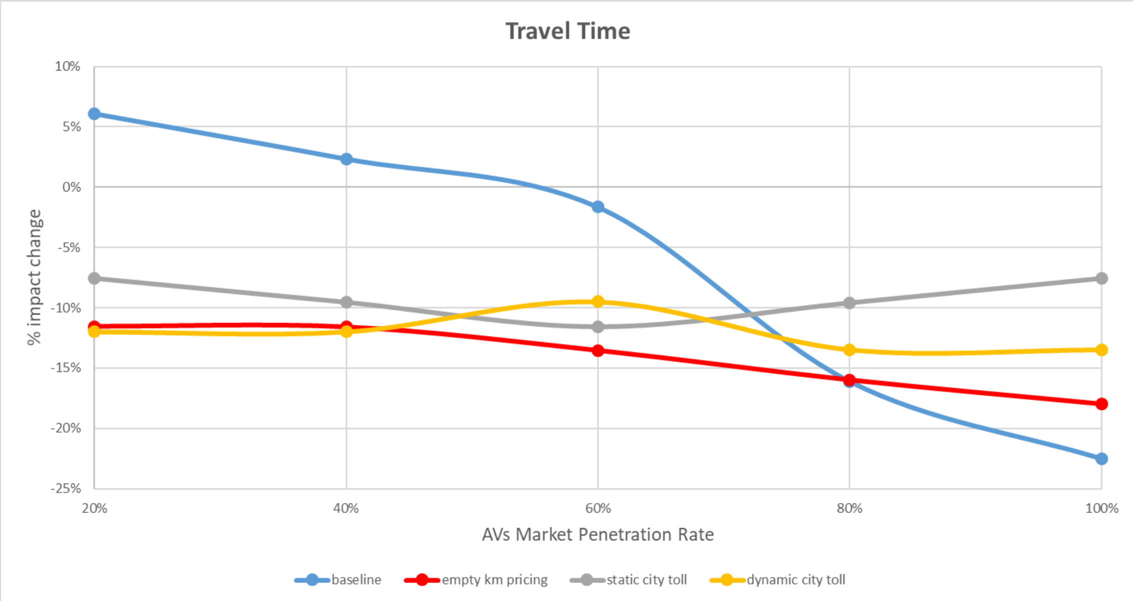


Figure 4.10: 1st round Delphi travel time results for the city toll scenarios

The majority of the 2nd round participants stated that they definitely (14%-29%) or moderately (43%-72%) agree with the resulted 1st round trends. Two experts (29%) suggested that all the studied scenarios will not significantly affect travel time, proposing an average impact of 5% for the baseline scenario and -5% for all the city toll scenarios.

Figure 4.11: 2nd Round Delphi travel time results for empty km pricing and static toll scenarios

These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

Table 4.6: Final PST coefficients for travel time for the city toll scenarios

	Baseline		**Empty km pricing**		**Static toll**		**Dynamic toll**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	Aggregate change	Aggregate change	PST coefficients
20%	6,0%	1,060	-10,8%	0,892	-7,4%	0,926	-11,6%	0,884
40%	2,5%	1,025	-10,8%	0,892	-9,3%	0,907	-11,6%	0,884
60%	-1,3%	0,987	-12,5%	0,875	-11,2%	0,888	-9,2%	0,908

80%	-14,9%	0,851	-14,7%	0,853	-9,3%	0,907	-13,0%	0,870
100%	-20,9%	0,791	-16,5%	0,835	-7,4%	0,926	-13,0%	0,870

4.1.3.2 Provision of dedicated lanes on Urban Highways

According to the experts' answers in the first round of the Delphi, the introduction of AVs dedicated lanes will lead to a progressive reduction of travel time reaching in the long term a maximal percentage of -24,5% for the AVs dedicated lane in the innermost motorway lane. The introduction of AVs dedicated lanes on the outermost motorway lane will reduce travel time by -18,1% in the long term. AVs dedicated lanes on the outermost motorway lane and A-road as well as the dynamically controlled AV dedicated lane on the outermost motorway lane will also positively affect travel time leading to a reduction of -14,1% and -10,1% respectively. On the other hand, according to experts travel time will not be significantly affected by the baseline scenario (introduction of AVs), leading to a small increase (4,2%) in the short term when AVs market penetration rate is about 40%, and thus conventional and automated vehicles share the urban roads.

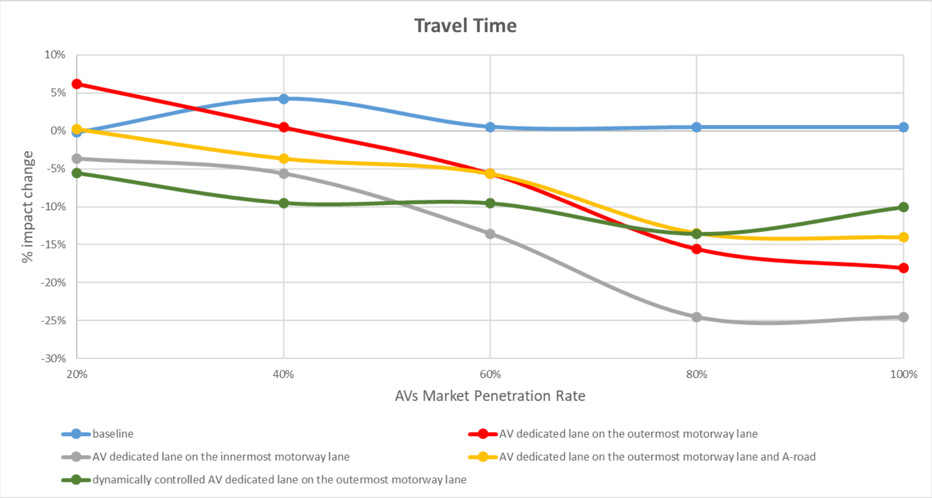
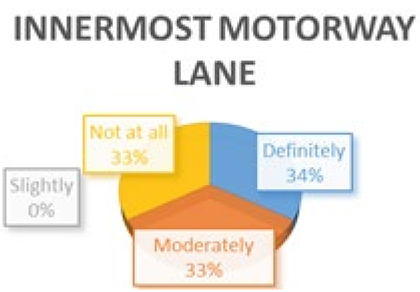


Figure 4.12: 1st round Delphi travel time results for AV dedicated lanes scenarios

The majority of the 2nd round participants stated that they definitely (0%-33%) or moderately (33%-67%) agree with the resulted 1st round trends. Two experts (33%) suggested that all the studied scenarios will not significantly affect travel time, proposing an average impact of 5%.



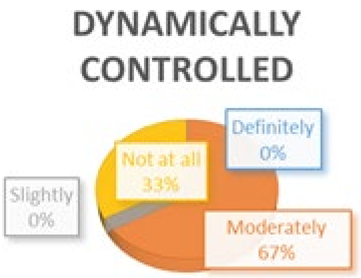


Figure 4.13: 2nd Delphi travel time results for AV dedicated lane on the innermost motorway lane and dynamically controlled AV dedicated lane

These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

Table 4.7:Final PST coefficients for travel time for the AV dedicated lanes scenarios

	Baseline		**Outermost motorway lane**		**Innermost motorway lane**		**Outermost motorway lane and A-road**		**Dynamically controlled AV dedicated lane**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	Aggregate change	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	0,1%	1,001	5,4%	1,054	-3,2%	0,968	0,2%	1,002	-4,9%	0,951
40%	4,0%	1,040	0,4%	1,004	-4,9%	0,951	-3,2%	0,968	-8,3%	0,917
60%	0,7%	1,008	-4,9%	0,951	-11,9%	0,881	-4,9%	0,951	-8,4%	0,916
80%	0,7%	1,007	-13,7%	0,864	-21,4%	0,786	-11,8%	0,882	-11,9%	0,881
100%	0,7%	1,007	-15,8%	0,842	-21,5%	0,785	-12,3%	0,877	-8,8%	0,912

4.1.3.3 Parking price policies

According to the experts' answers in the first round of the Delphi, the introduction of AVs will lead to a progressive reduction of travel time reaching in the long term a percentage of -31,6%. The introduction of CAVs parking behaviours will negatively affect travel time leading to an increase in the short term, which is compatible with the expected result since the induced parking behaviours will lead to more vehicles using the roads at the same time. More precisely, parking inside the city centre will increase travel time 21,9% for 100% AVs market penetration rate, returning to origin will lead to a 16,9% increase and driving around will increase travel time by 23,4%. On the other hand, according to experts travel time will not be affected by the CAVs parking outside behaviour regardless of AVs market penetration rate.

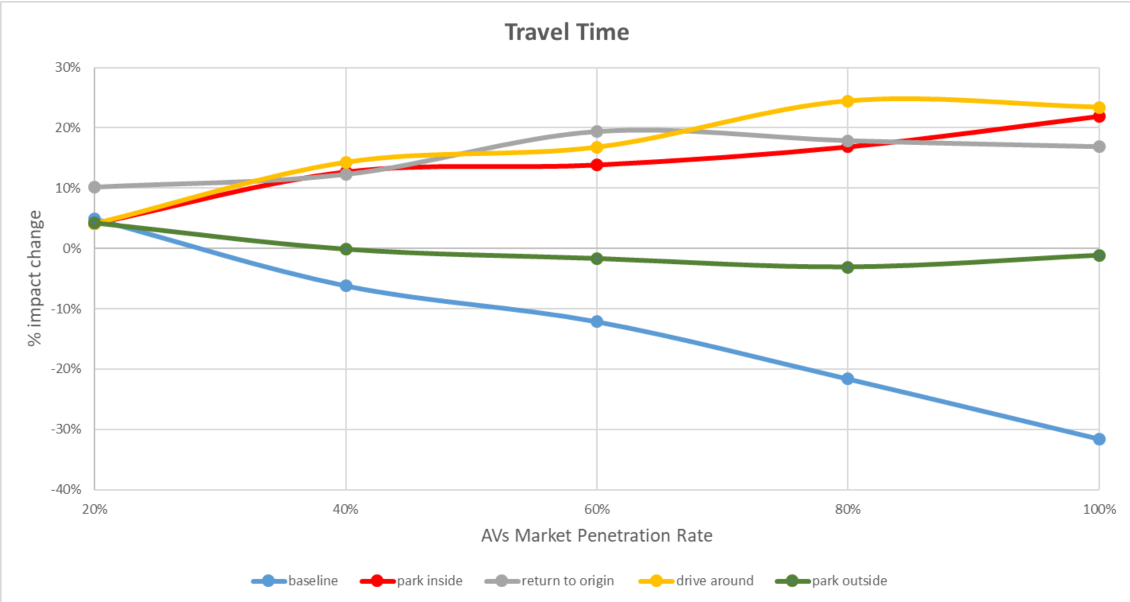


Figure 4.14: 1st round Delphi travel time results for CAV parking price policies scenarios

The 2nd round participants stated that they slightly or not at all agree (33%-67%) with the resulted 1st round trends. Regarding the proposed parking behaviours, experts suggested that parking inside will in fact reduce travel time since it is the only scenario that will not generate more trips. On the other hand, they proposed that parking outside will increase travel time at an average of 5% to 15% since it would require more driving and thus more empty kilometres.

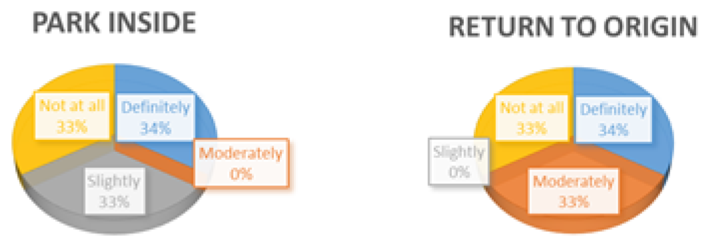


Figure 4.15: 2nd round Delphi travel time results for park inside and return to origin scenarios

These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

Table 4.8: Final PST coefficients for travel time for CAV parking price policies scenarios

	Baseline		**Park inside**		**Return to origin**		**Drive around**		**Park outside**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	Aggregate change	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	4,0%	1,040	0,6%	1,006	6,4%	1,064	2,4%	1,024	5,7%	1,057
40%	-5,0%	0,950	7,0%	1,070	10,1%	1,101	13,1%	1,131	0,5%	1,005

60%	-9,9%	0,901	7,9%	1,079	16,3%	1,163	15,3%	1,153	-0,7%	0,994
80%	-17,6%	0,824	10,1%	1,101	15,0%	1,150	22,0%	1,220	-1,7%	0,983
100%	-25,7%	0,743	13,9%	1,139	14,1%	1,141	21,1%	1,211	-0,2%	0,998

4.1.3.4 Parking space regulations

Before asking experts about the impact of each scenario, they were asked to suggest what is the best percentage of on-street parking space to be replaced by each scenario. Regarding space for public use experts proposed an average of 43% of on-street parking space to be replaced. The majority of experts answered that on-street parking must be replaced at a maximum of 25% by driving lanes. Finally, regarding pick-up/drop-off parking space 1st round results indicated that participants suggest 28% of on-street parking space to be replaced.

According to the experts' answers in the first round of the Delphi, the introduction of AVs will lead in the long term to a small reduction of travel time of -6,7%. Replacing on-street parking space with space for public use or with pick-up/drop-off parking space will both lead to a small increase of travel time of about 8% and 4% respectively. Finally, replacing on-street parking space with driving lanes will lead to an increase (10,7%) of travel time for AV market penetration rates up to 20% and then for higher AVs market penetrations rates travel time will reduce (-6,55%) according to experts.

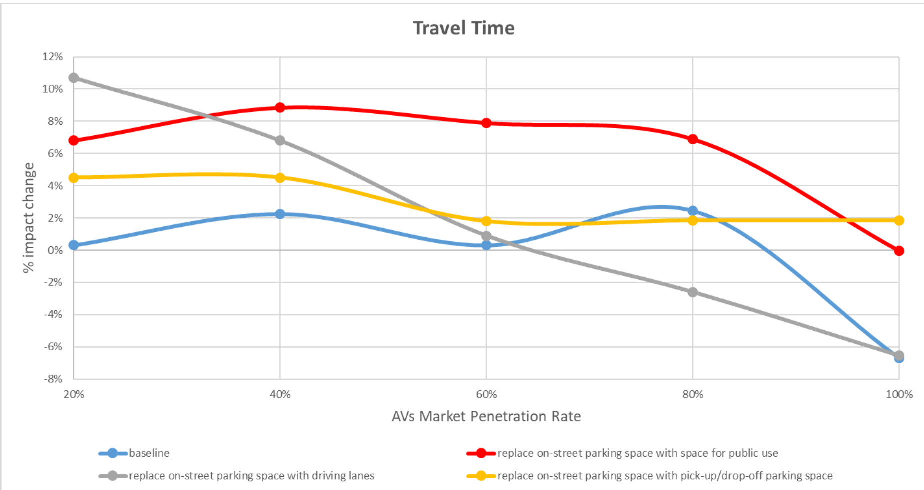


Figure 4.16: 1st round Delphi travel time results for parking space regulation scenarios

All of the 2nd round participants stated that they agree definitely (20%) or moderately (80%) with the resulted 1st round curve for the baseline scenario (as seen in figure 3). On the other hand 40% of 2nd round experts stated that they slightly agree with the trends of the parking space regulations scenarios, and suggested that replacing on-street parking space with space for public use, with driving lanes or with pick-up/drop-off parking space will not affect travel time. These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

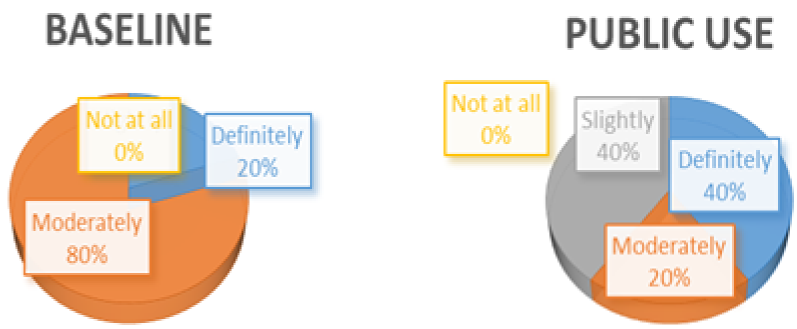


Figure 4.17: 2nd round Delphi travel time results for baseline and replacing on-street parking with spaces for public use

Table 4.9: Final PST coefficients for travel time for parking space regulation scenarios

	Baseline		**Space for public use**		**Driving lanes**		**Pick-up/drop-off**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	0,3%	1,003	5,6%	1,056	9,0%	1,090	3,6%	1,036
40%	2,3%	1,023	7,4%	1,074	5,6%	1,056	3,6%	1,036
60%	0,3%	1,003	6,6%	1,066	0,5%	1,005	1,3%	1,013
80%	2,5%	1,025	5,7%	1,057	-2,5%	0,975	1,3%	1,013
100%	-6,7%	0,933	-0,3%	0,997	-5,9%	0,941	1,3%	1,013

4.1.3.5 Automated Ride Sharing

According to the experts' answers in the first round of the Delphi, the introduction of AVs in the baseline scenario will lead in the short term to a slight increase (6,9%) in travel time but with the increase of AVs market penetration rate this scenario will progressively reduce travel time reaching in the long term a maximal percentage of -24,6%. The introduction of automated ridesharing will generally reduce (-25%) travel time.

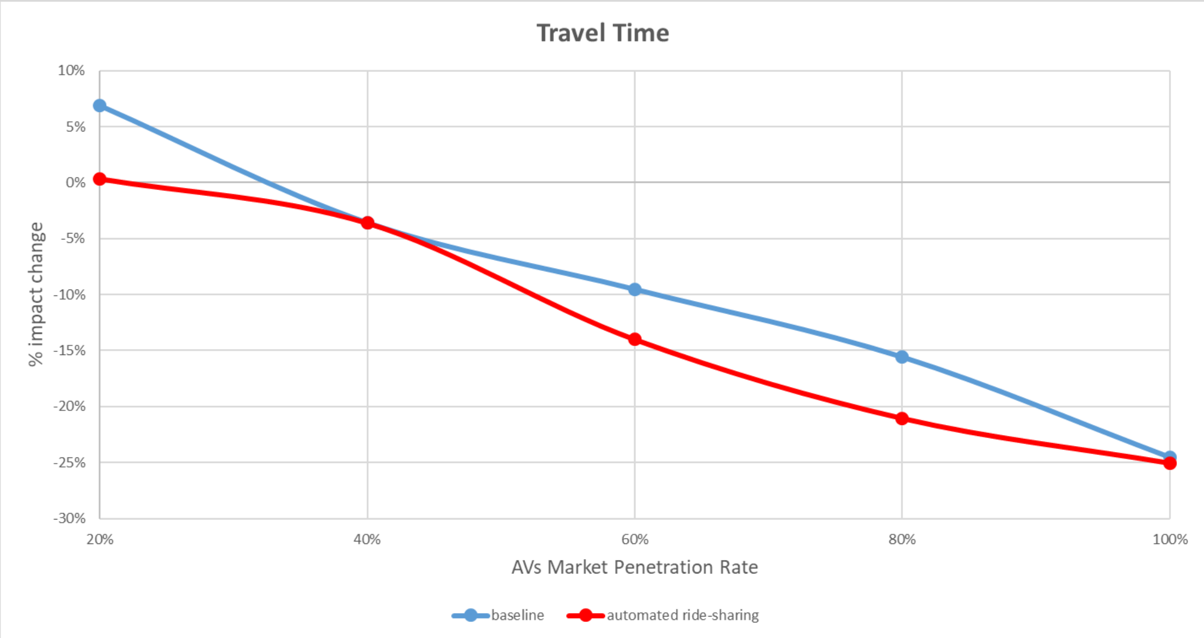


Figure 4.18: 1st round Delphi travel time results for the automated ridesharing scenarios

The majority (67%) of the 2nd round participants stated that they definitely or moderately agree with the resulted 1st round trends for the automated ridesharing scenarios. Two experts (33%) suggested that all the studied scenarios will not significantly affect travel time in the short term, proposing an average impact of 5% in the short term and -10% in the long term for all the scenarios. The majority of experts (67%) slightly or not at all agreed with the baseline scenario curve and claimed that for AVs market penetration rate less than 50% travel time will not be affected at all.

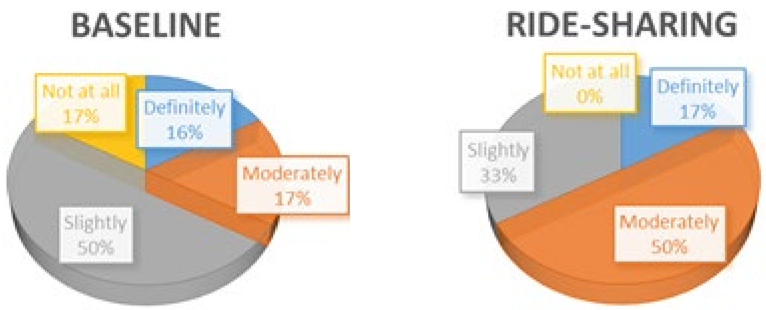


Figure 4.19: 2nd round Delphi travel time results for baseline and automated ridesharing scenarios

These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

Table 4.10: Final PST coefficients for travel time for the automated ridesharing scenarios

	Baseline		Automated ridesharing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	5,1%	1,051	0,3%	1,003

40%	-2,7%	0,973	-3,2%	0,969
60%	-7,5%	0,925	-12,6%	0,874
80%	-12,3%	0,877	-19,0%	0,810
100%	-19,4%	0,807	-22,9%	0,771

4.1.3.6 Green Light Optimal Speed Advisory (GLOSA)

According to the experts' answers in the first round of the Delphi, the introduction of AVs in the baseline scenario will lead in the short term to a slight increase (6,9%) in travel time but with the increase of AVs market penetration rate this scenario will progressively reduce travel time reaching in the long term a maximal percentage of -24,6%. GLOSA will not significantly affect travel time in the short term and only for 100% AVs market penetration rate, this scenario will reduce by -4,6% the studied impact.

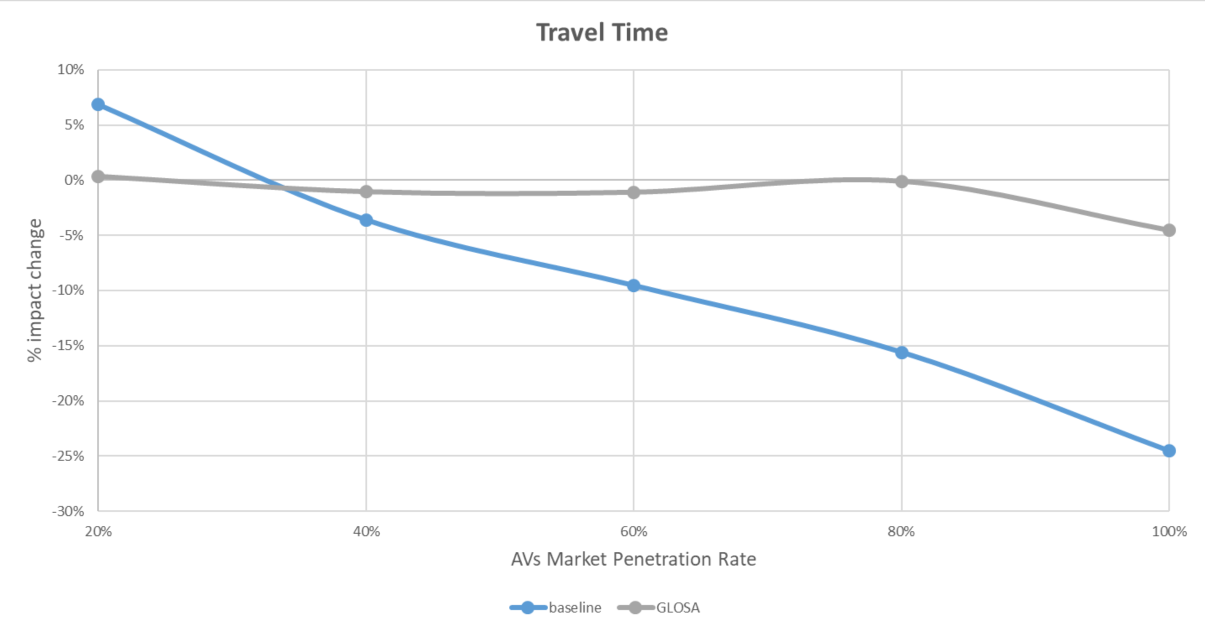


Figure 4.20: 1st round Delphi travel time results for GLOSA scenarios

The majority (67%) of the 2nd round participants stated that they definitely or moderately agree with the resulted 1st round trends for GLOSA scenarios. Two experts (33%) suggested that all the studied scenarios will not significantly affect travel time in the short term, proposing an average impact of 5% in the short term and -10% in the long term for all the scenarios. The majority of experts (67%) slightly or not at all agreed with the baseline scenario curve and claimed that for AVs market penetration rate less than 50% travel time will not be affected at all.

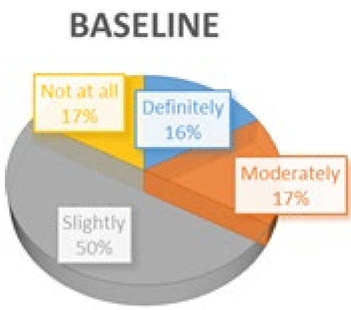


Figure 4.21: 2nd round Delphi travel time results for GLOSA baseline scenario

These suggestions were taken into consideration in the final coefficients that will then be introduced in the PST.

Table 4.11: Final PST coefficients for travel time for GLOSA scenarios

AV penetration rates	Baseline		GLOSA	
	Aggregate change	PST coefficients	Aggregate change	Aggregate change
20%	5,1%	1,051	-0,6%	0,994
40%	-2,7%	0,973	-1,9%	0,981
60%	-7,5%	0,925	-1,9%	0,981
80%	-12,3%	0,877	-1,0%	0,990
100%	-19,4%	0,807	-4,9%	0,951

4.2 Vehicle operating cost

Within LEVITATE, the vehicle operating cost is considered as the direct outlays for operating a vehicle per kilometre of travel (€/km). The impact on vehicle operating cost of the introduction of CAVs with various SUCs is estimated by the Delphi method.

4.2.1 Road use pricing

According to experts, the baseline scenario (no intervention) will increase (+6,2%) vehicle operating cost in the short term when AVs market penetration rates are lower, but with the increase of AVs MPR, vehicle operating cost will be reduced (-8,2%). The introduction of empty km pricing will slightly affect vehicle operating cost, presenting a small reduction (-3,6%) for AV market penetration rates up to 100%. Static and dynamic city tolls will both increase vehicle operating cost, especially in the short term, reaching an increase of 19,9% and 17,3% respectively. This increase will reduce in the long term with the increase of AVs market penetration rate, leading to 13,3% for the dynamic city toll and 9,3% for the static city toll scenario.

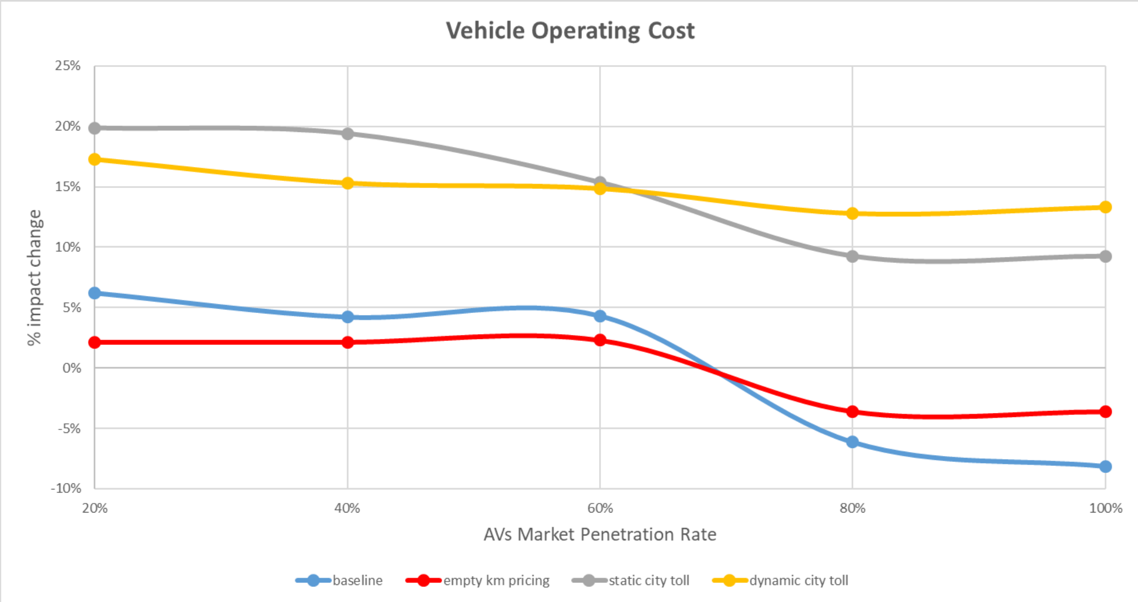


Figure 4.22: 1st round Delphi vehicle operating cost results for the city toll scenarios

All the 2nd round participants stated that they definitely (14%-43%) or moderately (57%-86%) agree with the resulted 1st round trends for the city toll scenarios. One expert (14%) not at all agreed with the baseline curve and suggested that the introduction of AVs will in fact increase vehicle operating cost, by an average of 5%.

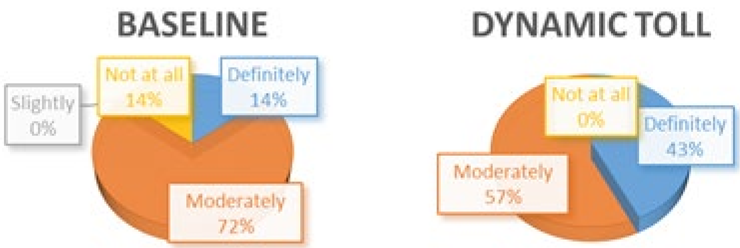


Figure 4.23: 2nd round Delphi vehicle operating cost results for baseline and dynamic toll scenarios

Table 4.12: PST coefficients for vehicle operating cost for the city toll scenarios

	Baseline		**Empty km pricing**		**Static toll**		**Dynamic toll**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	6,1%	1,061	2,3%	1,023	19,9%	1,199	17,3%	1,173
40%	4,2%	1,042	2,3%	1,023	19,4%	1,194	15,3%	1,153
60%	4,3%	1,043	2,5%	1,025	15,4%	1,154	14,9%	1,149
80%	-5,5%	0,945	-3,1%	0,969	9,3%	1,093	12,8%	1,128
100%	-7,4%	0,926	-3,1%	0,969	9,3%	1,093	13,3%	1,133

4.2.2 Provision of dedicated lanes on urban highways

According to experts, the baseline scenario (no intervention) will increase (11,7%) vehicle operating cost in the short term when AVs market penetration rates are lower, but with the increase of AVs MPR, this augmentation of vehicle operating cost will be reduced. The introduction of AV dedicated lanes also presents a reduction of vehicle operating cost for AV market penetration rates up to 100%. More precisely, dynamically controlled AV dedicated lane will have the biggest impact on vehicle operating cost, leading to a decrease of -18,5%. AV dedicated lane on the outermost motorway lane will reduce by -14% the studied impact. AV dedicated lane on the innermost motorway lane and AV dedicated lane on the outermost motorway lane and A-road will similarly affect vehicle operating cost leading in the long term to a reduction of 10%.

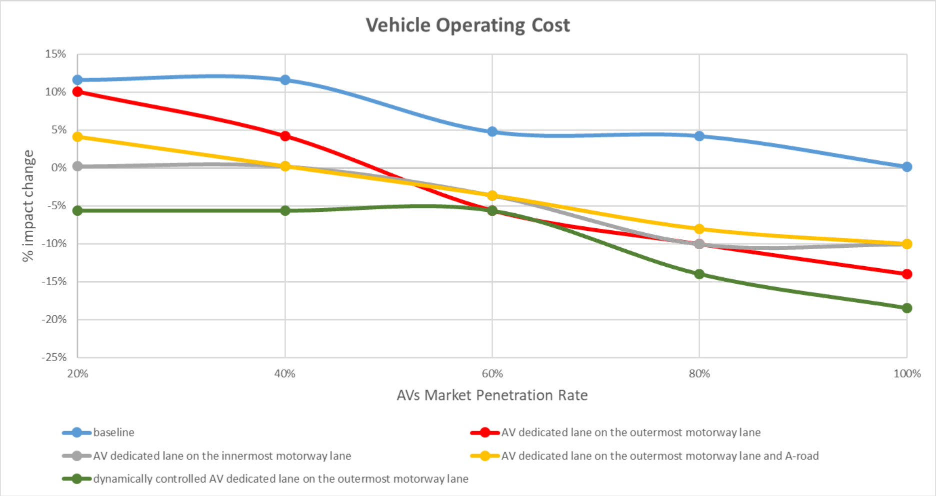


Figure 4.24: 1st round Delphi vehicle operating cost results for the AV dedicated lanes scenarios

All of the 2nd round participants stated that they agree definitely (33%) or moderately (67%) with the resulted trends of the baseline scenario and the scenarios of AV dedicated lanes and made no additional suggestions for improvement.

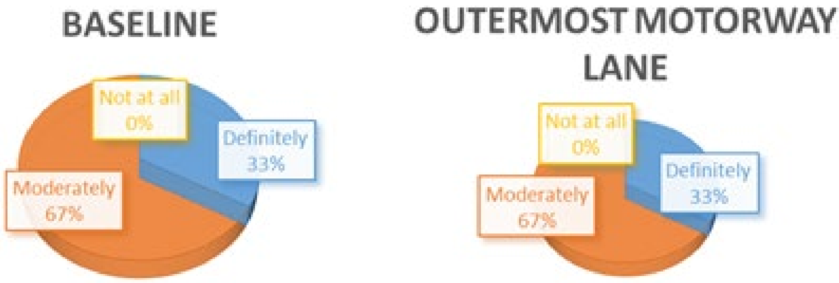


Figure 4.25: 2nd round Delphi vehicle operating cost results for baseline and AV dedicated lane on the outermost motorway lane scenarios

Table 4.13: Final PST coefficients for vehicle operating for the AV dedicated lanes scenarios

	Baseline		Outermost motorway lane		Innermost motorway lane		Outermost motorway lane and A-road		Dynamically controlled AV dedicated lane	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	11,7%	1,117	10,1%	1,101	0,3%	1,003	4,2%	1,042	-5,6%	0,944
40%	11,7%	1,117	4,3%	1,043	0,3%	1,003	0,3%	1,003	-5,6%	0,944
60%	4,8%	1,048	-5,6%	0,944	-3,6%	0,964	-3,6%	0,964	-5,6%	0,944
80%	4,3%	1,043	-10,1%	0,900	-10,1%	0,900	-8,1%	0,920	-14,0%	0,860
100%	0,2%	1,002	-14,0%	0,860	-10,1%	0,900	-10,1%	0,900	-18,5%	0,815

4.2.3 Parking price policies

According to experts, the baseline scenario (no intervention) will lead to a decrease (-22,5%) of vehicle operating cost for AV market penetration rates up to 100%. CAVs parking outside behaviour is the only parking behaviour that will reduce (-6,2) vehicle operating cost in the long term. All other CAVs parking behaviours will increase vehicle operating cost. More precisely, CAVs parking inside will increase by 15,9% the studied impact, CAVs returning to origin 23% and CAVs driving around will lead to a 20,9% increase of vehicle operating cost.

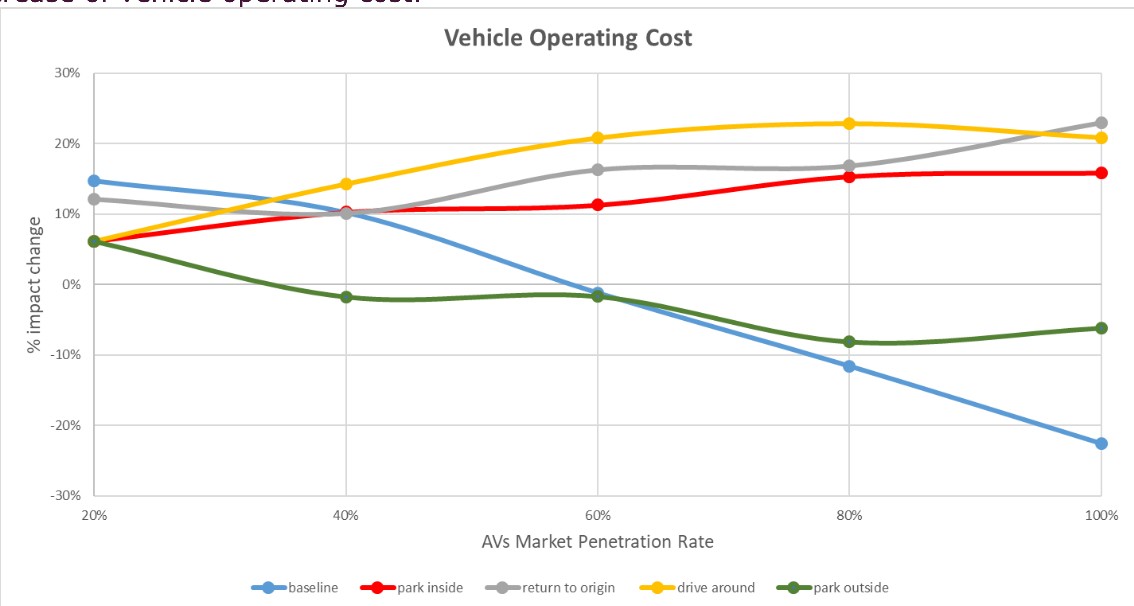


Figure 4.26: 1st round Delphi vehicle operating cost results for CAV parking behavior scenarios

The majority of the 2nd round participants stated that they agree definitely (33%-50%) or moderately (17%-33%) with the resulted trends of the baseline scenario and the scenarios of CAVs parking behaviours. Some experts (50%) suggested that parking inside will not at all affect vehicle operating cost and that parking outside will increase at an average of 10% to 20% the studied impact.

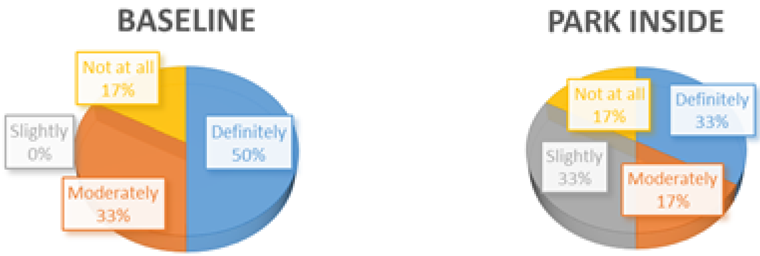


Figure 4.27: 2nd round Delphi vehicle operating cost results for baseline and park inside scenarios

Table 4.14: PST coefficients for vehicle operating cost for CAV parking behavior scenarios

	Baseline		**Park inside**		**Return to origin**		**Drive around**		**Park outside**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	12,9%	1,129	5,0%	1,050	12,6%	1,126	7,0%	1,070	7,5%	1,075
40%	9,0%	1,090	8,4%	1,084	10,8%	1,108	14,6%	1,146	1,1%	1,011
60%	-1,0%	0,990	9,2%	1,092	16,5%	1,165	20,8%	1,208	1,1%	1,011
80%	-10,1%	0,899	12,5%	1,125	17,0%	1,170	22,7%	1,227	-4,1%	0,959
100%	-19,7%	0,803	12,9%	1,129	22,8%	1,228	20,8%	1,208	-2,5%	0,975

4.2.4 Parking space regulations

According to experts, the baseline scenario (no intervention) will lead to an increase (12,8%) of vehicle operating cost for AV market penetration rates up to 100%. Replacing on-street parking with space for public use will not affect more than 5% the studied impact regardless of the different AV market penetration rates. On the other hand, replacing on-street parking with driving lanes or with pick-up/drop-off parking space will both increase vehicle operating cost especially in the long term when AVs market penetration rate reaches 100%, leading to an increase of 13,8% and 10,7% respectively.

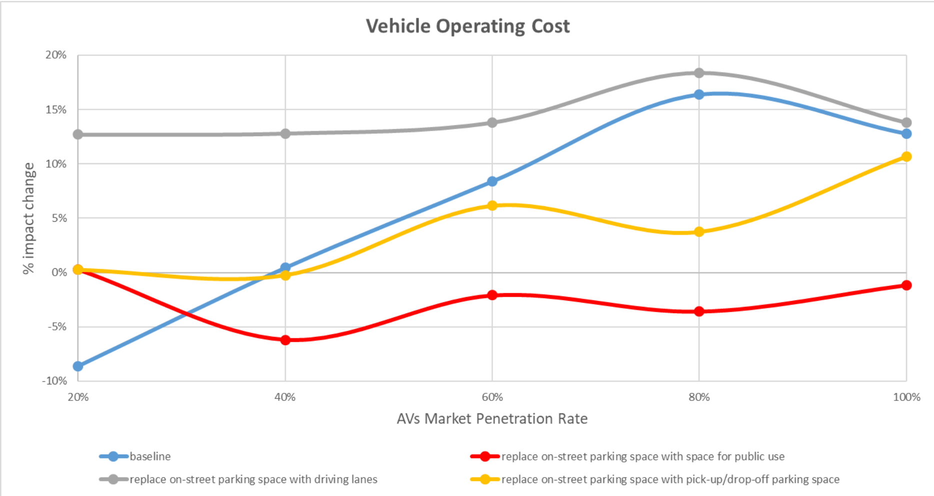


Figure 4.28: 1st round Delphi vehicle operating cost results for parking space regulation scenarios

All of the 2nd round participants stated that they agree definitely (20%-40%) or moderately (60%-80%) with the resulted trends of the baseline scenario and the scenarios of replacing on-street parking with driving lanes and pick-up/drop-off space. Some experts (40%) slightly agreed with the 1st round curve of the replacing on-street parking with space for public use scenario and proposed that this scenario will not at all affect this impact.

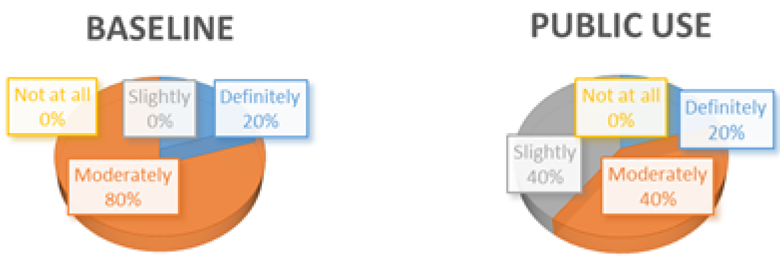


Figure 4.29: 2nd round Delphi vehicle operating cost results for baseline and replacing on-street parking with spaces for public use

The 2nd round results and experts' suggestions were used to define the final PST coefficients.

Table 4.15: PST coefficients for vehicle operating cost for parking space regulation scenarios

	Baseline		**Space for public use**		**Driving lanes**		**Pick-up/drop-off**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	-8,6%	0,914	0,6%	1,006	12,7%	1,127	0,3%	1,003
40%	0,5%	1,005	-5,0%	0,950	12,8%	1,128	-0,3%	0,998
60%	8,4%	1,084	-1,5%	0,985	13,8%	1,138	6,2%	1,062
80%	16,4%	1,164	-2,8%	0,972	18,4%	1,184	3,8%	1,038
100%	12,8%	1,128	-0,7%	0,993	13,8%	1,138	10,7%	1,107

4.2.5 Automated ride sharing

According to experts, the baseline scenario (no intervention) will increase (16.6%) vehicle operating cost in the short term when AVs market penetration rates are lower, but with the increase of AVs MPR, the trend will be reduced (9,2%). The introduction of automated ridesharing will mostly affect vehicle operating cost, leading to a reduction of -20,1% for AV market penetration rates up to 100%.

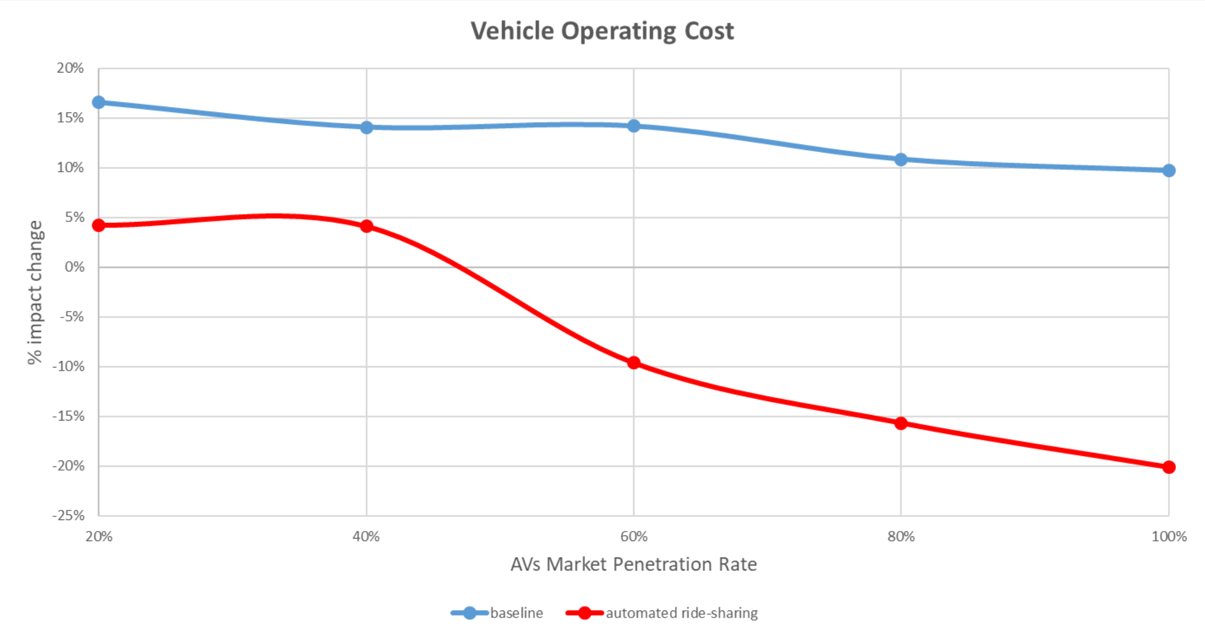


Figure 4.30: 1st round Delphi vehicle operating cost results for the automated ridesharing scenarios

All of the 2nd round participants stated that they definitely (17%) or moderately (83%) agree with the resulted 1st round trends for the automated ridesharing scenarios. The majority (67%) of participants agreed with the baseline scenario curve.

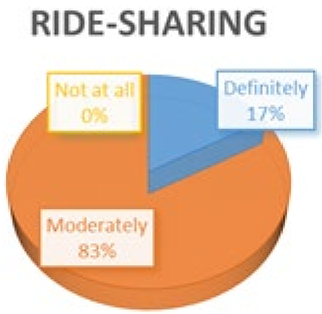


Figure 4.31: 2nd round Delphi vehicle operating cost results for automated ridesharing

The 2nd round results and experts' suggestions were used to define the final PST coefficients.

Table 4.16: PST coefficients for vehicle operating cost for the automated ridesharing and GLOSA scenarios

	Baseline		**Automated ridesharing**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	14,5%	1,145	4,3%	1,043
40%	12,3%	1,123	4,2%	1,042
60%	12,4%	1,124	-9,6%	0,904
80%	9,5%	1,095	-15,7%	0,844
100%	8,5%	1,085	-20,1%	0,799

4.2.6 Green Light Optimal Speed Advisory (GLOSA)

According to experts, the baseline scenario (no intervention) will increase (16.6%) vehicle operating cost in the short term when AVs market penetration rates are lower, but with the increase of AVs MPR, the trend will be reduced (9,2%). GLOSA will not significantly affect the studied impact (-3,5% to 3,8%).

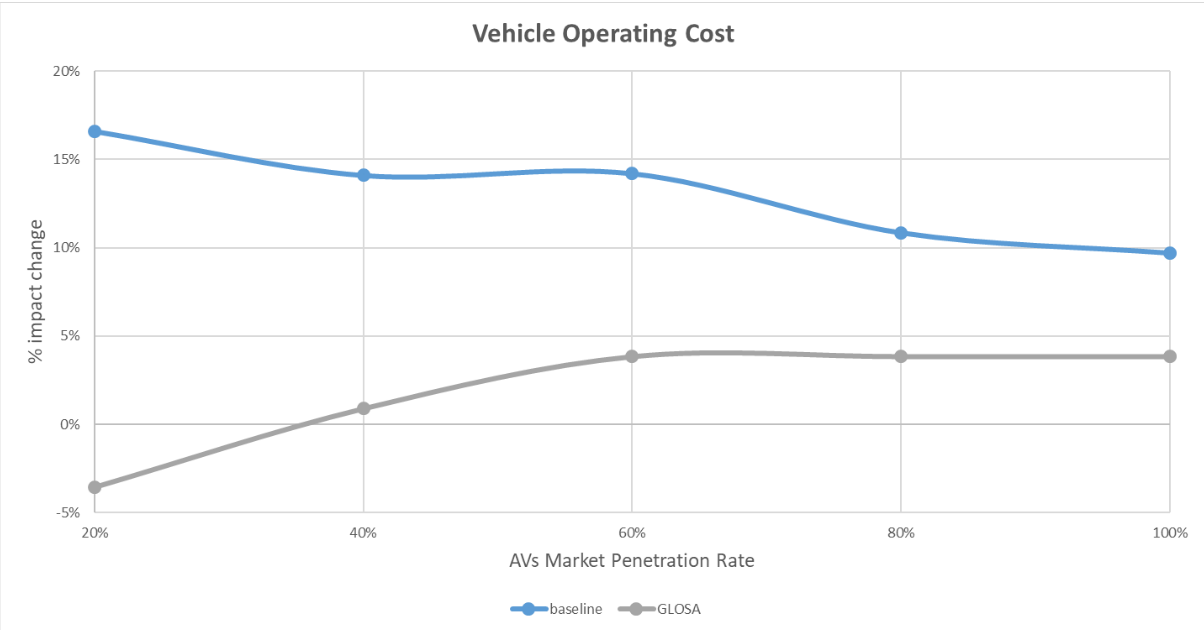


Figure 4.32: 1st round Delphi vehicle operating cost results for GLOSA scenarios

The majority (67%) of participants agreed with the baseline scenario curve. Regarding GLOSA, 50% of participants stated that this scenario will not at all affect the studied impact.

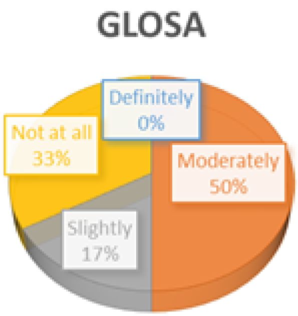


Figure 4.33: 2nd round Delphi vehicle operating cost results for GLOSA

The 2nd round results and experts' suggestions were used to define the final PST coefficients.

Table 4.17: PST coefficients for vehicle operating cost for GLOSA scenarios

	Baseline		GLOSA	
AV penetration rates	**Aggregate change**	**PST coefficients**	**Aggregate change**	**PST coefficients**
20%	14,5%	1,145	-3,2%	0,968
40%	12,3%	1,123	0,4%	1,004
60%	12,4%	1,124	2,8%	1,028
80%	9,5%	1,095	2,8%	1,028
100%	8,5%	1,085	2,8%	1,028

4.3 Access to travel

Within Levitate, the access to travel is defined as the opportunity of taking a trip whenever and wherever wanted (10 points Likert scale). The estimate of the impact of automation with different SUCs on access to travel was made by using the Delphi method.

4.3.1 Road use pricing

The general experts’ opinion was that the introduction of automation in the urban environment will progressively increase access to travel, reaching 26,4% in the long term. Regarding the city toll scenarios, they all reduce access to travel depending on AVs market penetration rate, but all the negative impact is minimized in the long term. All city toll scenarios will reduce the studied impact by -8% in the short term. The scenario of empty km pricing and dynamic city toll will both slightly increase (2,3% and 4,4% respectively) access to travel for 100% AVs market penetration rate. Static city toll will lead to an unsignificant reduction of -1,7% of access to travel.

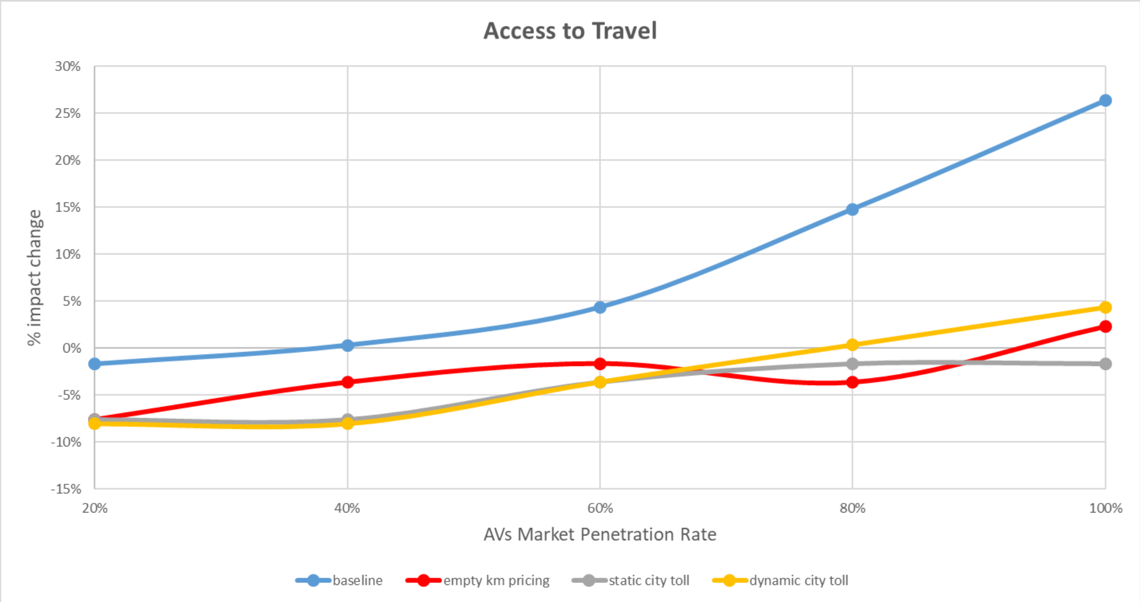


Figure 4.34: 1st round Delphi access to travel results for the city toll scenarios

The majority of the 2nd round participants stated that they definitely (14%-29%) or moderately (29%-72%) agree with the resulted 1st round trends. Some experts slightly (14%-29%) or not at all (0%-14%) agreed with the scenarios curves and suggested that all studied scenarios will have a negative impact of -5% to -10% on access to travel.

Figure 4.35: 2nd round Delphi access to travel results for results empty km pricing and dynamic city toll scenarios

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.18: Final PST coefficients for access to travel for the city toll scenarios

	Baseline		Empty km pricing		Static toll		Dynamic toll	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	-1,8%	0,982	-7,5%	0,925	-7,6%	0,924	-7,9%	0,921
40%	0,0%	1,000	-4,2%	0,958	-7,6%	0,924	-7,9%	0,921
60%	3,5%	1,035	-2,5%	0,975	-4,1%	0,959	-3,7%	0,963
80%	12,8%	1,128	-4,2%	0,958	-2,3%	0,977	0,0%	1,000
100%	23,0%	1,230	0,7%	1,007	-2,3%	0,977	3,8%	1,038

4.3.2 Provision of dedicated lanes on urban highways

The general experts' opinion was that the introduction of automation in the urban environment will progressively increase access to travel, reaching 26,9% in the long term. Regarding the AVs dedicated lanes scenarios, they all presented some oscillations depending on AVs market penetration rate, but all increased access to travel in the long term. The scenario of an AV dedicated lane on the outermost motorway lane and A-road, as well as the dynamically controlled AV dedicated lane will mostly affect the studied impact, among the other AV dedicated lane scenarios, reaching an increase of 14,7% and 16,7% respectively.

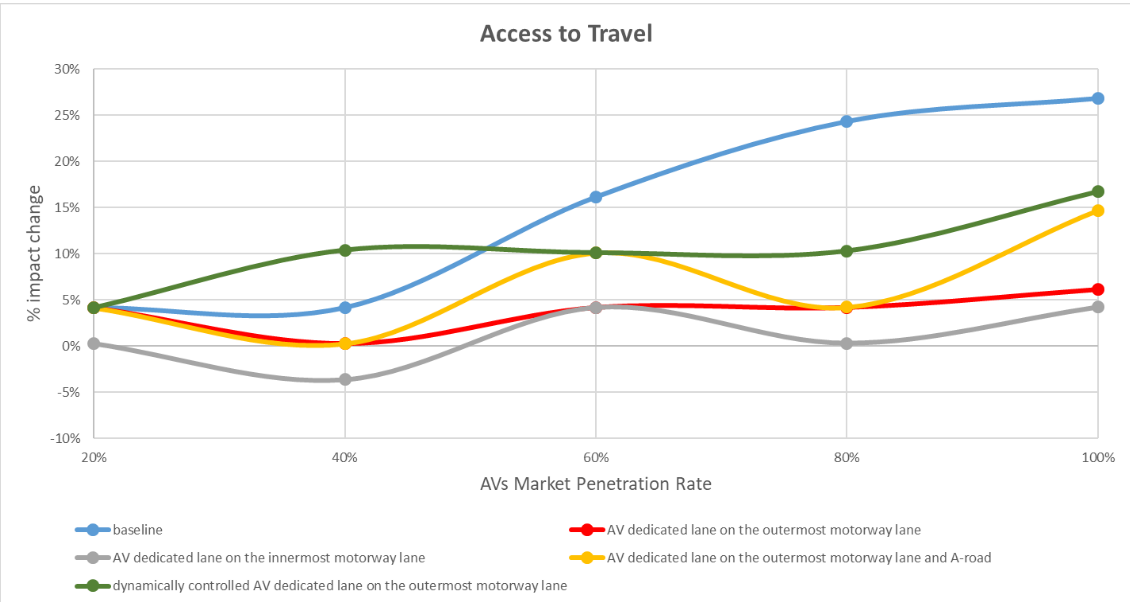


Figure 4.36:1st round Delphi access to travel results for the AV dedicated lanes scenarios

In the second Delphi round all experts stated that they definitely (67%) and moderately (33%) agree with the resulted trend for the baseline scenario. On the other hand, the majority of 2nd round participants stated that the slightly (33%) or not at all (33%) agree with the curves of the AV dedicated lanes scenarios, and they suggested that the curve of all these scenarios should be identical to the baseline scenario and proposed an average increase in access to travel of 15%.

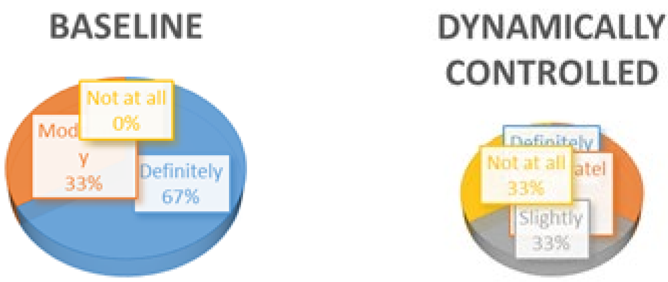


Figure 4.37: 2nd round Delphi access to travel results for baseline and dynamically controlled AV dedicated lane scenarios

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.19: Final PST coefficients for access to travel for the AV dedicated lanes scenarios

	Baseline		**Outermost motorway lane**		**Innermost motorway lane**		**Outermost motorway lane and A-road**		**Dynamically controlled AV dedicated lane**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	4,2%	1,042	5,8%	1,058	4,3%	1,043	7,2%	1,072	7,2%	1,072
40%	4,2%	1,042	2,4%	1,024	1,3%	1,013	4,3%	1,043	11,9%	1,119
60%	16,2%	1,162	5,8%	1,058	7,2%	1,072	11,6%	1,116	11,6%	1,116
80%	24,4%	1,244	5,8%	1,058	4,3%	1,043	7,2%	1,072	11,8%	1,118
100%	26,9%	1,269	7,5%	1,075	7,2%	1,072	15,1%	1,151	16,6%	1,166

4.3.3 Parking price policies

The general experts' opinion was that the introduction of automation in the urban environment will increase access to travel by 54% in the long term. Regarding the CAVs parking behaviors, parking inside, returning to origin and driving around will increase access to travel reaching 34,5%, 31,4% and 29,5% respectively for AVs market penetration rate up to 100%. Finally, according to 1st round results parking outside will affect access to travel the least, leading to an increase of 8,8%.

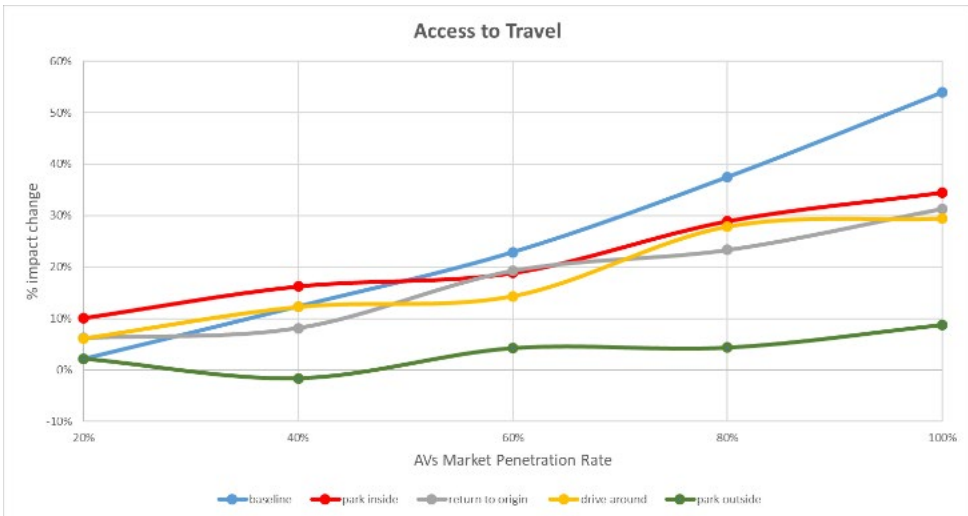


Figure 4.38: 1st round Delphi access to travel results for CAV parking price policies scenarios

In the second Delphi round experts stated that they definitely (33%) and moderately (50%) agree with the curves of the 1st round for the CAVs parking behaviours scenarios. One expert suggested that all scenarios will increase access to travel as proposed in the resulted trends, but with an average of only 5%.

Figure 4.39: 2nd round Delphi access to travel results for results baseline and CAVs driving around scenarios

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.20: Final PST coefficients for access to travel for CAV parking behavior scenarios

	Baseline		**Park inside**		**Return to origin**		**Drive around**		**Park outside**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	2,3%	1,023	9,8%	1,098	6,1%	1,061	6,0%	1,060	2,4%	1,024
40%	11,9%	1,119	15,5%	1,155	8,0%	1,080	11,8%	1,118	-1,2%	0,988
60%	21,8%	1,218	18,0%	1,180	18,4%	1,184	13,8%	1,138	4,3%	1,043
80%	35,5%	1,355	27,4%	1,274	22,2%	1,222	26,5%	1,265	4,4%	1,044
100%	50,9%	1,509	32,6%	1,326	29,7%	1,297	27,9%	1,279	8,6%	1,086

4.3.4 Parking space regulations

The general experts' opinion was that the introduction of automation in the urban environment will reduce access to travel by -14,2%. Additionally, replacing on-street parking space with space for public use will also negatively affect access to travel up to -16%. Regarding the replacement of on-street parking with driving lanes, experts stated that this scenario will increase access to travel reaching 6,8% for AVs market penetration rate up to 100%. Finally, according to 1st round results replacing on-street parking space with pick-up/drop-off parking space will not affect access to travel, regardless of the AV market penetration rate.

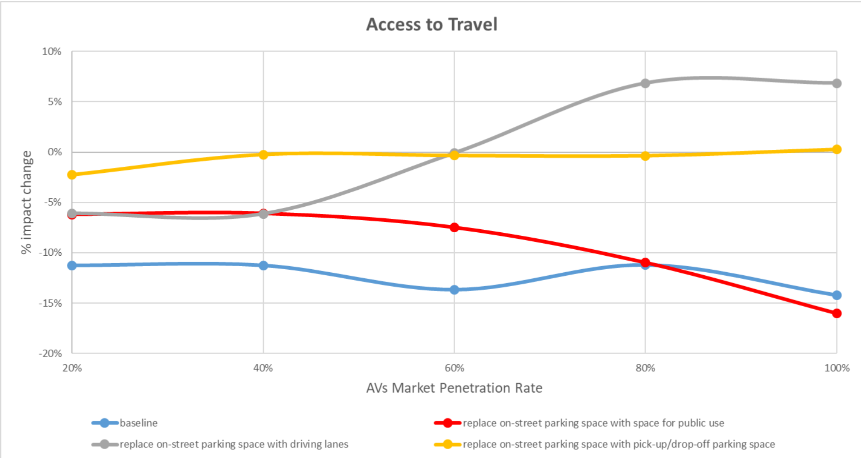


Figure 4.40: 1st round Delphi access to travel results for parking space regulation scenarios

In the second Delphi round experts stated that they definitely (60%) and moderately (40%) agree with the curves of the 1st round for the parking sapce regulations scenarios. One expert suggested that replacing on-street parking space with space for public use will lead to an average reduction of -10% of access to travel, and that replacing on-street parking space with pick-up/drop-off parking space will increase by 10% access to travel. Regarding the baseline scenario 40% of experts stated that they slightly agree with the resulted trend, since according to their suggestions the introduction of AVs will in fact positively affect access to travel leading to an average increase of 5-10%.

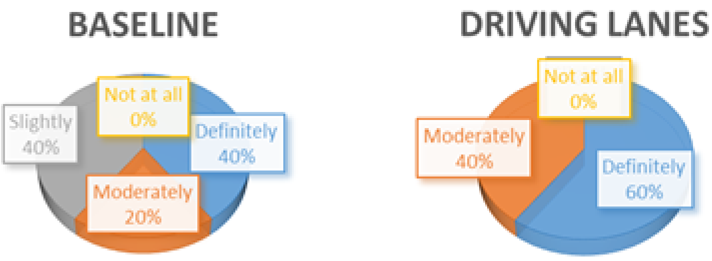


Figure 4.41: 2nd round Delphi access to travel results for baseline and replacing on-street parking space with driving lanes scenarios

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.21: Final PST coefficients for access to travel for parking space regulation scenarios

	Baseline		Space for public use		Driving lanes		Pick-up/drop-off	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	-8,8%	0,913	-6,5%	0,935	-6,1%	0,939	-1,4%	0,986
40%	-8,8%	0,913	-6,4%	0,936	-6,2%	0,939	0,4%	1,004
60%	-10,8%	0,892	-7,7%	0,923	-0,1%	0,999	0,3%	1,003
80%	-8,7%	0,913	-10,9%	0,891	6,9%	1,069	0,3%	1,003
100%	-11,3%	0,887	-15,6%	0,844	6,9%	1,069	0,9%	1,009

4.3.5 Automated ride sharing

The general experts' opinion was that the introduction of AVs and automated ridesharing in the urban environment will progressively increase access to travel, reaching 30% and 42% respectively in the long term.

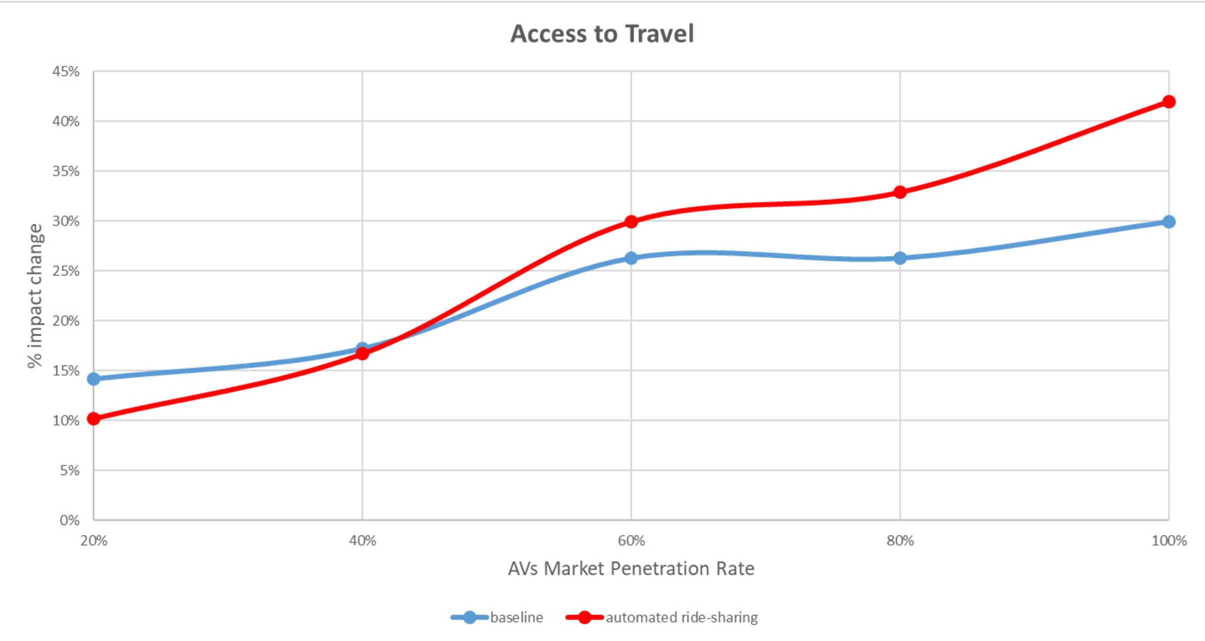


Figure 4.42:1st round Delphi access to travel results for the automated ridesharing scenarios

The 2nd round participants stated that they definitely (50%) or moderately (33%) agree with the resulted 1st round trends for the automated ride sharing scenario. One expert (17%) stated that ridesharing will improve access to travel less than proposed during 1st round, at an average of 20%. According to experts' suggestions the baseline scenario will have an average impact of 5-10% on access to travel.

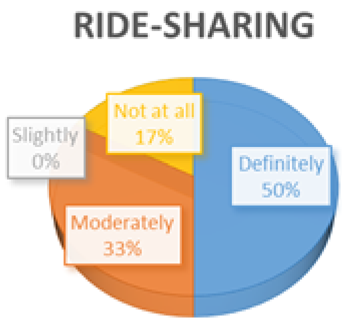


Figure 4.43: 2nd round Delphi access to travel results for automated ridesharing

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.22: Final PST coefficients for access to travel for the automated ridesharing scenarios

	Baseline		Automated ridesharing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	13,1%	1,131	10,8%	1,108
40%	15,6%	1,156	16,9%	1,169
60%	22,9%	1,229	29,3%	1,293
80%	22,9%	1,229	32,1%	1,321
100%	25,9%	1,259	40,6%	1,406

4.3.6 Green Light Optimal Speed Advisory (GLOSA)

The general experts' opinion was that the introduction of AVs in the urban environment will progressively increase access to travel, reaching 30% in the long term. Regarding the GLOSA scenario, experts' answers indicated that there will be a slight improvement (0,3%-4,2%) on access to travel.

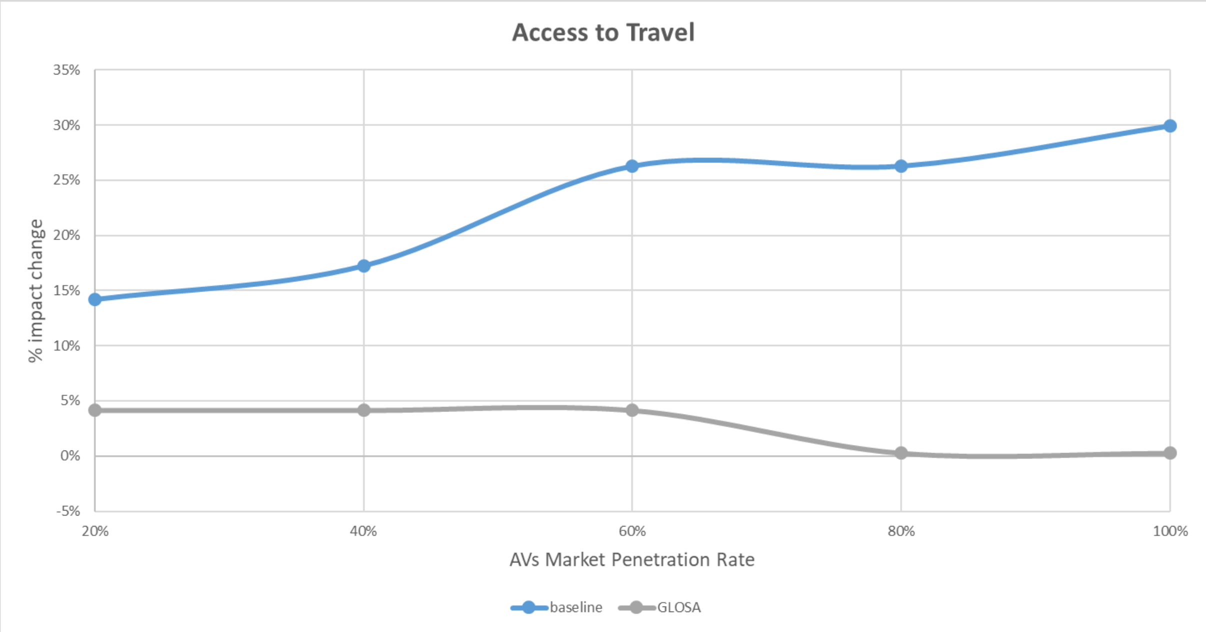


Figure 4.44:1st round Delphi access to travel results for GLOSA scenarios

Regarding GLOSA and the baseline scenario 50% of participants stated that they slightly or not at all agree with the trends. According to experts' suggestions GLOSA will not at all affect the studied impact and the baseline scenario will have an average impact of 5-10% on access to travel.

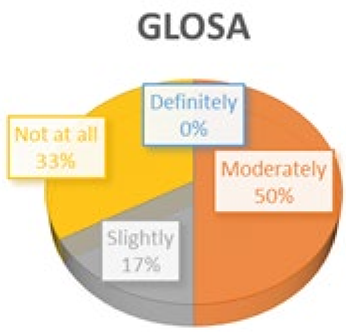


Figure 4.45: 2nd round Delphi access to travel results for GLOSA

The experts' opinion regarding the 1st round results was used to calculate the final coefficients that will be added in the PST.

Table 4.23: Final PST coefficients foe access to travel for GLOSA scenarios

AV penetration rates	Baseline		GLOSA	
	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	13,1%	1,131	3,4%	1,034
40%	15,6%	1,156	3,4%	1,034
60%	22,9%	1,229	3,4%	1,034
80%	22,9%	1,229	0,2%	1,002
100%	25,9%	1,259	0,2%	1,002

5 Discussion

The key policy interventions (sub-use cases) for introduction of connected and automated vehicles, identified through previous literature and by the stakeholders' reference group, were tested for passenger transport to analyse their short-term/direct impacts, including travel time, operating cost, and access to travel. Since no real-world data is available, CAVs behaviours were modelled according to the available knowledge found through existing literature and experimental studies' findings on early automated systems. The analysis performed with various policy interventions using different methods provided several insightful findings on the short-term impacts, which are discussed impact wise, as follows.

Travel Time

Regarding road use pricing SUC, mesoscopic simulation results for almost all assumed scenarios show a consistent albeit minor decrease of average travel times within the inner-city domain when vehicle automation becomes more widely available. This reflects the slight improvements of traffic fluidity that automated vehicles bring about. The exception is the case of expensive, dynamic tolling of the inner-city area. Here, almost no car traffic is affordable anymore within the region and no benefits in travel time can be gained by a more fluid car traffic, consequently. On the initial introduction of tolling fees at a tangible price, a bigger change of +2 % in average travel time within the tolling area can be identified. Raising those tolling fees to prohibitive prices (to the maximum of 100 €) leads to a total of +5 % in average travel time within the tolling area. Such behaviour is understood as the rising avoidance of pricey car trips directly to or from the destinations and the necessary shift to e.g., public transport or walking. Modes, which are either less direct or slower and hence mean higher, but still preferable costs in travel time. Measures implemented as static road use pricing show more consistent model behaviour with respect to the average travel time, i.e., simple tolling rules appear more predictable. The dynamic road use pricing implementation on the other hand allows room for effects in traffic flow and mode choice interactions that exhibit higher complexity and thus are harder to predict. Most of the Delphi study participants also indicated that city toll policies, in general, would decrease in travel time. In particular, they suggested the empty km pricing toll intervention to be more effective than static and dynamic city toll, leading to 18% saving in travel time in the long term. Static and dynamic city tolls were predicted to reduce travel time potentially up to nearly 7% and 13.5%, respectively.

The microsimulation method was used for testing the other sub-use cases within this deliverable. Baseline scenario (introduction of CAVs) results on travel time using microsimulation method indicated, on average, decrease in travel time becoming more consistent at higher MPRs. However, some irregularities in the trend were observed from low to moderate MPR of CAVs tested on various study networks used in the project. This can primarily be attributed to the assumption used to model 1st and 2nd Generation CAVs. In particular, irregularities were found under mixed fleet scenarios with low MPR of 1st or 2nd Gen CAVs, potentially due to variations in the interactions between conventional vehicles and CAVs. In this regard, mixed opinions were found from a variety of experts where some indicated a progressive reduction in travel time with increasing MPR of AVs while others predicted small or no significant reduction in the long term (at high MPRs).

The impact of providing a dedicated lane for CAVs was tested on a major highway (A6) and motorway (M602) in a calibrated and validated model of a sub-urban area in Manchester. With one CAV dedicated lane, the results indicated the most optimal performance under a moderate fleet penetration scenario (60-40-0). Traffic performance was found to be negatively impacted under low and high MPR scenarios under a single dedicated lane for CAVs. Regarding placement strategies, the results indicated that left-most lane placement gives better network performance as compared with right-most lane. Maximum travel time saving was found to be 10% under A road left-most lane case with moderate MPR (60-40-0). Experts' opinions through the Delphi study also indicated the innermost placement of dedicated lanes to be the most effective in terms of travel time savings.

Several strategies were tested in terms of parking policies, generating different parking behaviours including balanced, drive around, and heavy return to origin and park outside. Overall, an increase in travel time was found due to the tested parking policies and the resulting behaviours as compared to the no policy intervention scenario. This is because vehicles are never parked under driving-around scenario, thus increasing the traffic volume on the road and, consequently, travel time. Whereas under the case of heavy return to origin and park outside, a higher number of vehicles will circulate the network to reach the parking location, leading to increased traffic flow and negatively impacting travel time, The balanced parking behaviours relatively generated lesser travel times as compared to drive around and heavy return to origin and park outside. On average, a maximum increase in travel time, as compared to baseline scenario, was observed under 'drive around' behaviours, reaching up to 31%. The results of Delphi also suggested similar trends. Experts' opinions indicated a decrease in travel time with the increased MPR in baseline scenario. However, the CAVs parking behaviour was indicated to negatively affect the travel time. The travel time was indicated to either remains almost constant or increases with the parking price policies. The 1st round results suggested that travel time will increase in all parking price policies interventions except for parking outside, where experts predicted that travel time will remain constant regardless of the AV MPR. The 2nd round results disagreed with the trends proposed for policies involving parking inside and parking outside behaviours. They suggested that the first policy intervention will reduce the travel time since all vehicles will park inside the city centre, which is in line with the microsimulation results for the no policy intervention scenario (100% vehicles park inside). The intervention with parking outside behaviours is believed to have an increasing impact on travel due to extra empty trips required to reach the parking space, which is also consistent with the findings of heavy return to origin and park outside scenario from microsimulation.

With regard to parking space regulations with the introduction of CAVs, different strategies for replacing on-street parking were tested in this project. In general, replacing on-street parking with driving lane, cycle lane, and public spaces showed a better performance than removing half of the on-street parking spaces and replacing them with pick-up/drop-off points. It was found that between 27% to 30% reduction in travel time can be achieved. The results indicated that replacing on-street parking with pick-up/drop-off areas can potentially generate queue in the traffic stream while vehicles pick-up and drop-off passengers, and eventually can build up congestion in the network. Dynamic pick-up/drop-off points could be introduced in the network to mitigate this impact as an improvement measure. The results also suggest that replacing half of the on-street parking spaces may not provide the expected improvement to the traffic conditions in the city centre, especially with a congested network. In general, Delphi study results indicated that introduction of AVs would lead to small reduction in travel time in the long term up to -7%. With regard to impact on travel time with different parking space regulation strategies, experts' opinion was wound to be somewhat different. Their response showed small reduction in travel time, as compared to baseline, under replacement of on-street parking with driving lanes and even that only under higher MPRs. In case of replacement with pick-up/drop-off areas and spaces for public use, the experts indicated an increase in travel time compared to the baseline where larger increase was predicted in case of the later one. However, in the 2nd round of Delphi study (fewer experts), the findings indicated that replacing on-street parking with public use, driving lanes, pick-up/drop-off locations will not affect travel time. The introduction of an automated ridesharing service is expected to trigger an increase in travel time as compared to no-policy intervention (baseline) scenario. This increase can be attributed to the traffic congestion caused by the empty pick-up trips and circulation within the network using low capacity and secondary roads. The results were found to be consistent with previously reported findings by Overtoom et al. (2020). The negative impact on travel time is also dependant on how travellers choose to use such a service i.e., either as a ridesharing service or as a car-sharing service for individual trips. The preferences for individual and shared trips were studied using different rates of willingness to share (20%, 50%, 80%, and 100%). Travel time was found to reduce with increased willingness to share the ride, especially under higher MPR of CAVs. The results from Delphi study; however, showed a different perspective of experts which could very likely be due to their interpretation of the question and assumption on willingness to share the ride. In the first round of Delphi, experts suggested that the introduction of automated ridesharing service will generally reduce travel time up to 25% at full MPR. Most of the experts in the second round (67%) showed agreement (either moderate or definite) with the first-round results, while the rest argued that this new service would not significantly impact travel time (+5% in short term and -10% in the long term).

Implementation of the GLOSA system with fixed time signal controllers revealed travel time savings compared with the baseline scenario (without GLOSA). The implementation was tested on one vs. two vs. three intersections on the study corridor. Maximum benefits were found under the system application o on all 3 intersections. Delphi results on GLOSA indicated no significant effect on travel time in the short term. Following experts' opinion, travel time can be reduced to 4.6% at 100% AVs market penetration rate.

Vehicle Operating Cost

The potential impact of AVs on vehicle operating costs were estimated using the Delphi method. According to Delphi results, experts suggested that the introduction of AVs will increase vehicle operating costs in the short term that will be reduced with increasing AV market penetration rate. Fully automated vehicles are generally believed to have lower operating costs than conventional vehicles due to their ability in reduce energy consumption, maintenance costs, parking fees, etc. (Wadud, 2017). However, it is expected that during the early stage of deployment, owning and maintaining an AV would be more expensive than conventional vehicles due to the cost of technology underlying AVs, which would decrease with further development and mass production (Wadud, 2017).

Regarding road use pricing, experts suggest that static and dynamic city toll scenarios will introduce an increase in vehicle operating costs that will be reduced with increasing AV MPR. In terms of empty km pricing scenario, the results indicated that this scenario will have a slight effect on operating costs reaching a maximal reduction value of 3,8% in the long term.

According to the experts, the introduction of AV dedicated lanes will reduce vehicle operating cost regardless of the configuration for providing AV dedicated lane.

Regarding parking price policies, the Delphi results indicated that the pricing policy requiring CAVs to park outside the city centre will have positive impact on vehicle operating cost. Policies that encourage CAVs to park inside the city centre, return to origin to park, and drive around until pick-up will increase vehicle operating cost by almost 16%, 23%, and 21%, respectively at full MPR. In the 2nd round results, 50% of experts estimated that parking inside city centre will not affect vehicle operating while parking outside will increase at an average of +10% to +20%.

The impact of parking space regulation may differ based on the introduced policy measure. The responses from experts in the 1st round indicated that replacing on-street parking spaces with driving lanes and pick-up/drop-off spaces will increase vehicle operating costs by almost 14% and 11% respectively at full MPR.

In general, experts' opinion indicated that the introduction of an automated ridesharing service will reduce vehicle operating cost up to 21% at full MPR.

The Delphi results indicated that GLOSA system will not have a significant impact on vehicle operating cost. Experts in the first round predicted a slight decrease of 3,5% at low MPR and an increase of 3.8% at full MPR, while 2nd round results suggest that GLOSA will not at all affect the vehicle operating cost.

Access to Travel

Impacts on access to travel were estimated through the Delphi study. Overall, the experts' opinion indicated an increase in access to travel with increasing AVs in the transport system. However, various policy interventions can positively or negatively impact access to travel in the long term. For instance, an insignificant decrease is predicted under static tolling, while empty km tolling and dynamic city tolling can potentially lead to a slight increase at full MPR. All dedicated scenarios, including motorway innermost and outermost lane placement, outermost lane on motorway and A road and dynamically controlled AV dedicated lane, can have some irregularities in the short to medium term. However, in the long term, they are expected to increase access to travel. Parking price policies are predicted to increase access to travel in the long term. Policies involving parking inside the city centre, returning to origin, and driving around, and parking outside were estimated to increase access to travel at full MPR of CAVs by almost 35%, 31%, 30%, and 9%, respectively. With on-street parking space regulation strategies, experts envisaged an increase in access to travel if on-street parking lanes are replaced with driving lanes. However, it was predicted to be negatively affected if on-street parking is replaced with public spaces, whereas no impact is indicated in case of replacement with and pick-up/drop-off areas. The experts indicated marginal to almost no change in access to travel with the implementation of GLOSA. As can be expected, the most significant impact on access to travel can be caused by automated ride-sharing services where a maximum value of 42% is predicted.

6 Conclusions

Following the discussions on results in the previous section, some of the conclusions related to short term impacts of CAVs on passenger transport that can be drawn from the tested policy interventions are as follows:

- Presupposing the currently dominant city structure gives car traffic a rather direct access to most locations within a city. This considerably reduces the share of the first and last stages of walking. Changing the very direct access of cars to most locations within the inner city by means of RUP implementation results in longer walking stages, which becomes apparent via slight increases of average travel times within the tolling area.
- The benefits from Road Use Pricing policy may be slower but will potentially lead to sustainable benefits. Tolling policy with increasing automated vehicles can have positive impacts on travel time; however, increasing automation alone without any road use pricing policy was found to cause no significant improvement.
- The benefits of an automated ridesharing service increased with a greater willingness to share
- Parking space management through replacing with driving lanes can considerably reduce travel time; however, this may also encourage increased number of vehicles on the road. Replacement with cycle lane and public space can also provide travel time savings and can have added societal benefits due to encouraging active travel
- Increasing the price of parking can have an adverse impact if the right policy measures are not adopted/implemented. The advantage of CAVs start decreasing as we change parking criteria. The travel time could increase from 0 to 31% with different parking strategies.
- Travel time saving benefits can be maximised through the implementation of GLOSA systems on multiple intersections (or at corridor level) controlled by fixed time controllers.
- Vehicle operating costs are expected to increase in short-term with introduction of automated vehicles but reduce with higher MPR. Automated ride sharing services can potentially have a significant impact in reducing vehicle operating costs.
- Most significant impact on access to travel can be expected with the introduction of automated ride sharing services. Whereas policies related to parking price are also predicted to have a strong impact on access to travel. Replacement of on-street parking with driving lanes would likely cause increase in access to travel as well.

The project has focused on CCAM services and technologies which make use of automated vehicles in order to inform the policy goals of cities and national administrations. Overall, the findings highlight the importance of the transition phase to full fleet penetration and the cities have to prepare to manage potentially adverse impacts. First generation CAVs are anticipated to be less capable than human drivers, this adversely affects many traffic indicators. Cities cannot control the introduction of automation and connectivity, but they can manage the consequences. The findings also indicated that increasing MPR of CAVs alone, may by itself does not have positive impacts and appropriate policy interventions are necessary for optimizing the traffic performance with the introduction of CAVs in transport systems. The forecasting methods developed to test the policy interventions (sub-use cases) can be applied to other interventions and to large scale trials of vehicles.

Future Work

Future efforts include testing and analysing these impacts on different study areas to identify the variations and transferability of the findings. Additionally, it is proposed to investigate the combined effect under implementation of different policy interventions.

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