The medium-term impacts of cooperative, connected, and automated mobility on urban transport

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Legal Disclaimer

List of abbreviations

AUSS	Automated Urban Shuttle Service
ADAS	Advanced Driver Assistance Systems
AEB	Autonomous Emergency Braking
AV	Automated Vehicle
CACC	Cooperative Adaptive Cruise Control
CAFE	Corporate Average Fuel Economy
CCAM	Cooperative, Connected and Automated Mobility
C-ITS	Cooperative Intelligent Transport Systems
CV	Connected Vehicle
DisA	Distraction Alert
DrowA	Drowsiness Alert
ERTRAC	European Road Transport Research Advisory Council
EU	European Union
FCW	Forward Collision Warning
FHWA	Federal Highway Administration
FORS	Fleet Operation Recognition Scheme
GDPR	General Data Protection Regulation
IMA	Intersection Movement Assist
ISA	Intelligent Speed Assist
IVS	In-vehicle Signage
LCA	Lane Change Assist
LDW	Lane Departure Warning
LKA	Lane Keeping Assist
MPR	Market Penetration Rate
mUoM	marginal Utility of Money
NHTSA	National Highway Traffic Safety Administration
NRC	National Research Council
PST	Policy Support Tool
SAE	Society of Automotive Engineers
SRG	Stakeholder Reference Group
SUC	Sub-Use Case
TA	Turn Assist
TTC	Time to Collision
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to everything
VKT	Vehicle Kilometers Travelled

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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 mobility, maximize the benefits and utilize 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). These systems include impacts on safety, environment, economy and society.

This report specifically focuses on urban transport, providing an analysis for the medium-term impacts of different urban transport sub-use cases. The impacts to be studied have been defined in the Deliverable 3.1 (Elvik et al., 2019), which provided a preliminary taxonomy of the potential impacts of CCAM. The medium-term impacts of CCAM developed in the present report are those described as systemic impacts; namely changes that influence the wider transport system. More precisely, the amount of travel, congestion, modal split using public transport and active travel, shared mobility rate, vehicle utilization rate and vehicle occupancy are considered. After an extensive literature review and a Stakeholder Reference Group (SRG) workshop, a preliminary list of the urban transport sub-use cases was developed, presented in the Deliverable 5.1 (Roussou et al., 2019). The proposed automated urban transport sub-use cases have been prioritized for their consideration in further investigation. During prioritizing, factors such as widespread studies being followed on those sub-use cases and the feasibility of impact assessment have been considered. The resulting sub-use cases that are presented in this report, are (i) the point-to-point automated urban shuttle service and (ii) the on-demand automated urban shuttle service that includes the anywhere to anywhere, last-mile and e-hailing services.

The next step of the impact assessment was to identify the appropriate methods to be used for each impact. The medium-term impacts presented in this report were quantified using the mesoscopic simulation, the microscopic simulation and the Delphi method. The mesoscopic simulation framework MATSim, is an agent-based modelling (ABM) framework, allowing the simulation of mobile agents that strive to fulfil their daily plans of activities (the "activity chain") and the trips in between their locations. This method was used to quantify the short-term impacts (Deliverable 5.2 – Roussou et al., 2021) as well as the medium-term impacts of CCAM. The microscopic simulation is used to quanitfy the impacts of the adoption of CCAM on traffic, including traffic volume and traffic emissions to the environment under several traffic simulation scenarios and to evaluate the influence of difference traffic volume levels the presence of automation features both on a microscopic and a macroscopic level. The Delphi method is a process used to arrive at a collective, aggregate group opinion or decision by surveying a panel of experts. Within LEVITATE, the Delphi method was used to determine all impacts that cannot be defined by the other quantitative methods. Regarding the medium-term CCAM impacts, this method was used to identify the changes on modal split, shared mobility rate, vehicle utilization rate and vehicle occupancy.

The overall results of the impact assessment demonstrated that the introduction of CCAM in the urban transport will reduce congestion and the amount of travel, especially for high CAV market penetration rates since more people will use the urban transport services thus reducing traffic. Modal split using public transport is expected to slightly increase since the automated urban shuttle services will connect various public transport stations with suburban areas or lower-density areas. On the other hand, active travel may be negatively affected due to the more transport possibilities that will be available. The shared mobility rate, vehicle utilization rate and vehicle occupancy will significantly increase after the implementation of the on demand AUSS since more people will be able to travel using urban transport even if they do not possess a private vehicle. The results regarding the medium-term/systemic impacts of CCAM will be included in the final LEVITATE product which is the LEVITATE Policy Support Tool (PST).

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 Cooperative, Connected and Automated Mobility (CCAM), maximise the benefits and utilise the technologies to achieve societal objectives.

Specifically LEVITATE has four key objectives:

- 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.
- 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.
- 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.
- To incorporate the methods within a **new web-based policy support tool** to enable city and other authorities to forecast impacts of CCAM on urban areas. The methods developed within LEVITATE will be available within a tool box 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 5 and Deliverable 5.3 within LEVITATE

WP5 focuses on the impacts that the deployment of cooperative, connected and automated vehicles are expected to have on urban transport operations, through advanced city shuttles and other micro-transit vehicles. Forecasting of impacts will consider three main components: (i) Mode of transport: public transport, motorised individual transport, active mobility and automated urban shuttle services (AUSS); (ii) Actors: drivers / operators, passengers, transit companies / authorities, cities authorities; (iii) The SAE automation levels: urban shuttle modes are directly considered at SAE 4. Forecasting will be based on the methodology developed in WP3 (Deliverable 3.1, 2019) and the scenarios developed in WP4 to identify and test specific scenarios regarding the impacts of CCAM on urban transport. More specifically, the objectives of Work Package 5 (WP5) are:

- To identify how each area of impact (safety, mobility, environment, economy, and society) will be affected by Cooperative, Connected and Automated Mobility (CCAM) in urban transport operations, 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 CCAM for urban transport.
- To test interactions of the examined impacts in urban transport scenarios and
- To prioritise considerations for a public policy support tool to help authority decisions.

The purpose of Deliverable 5.3 is to present the medium-term impacts of a range of mobility policies and interventions against the background of increasing CAV deployment in the vehicle fleet. The impacts to be studied have been defined in the Deliverable 3.1 (Elvik et al., 2019), which provided a preliminary taxonomy of the potential impacts of CCAM. The medium-term impacts of CCAM developed in the present report are those described as systemic impacts; changes that influence the wider transport system and more precisely, the amount of travel, congestion, modal split using public transport and active travel, shared mobility rate, vehicle occupancy and vehicle utilisation rate. The main methodological approaches to forecast the medium-term impacts are mesoscopic simulation, microscopic simulation and the Delphi method. In the following table all the impacts studied within the LEVITATE project are presented with the method used to quantify them.

Table 1.1: Overview of the impacts in WP5. Highlighted are the medium-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/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		
Amount of travel	*Person kilometres of travel per year in an area*	*Mesoscopic simulation/Microscopic simulation*
Congestion	*Average delays to traffic (seconds per vehicle-kilometer) as a result of high traffic volume*	*Microscopic simulation*
Modal split using public transport	*% of trip distance made using public transportation*	*Mesoscopic simulation/Delphi*
Modal split using active travel	*% of trip distance made using active transportation (walking, cycling)*	*Mesoscopic simulation/Delphi*
Shared mobility rate	*% of trips made sharing a vehicle with others*	*Mesoscopic simulation/Delphi*
Vehicle utilisation rate	*% of time a vehicle is in motion (not parked)*	*Mesoscopic simulation/Delphi*
Vehicle occupancy	*average % of seats in use*	*Mesoscopic simulation/Delphi*
Long term impacts / wider impacts		
Road safety	*Number of traffic conflicts per vehicle-kilometer 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-kilometer (due to road transport only)*	*Microscopic simulation*
CO_2 due to vehicles	*Concentration of CO_2 pollutantsas grams per vehicle-kilometer (due to road transport only)*	*Microscopic simulation*
PM_{10} due to vehicles	*Concentration of PM_{10} pollutantsas grams per vehicle-kilometer (due to road transport only)*	*Microscopic simulation*

Public health	*Subjective rating of public health state, related to transport (10 points Likert scale)*	*Delphi*
Accessibility of transport	*The degree to which transport services are used by socially disadvantaged and vulnerable groups including people with disabilities (10 points Likert scale)*	*Delphi*

2 Sub-use cases

Sub-use case in this deliverable refers to subcategory (interventions) under automated urban shuttle services (AUSS) use-cases developed to study the quantifiable impacts of CCAM within urban transport. A stakeholder reference group workshop (presented in detail in D5.1 - Roussou et al, 2019) was conducted to gather views on future of CCAM and possible use cases of urban transport, termed sub-use cases, from city administrators and industry. A list of sub-use cases of interest for urban transport from the perspective of CCAM has been developed. Within LEVITATE, this list has been prioritized and refined within subsequent tasks in the project to inform the interventions and scenarios related to urban transport. In turn, these sub-use cases 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/studies: They indicate 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: They indicate the relevance of sub-use cases from the industrial/ political point of view, independent of available scientific methodologies.
- SRG Workshop: They contain first hand feedback for the sub-use cases, but might only reflect the opinions of organisations and people who participated.

The automated urban transport related sub-use cases that were formulated after this procedure are the following:

- **Point-to-point automated urban shuttle service** (AUSS): Automated urban shuttles travelling between fixed stations, complementing existing urban transport.
    - **Point-to-point AUSS connecting two modes of transport**
    - **Point-to-point AUSS in a large-scale network**
- **On-demand automated urban shuttle service**, including:
    - **Anywhere-to-anywhere AUSS**: Automated urban shuttles travelling between not fixed locations.
    - **Last-mile AUSS**: Automated urban shuttles providing convenient first/last mile solutions, complementing public transport.
    - **E-hailing**: on-demand last-mile AV shuttles.

2.1 Point-to-point automated urban shuttle service

The point-to-point AUSS, operate on fixed stations in a defined area in the city. The minibuses use dedicated lanes on the network which connect the AUSS stops. The importance of this service was highlighted by the stakeholders during the SRG workshop, as this will be the first CCAM service to be introduced in the cities, in a smaller or larger scale depending on the cities goals. This SUC was divided in two separate SUCs for the impact assessment using microscopic simulation. These SUCs are the point-to-point AUSS connecting two modes of transport and the point-to-point AUSS in a large-scale network. The point-to-point AUSS connecting two modes of transport, concerns a service that connected the metro station "Eleonas" with the Athens intercity bus hub. This small-scale service was studied in order to design the system and verify the selected parameters before assessing the impacts of the introduction of this SUC in a city level. The point-to-point AUSS in a large-scale network was designed as an automated shuttle service operating in parallel with the existing transit service, connecting various destinations and areas with low transit coverage. Since the microsimulation provides a high number of precise impacts, it was decided to retain this division for all methods.

Concerning the road sector, automation will not only refer to private passenger cars, but also to public transportation. One of the modes that will be influenced by automation technologies and their various functions are the shuttle buses where driverless minibuses will transfer passengers from one point to another. Shuttle services widely exist worldwide serving transfer and connection purposes for medium and short distances. Automated shuttles and more specifically those that are electrically powered, are expected to reduce operational costs while increasing ridership (Popham, 2018), as well as costs related to fuel consumption and driver employment (Zhang et al., 2019).

There are many projects concerning the use of automated shuttles for transit purposes, such as Park Shuttle I and II for transferring people from a car park to the airport of Amsterdam and within Rivium Business Park in Rotterdam respectively (Pruis, 2000; Prokos, 1998; Bootsma & Koolen; 2001, Ritter, 2017). Both projects revealed the efficiency of automated shuttles as well as their attractiveness as a large number of people are using them on daily basis. The same results were achieved by the use of small automated vehicles for connecting Heathrow Airport in London with the business car park within the CityMobil European Project (City Mobil European Project). Automated shuttles exist also in Las Vegas, USA (Parent & Bleijs, 2001).

Real-time experiments and simulation tests or surveys have been conducted worldwide in order to reveal and assess the impacts of automated shuttle bus on traffic conditions, safety and environment in order to make them more attractive to passengers. The issue of scheduling automated shuttle buses was investigated by Cao & Ceder (2019) who applied the deficit function for skip-stop and departure time optimization based on real-time passenger demand, showing a reduction in total passenger travel time and in the number of vehicles. Low-speed automated vehicle and shuttles have been analyzed in terms of their behavior in crowded areas and their interaction with vulnerable road users by applying the collision avoidance algorithm (Wang et al. 2018, Ararat & Aksun-Guvenc, 2018, Emirler et al., 2016), based on real-world conditions or simulation studies.

2.2 On-demand automated urban shuttle service

In contrast to the point-to-point AUSS, on-demand AUSS is designed more flexibly. The points for pick up and drop off passengers are not predefined but can take place at any location in the operation area. There are also no dedicated lanes reserved for AUSS but the vehicles are instead using the common network structure for cars. The vehicles of the on-demand AUSS are automated shuttle buses of 8 and 15 people capacity.

Public transportation was estimated to potentially benefit from the deployment of AV technology as it can be more cost effective and customizable than human-operated bus service to fill service gaps, reduce road congestion and improve road safety (Nesheli et al., 2021). A relevant problem that arises for transport planners is the first/last mile problem. The first/last mile problem refers to the beginning/end segment of an individual’s transit trip and the challenge comes from the fact that public transport is typically unable to take people directly from their homes to their destinations. It is well established that this gap in the public transport network is a major reason why many people prefer the convenience of private cars over taking public transport. The automation of street transit can also potentially reduce operating costs by eliminating the need for human drivers while simultaneously improving the experience of passengers by providing flexible and demand responsive services that connect users to high frequency transit services.

Automation can also facilitate a transition to Mobility as a Service (MaaS) that could limit the negative effects of road transport, such as congestion, air and noise pollution, fuel overconsumption and safety risks (European Commission, 2017), as long as it promotes car sharing, ride sharing or sourcing and not private mobility solutions. According to Firnkorn & Müller, (2015), automation could attract more people to car sharing for the first or last mile of their trip instead of walking, cycling or using a private car. Automated taxis or car sharing could be considered as part of the public transport as with suitable business models they can promote sustainability, reducing the number of private cars and accordingly, the congestion. Fewer vehicles that operate more efficiently would reduce car traffic and advance public transport (Pakusch & Bossauer, 2017).

The experiences with early pilot projects have greatly impacted the advancement of on-demand automated urban shuttle service. Small automated cars for people or good transfer were designed within the framework of CyberCars (www.2getthere.eu) and CyberCars2 (ttp://www.cvisproject.org/en/links/cybercars-2.htm) projects offering door-to door and on demand services. The development and on-road testing of co-operative Cybernetic Transport Systems, within these projects, demonstrated that CAVs will improve road safety, traffic efficiency and fuel consumption (CyberCars2, 2009). Within the framework of the Railcab project, an automated shuttle system was developed based on on-demand scheduling providing both passenger and goods transfer, and suggested that safety is ensured in all operating modes (Diethelm et al., 2005; Giese & Klein, 2005; Khendek & Zhang, 2005). The automated on-demand services in public transportation has also been investigated by Vernier et al. (2016), Chong et al., (2013) and Salazar et al. (2018). In addition, Gelbal et al. (2017) proposed an architecture for automated driving using passenger cars and an automated electric shuttle.

In Europe there already exist particular solutions involving high automation with low velocity vehicles and specific infrastructure. A study by OECD (2016) study has further explored the potential of all car trips replacement with shared or on-demand vehicles. According to the ERTRAC Connected Automated Driving Roadmap (2019), there are two development paths that relate to high levels of automation in the urban environment: The first is the Personal Rapid Transit (PRT) including urban shuttles and the second are city-buses and coaches. PRT involves smaller vehicles mostly utilised for the transportation of people, e.g. for first and last mile use or even longer distances. They can operate both in a collective or individual mode on restricted, specific or open roads. Automated PRT or shuttles that will operate on dedicated infrastructure and on designated lanes could be enriched by other automated functions to improve traffic flow and safety, possibly regulating other vehicles as well. These services could be incorporated into public transport.

Within the LEVITATE project on-demand AUSS includes three different services: (i) the anywhere-to-anywhere AUSS, (ii) last-mile AUSS and (iii) e-hailing. These three SUCs where prioritized by the stakeholders during the SRG workshop as the most important after the point-to-point AUSS. The actual implementation of the services is very similar while the usage may vary since each scenario covers a specific application of AUSS and will all complement the existing urban transport system. More precisely, last-mile AUSS enables transit users' access to and from stations/stops in the networks of urban rail transit and buses or other slower modes of transit. This service is expected to contribute to improvements in transit accessibility, particularly in suburban areas or lower-density areas (Ohnemus & Perl, 2016). The anywhere-to-anywhere AUSS refers to a service allowing users to travel between various not fixed locations around the city, not necessarily close to each other. Finally, e-hailing is a much-studied service that provides passengers the possibility to book an automated shuttle bus (usually using a smartphone app), in order to travel between convenient points, and thus e-hailing will be used as a demand-responsive feeder for existing public transit services. For the needs of microscopic simulation these SUCs will be modelled as one on-demand AUSS SUC; this is the form with which the results will be presented in the PST as well.

3 Methods

A taxonomy of potential impacts of connected and automated vehicles at different levels of implementation (Elvik et al., 2019) have all been estimated and forecasted using appropriate assessment methods, such as a mesoscopic traffic simulation, a microscopic traffic microsimulation, a system dynamics approach and the Delphi panel method. For the medium-term impacts described in this deliverable, we refer to results from the mesoscopic and microscopic traffic simulation as well as the Delphi method. Traffic simulation provides 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 (Deliverable 5.4 – Roussou et al., 2021). For the sake of simplicity and transferability of assessment methods, it is assumed that for each 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 users. Table 3.1 provides an overview over the different methods and their use in the different sub-use case and scenarios. The methods used to show the medium-term impacts in this Deliverable are highlighted in green.

Table 3.1: Overview of methods applied to the sub-use cases and their scenarios.

Sub-use Case	Scenario	Method			
		Microscopic simulation	Mesoscopic simulation	Delphi	System Dynamics
Point-to-point AUSS	Point-to-point with two modes	x		x	
	Point-to-point large scale network	x		x	
On-demand AUSS	Anywhere-to-anywhere	x	x	x	
	Last mile	x	x	x	x
	E-hailing	x		x	

3.1 Microscopic simulation

Traffic microscopic simulation (microsimulation) is one of the main assessment methods used in LEVITATE. The purpose of traffic simulation is: (i) to identify the impacts of the adoption of CCAM on traffic, including travel time, traffic volume, and traffic emissions to the environment under several traffic simulation scenarios and (ii) to evaluate the influence of difference traffic volume levels the presence of automation features both on a microscopic and a macroscopic level. Traffic microsimulation provides information related to single vehicles, whereas more macroscopic model refers to entire flow streams. There are also certain hybrid models, such as the model of AIMSUN, which allow for all levels of analysis, namely macroscopic, mesoscopic and microscopic analysis. The simulation inputs include data from various sources such as the road geometry and design, traffic volume, modal split, O-D matrices etc. This analysis examined impacts mainly on traffic, environment and energy efficiency and provided insights into the impacts of microscopic flow characteristics of CCAMs. The tools used for this analysis mainly included microscopic modelling tools for automated transport.

Microscopic simulation in urban transport studied three sub-use cases. The point-to-point automated urban shuttle service connecting two modes of transport, the point-to-point AUSS (Automated Urban Shuttle Service) in a large-scale network and on-demand AUSS.

3.1.1 Point-to-point AUSS connecting two modes of transport

In a generation where automation is evolving, automated point-to-point shuttles are considered to arise as the first mobility on demand service. However, the inquiry is what the effects of that kind of service are in the implementation area. The scope of this sub-use case is to evaluate the impacts of an automated shuttle bus service in different traffic conditions, road safety and environment. For the above to be achieved, a shuttle bus route was designed to operate in a part of the road network of Athens while different scenarios were established; peak and off-peak hours, existence of a dedicated lane for the shuttle bus, incident occurrence and different penetration rates and profiles of automated vehicles.

3.1.1.1 Network description

The study network that has been used for the traffic microsimulation in Aimsun Next mobility modelling software is a part of the city of Athens. The network is presented in Figure 3.1 and consists of 728 nodes and 1,636 sections. In addition, the total length of road sections is 70 km and the network size reaches approximately 3 km^2.

Figure 3.1: The study network in AIMSUN software

The OD matrices consisted of 58×59 centroids of the study network and a total number of 27,500 car trips and 5,990 truck trips for a peak hour. Furthermore, the Athens model included 14 buses and 1 trolley bus line and 150 public transport stations as well as service frequencies and waiting times at stops.

3.1.1.2 Assumptions and parameters

For the present sub-use case, some assumptions were made, to allow the definition of unknown parameters. Two general assumptions were that all automated vehicles are electric and used two main driving profiles for automated vehicles that are presented below:

- 1st Generation (Cautious): 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 (Aggressive): advanced sensing and cognitive ability, data fusion usage, confident in taking decisions, small gaps, early anticipation of lane changes than human driven vehicles and less time in give way situations.

Another assumption of this work is that, the shuttle bus modeled as a cautious AV profile, as a cautious driving was considered more appropriate for a public transport service. Similarly, automated trucks were simulated as 1st generation CAVs, as well. Moreover, the shuttle bus service tested operating on a dedicated lane and assumed that is one of the existing lanes that is converted to the shuttle service dedicated lane or one of the already dedicated bus lanes. In addition, the duration of the simulation scenarios is one hour, for both peak and off-peak conditions scenarios, which means that as the frequency of the shuttle bus service is decided to be 15 minutes, the maximum number of shuttle buses operating at the same time is four.

Regarding modal split, in the present sub use case the addition of one automated shuttle bus service in a network of 728 nodes and 1,636 road sections did not show any changes in demand. Hence, the traffic demand remained the same for all the simulation scenarios. In addition, another assumption that have been made is that the automated shuttle bus route and its characteristics as well as the existent public transport were constant while the market penetration rate of automated vehicles was changing.

3.1.1.3 Service

For the present sub-use case one shuttle bus line was implemented in the Athens network in order to connect two modes of transport. The shuttle bus connects the metro station "Eleonas" with the Athens intercity main bus terminal (Point A and point B respectively in Figure 3.2).

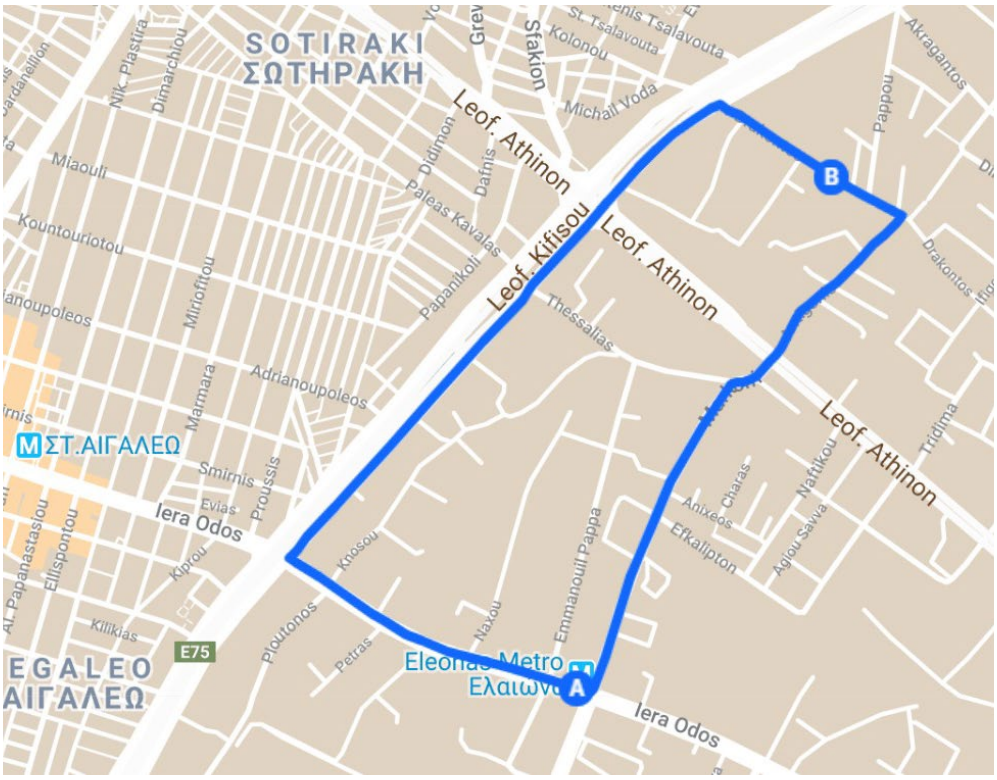


Figure 3.2: The shuttle service bus line

The four shuttle buses of the service are considered to have a total capacity of 10 passengers. Their dimensions are 5 meters in length and 2.5 meters in width. The maximum operating speed of the buses is 40.0km/h, the mean speed 25.0km/h. The frequency of the service is 15 minutes. The route includes signalized arterials and secondary streets and its total length is 3.4 kilometers.

3.1.1.4 Scenarios

The shuttle service simulation sets included peak and off-peak hour traffic conditions, the use of a dedicated lane and an incident condition on the shuttle bus route, as shown in Table 3.2. More specifically, in the first simulation set the shuttle buses are operating in mixed traffic conditions during peak hour, as well as in the fourth set that respectively concerns off-peak hour conditions. Similarly, the second and the fifth simulation sets include the shuttle bus service that operates using dedicated lanes in order to capture the impacts of a different implementation of the shuttle bus service. The third simulation test includes an incident condition occurring in the shuttle bus route. In this scenario, a part of a road segment is blocked as there an incident occurred and the shuttle buses as well as the surrounding traffic are forced to change lane and overtake the blocked segment. This set was considered only during peak hour conditions as the network is more congested. It is considered more reasonable to investigate the impacts of this kind of emergency condition during peak hour than off peak hour when the congestion levels are lower and lane changes are performed easier.

Table 3.2: Simulation sets

# of Simulation sets	Sub-use case specific scenarios			
	Scenario Parameters			
	Traffic Demand	Route	Condition	Service Frequency
1st set	Peak hour	-	-	15min
2nd set	Peak hour	dedicated lane	-	15min
3rd set	Peak hour	-	Incident	15min
4th set	Off Peak hour	-	-	15min
5th set	Off Peak hour	dedicated lane	-	15min

The impact assessment of the shuttle bus service is analyzed for each one different simulation set for different automated vehicles penetration rate in the prevailing traffic. Regarding the implementation of CAVs, different penetration rate scenarios were simulated and are presented in Table 3.3. The cautious CAVs, since they were considered to be the first generation, appeared first in the scenarios and then followed by the aggressive CAVs until the last scenario, where only 2nd generation CAVs were included.

Table 3.3: The CAV market penetration rate scenarios

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Car	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (Aggressive) CAV	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven Truck	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

For each one of these scenarios, the different implementations of the automated shuttle bus service was also simulated. Therefore, 48 scenarios were simulated in total (8 market penetration rate scenarios for each of the baseline and 5 shuttle bus service scenarios). In addition, for each scenario, 10 different replications with random seeds generating stochastic results were simulated as well in order to achieve greater precision. The averages were then obtained to receive the final results. The simulation duration of each scenario was one hour and the simulation time step was 5 minutes.

3.1.2 Point-to-point AUSS in a large-scale network

Network

The study network used for the traffic microsimulation in Aimsun Next mobility modelling software is the city of Athens. The network is presented in Figure 3.3 and consists of 1,137 nodes and 2,580 sections. In addition, the total length of road sections is 348 km and the network size reaches approximately 20 km2.

Figure 3.3: The city of Athens network in AIMSUN software

The origin-destination (OD) matrices of the study network consisted of 290×292 centroids and a total number of 82,270 car trips and 3,110 truck trips for peak hour. Furthermore, the Athens transport network includes 170 public transport lines and 1.030 public transport stations. More specifically, there are 95 bus lines, 14 trolley lines, 4 metro lines, 2 tram lines, 5 suburban train lines and 50 intercity bus lines which are presented in Figure 3.4 and were included in the simulation model, as well as their frequencies and waiting times at stops.

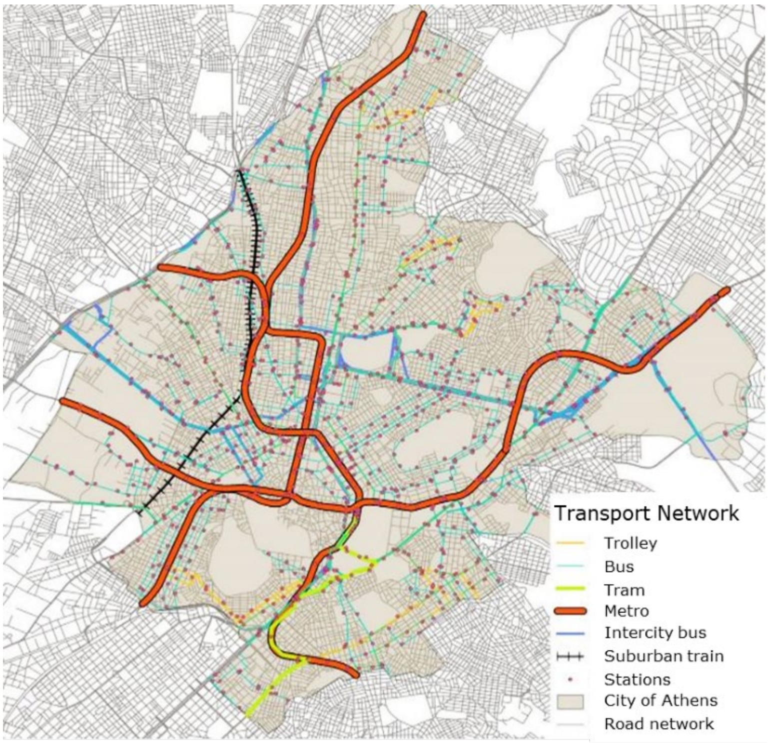


Figure 3.4 The Athens transport network

3.1.2.1 Assumptions and parameters

For the present sub-use case the assumptions made regarding the AVs and their driving profiles are the same as presented in section 3.1.1.2. Similarly, to the point-to-point AUSS connecting two modes of transport, this SUC was tested operating on a dedicated lane and during peak and off-peak hour scenarios.

Regarding modal split, in the present sub use case the addition of one automated shuttle bus service in a network of 1,137 nodes and 2,580 road sections did not show any changes in demand. Hence, the traffic demand remained the same for all the simulation scenarios. In addition, another assumption that was made is that the automated shuttle bus routes and their characteristics as well as the existent public transport were constant while the market penetration rate of automated vehicles was changing.

3.1.2.2 Service

For the present sub-use case 4 shuttle bus lines were implemented in the city of Athens in order to complement the existing public transport as shown in Figure 3.5. The first shuttle bus line, **Line 1**, connects the metro station "Viktoria" (A) with the metro station "Panormou" (B), the second shuttle bus line, **Line 2**, connects the National Garden (A) and Greek Parliament with the National Archaeological Museum (B), the third, **Line 3**, connects Omonoia Square (A) with Acropolis - Parthenon (B) and the fourth, **Line 4**, connects metro station "Rouf" (A) with metro station "Neos Kosmos" (B).

Figure 3.5 The Shuttle service bus lines

In addition, 16 shuttle buses of the service are considered to have a total capacity of 10 passengers. Their dimensions are 5 meters length and 2.5 width. The max operating speed of the buses is 40.0km/h, the mean speed 25.0km/h. The frequency of the service is 15 minutes. The total length of the shuttle bus service routes are 8 km (Line 1), 6 km (Line 2), 6 km (Line 3) and 8 km (Line 4).

3.1.2.3 Scenarios

The shuttle service simulation sets included peak and off-peak hour traffic conditions and the use of a dedicated lane during peak hour conditions, as shown in Table 3.4. More specifically, in the first simulation set the shuttle buses are operating in mixed traffic conditions during peak hours, as well as in the third set that respectively concerns off-peak hour conditions. The second simulation set includes the shuttle bus service that operates using dedicated lanes in order to capture the impacts of a different implementation of the shuttle bus service. This set was considered only during peak hour conditions as the network is more congested and a provision of a dedicated lane for the service is considered to be more reasonable. Another thing to point out is that, in the present sub-use case the investigation of the impacts of an emergency condition, for instance a simulation scenario including an incident condition like the first sub-use case's one, was not examined. The simulation model of this sub-use case concerns a very congested and dense network in which the shuttle buses have perform overtaking and lane changing frequently during their operation. This means that an incident occurrence will not affect the investigated impacts.

Table 3.4 Simulation sets

# of Simulation sets	Sub-use case specific scenarios		
	Scenario Parameters		
	Traffic Demand	Route	Service Frequency
1st set	Peak hour	-	15min
2nd set	Peak hour	dedicated lane	15min
3rd set	Off Peak period	-	15min

The impact assessment of the shuttle bus service is analyzed for each one different simulation set for different automated vehicles penetration rate in the prevailing traffic. Regarding the implementation of CAVs, different penetration rate scenarios were simulated and are presented in Table 3.5. The cautious CAVs, since they were considered to be the first generation, appeared first in the scenarios and then followed by the aggressive CAVs until the last scenario, where only 2nd generation CAVs were included.

Table 3.5: The CAV market penetration rate scenarios

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Car	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (Aggressive) CAV	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven Truck	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

For each one of these scenarios, the different implementations of the automated shuttle bus service was also simulated. Therefore, 32 scenarios were simulated in total (8 market penetration rate scenarios for each of the baseline and 3 shuttle bus service scenarios). In addition, for each scenario, 10 different replications with random seeds generating stochastic results were simulated to achieve greater precision. The simulation duration of each scenario was one hour and the simulation time step was 5 minutes.

3.1.3 On demand AUSS

This sub-use case aims to model, optimize and investigate the impacts of an automated shuttle bus fleet through microsimulation. The fleet was designed to operate in the city center of Athens, Greece with varied vehicle capacities. The proposed service will be able to serve customers from anywhere-to-anywhere, meaning the there are no fixed stops or routes, but these characteristics will be manifested optimally based on the demand. To model the service, a variation of the Dial-a-Ride optimization Problem (DARP) will be formulated, without the attribute of time. From the optimization process, important factors will be calculated, such as fleet size, demand to vehicle allocation and automated shuttle bus final routing. The resulting data will then be investigated by a sophisticated traffic micro-simulator software, AIMSUN, in order for the other parameters, like emissions, safety during conflicts with other vehicles and congestion effects, to be also estimated.

3.1.3.1 Designing and Assessing the Impacts of On-demand Services

The emergence of on-demand passenger mobility services by organized and coordinated vehicle fleets (e.g. Uber, 2020) in recent years has encouraged the allocation of significant research efforts to Vehicle Routing Problems (VRPs) for passenger transportation and comparably extensive assessment studies regarding their impacts. On-demand services are part of a wide range of globally trending innovations in urban mobility and along with mobility-as-a-service applications, shared mobility, electric, connected and automated vehicles, are founding the future transportation ecosystem (Simpson et al., 2019).

Shared mobility systems and on-demand services complement each other in the pursuit of optimal, environmentally cleaner, most efficient urban mobility solutions. Through implementations such as On-Demand Multiple Passenger Ride-Sharing (Linares et al., 2017), sophisticated vehicle assignment and routing optimization frameworks are provided, with innovative features like Decision Support Systems, in order to guide the assignment of the passenger demand to the fleet of available vehicles.

While the above examples fall in the category of Dial-a-Ride (DARP) or shared-taxi implementation, which utilize professional drivers and dedicated fleets of vehicles, other variants of shared mobility exist, like dynamic ride-sharing systems, that use non-professional drivers who want to share their ride (Mourad et al., 2019). Moreover, on-demand Shared Automated and Electric Vehicles (SAEVs) could be a prominent complementation to public transport, by providing first and last-mile services and "feeding" means of public transport, an approach which had positive results when replacing low demand bus routes (Shen et al., 2018). High occupancy shared vehicles are in the center of attention in many studies, for their benefits regarding the environment and traffic congestion, and their operation in terms of routing and needed detours, based on the various incentives given by authorities, such as toll or fare discounts and dedicated lanes, is being incorporated in transportation optimization problems in order to reach optimal levels (Wang et al., 2016).

In order for these shared on-demand systems to operate efficiently, sophisticated optimization procedures are necessary in vehicle distribution, assignment, routing and other aspects. With the available methodologies and frameworks, like Google's OR-Tools, simple applications of VRPs can be easily conducted to accommodate for the needs of companies and operators (Romero-Gelvez et al., 2020). Nevertheless, extensive research is being constantly conducted to examine and evaluate the performance of the solution methodologies and the algorithms used (Bräysy & Gendreau, 2005), and also to contribute to the field by providing additional optimization criteria, like environmental emissions (Úbeda et al., 2014). When it comes to solving VRPs that involve passengers, additional constraints need to be taken into consideration, like the minimization of passengers in-vehicle time and maximum detours of the optimized route, that adds another layer of complexity to the problem (Xiong et al., 2020).

The problems described above have been modeled in many ways. Data driven optimization approaches examine the efficiency and improvement of proposed algorithms and methodologies, (Sombuntham et al., 2010; Vidal et al., 2015), or analyze the results of case studies implementations, (Huang et al., 2020). Simulation tools, either custom made, (Winter et al., 2018) or commercial software, like AIMSUN, (Linares et al., 2017) help to better portray the effects of the introduced mobility concepts, by realistically utilizing time or event steps, simulating their application. Moreover, an advanced agent-based traffic simulation model and the replacement of an existent regular bus service by an on-demand mini-bus service was found to result in a more than 78% reduction in waiting times at any time of the day and a 55% reduction of trip completion times, among other findings (Liyanage & Dia, 2020).

The impacts of on-demand systems have been consistently studied regarding across various aspects and through a variety of approaches. In Lu et al., (2020), the effects of on-demand systems on road capacity and other important traffic parameters like density and speed, both in an artificial grid network and in a real urban environment, were studied for different AV penetration rates, employing macroscopic fundamental diagrams (MFDs) and microscopic simulation through SUMO. They discovered that the capacity grows quasi-linearly with higher AV penetration rates, where, at maximum, penetration traffic flows increase by 16-23%. Similarly, a total replacement of conventional vehicles by CAVs was modelled using a POLARIS agent-based model, backed by several data-sources, regarding demographics, transportation and more, and utilizing machine learning algorithms like k Nearest Neighbours (kNN) and random forests. Results showed that traffic flows are most likely going to be increased with the implementation of CAVs and that road properties, like number of lanes, have the highest impact in average daily traffic (Parsa et al., 2020).

Furthermore, traffic safety is undoubtably of another field of critical importance. Since no historical road safety data currently exist regarding innovative services that utilize automated mobility, the only way to study their impacts on safety is through simulation models. In Papadoulis et al. (2019), Vissim traffic simulator and its External Driver Model API were employed in order to develop a decision-making CAV control algorithm. A real motorway was then investigated, for varied traffic conditions and for a wide range of CAV market penetration rates. Road safety evaluation through the Surrogate Safety Assessment Model led to 12% to 94% reduction of vehicle conflicts for 25% and up to 100% CAV penetration rates respectively, with efficient traffic flow. Finally, in the absence of any crash data, novel approaches have taken place in the effort to evaluate road safety through surrogate safety measures (SSM), which are indicators that identify unsafe traffic situations through microscopic traffic data. The extensive evaluation of the reliability of existing SSMs and the novel methodology for calculating rear-end collision risk, utilizing a dataset of microscopic car-following traffic data, that took place in (Nadimi et al., 2021), aids in enhancing the road safety levels that can be achieved for innovative intelligent vehicles.

3.1.3.2 Problem setup

In order to model and optimize an on-demand automated shuttle bus service, an initial step was to inspect the available data for the place where the service would be implemented, namely, the city center of Athens, Greece. Accurate and reliable demand data regarding the trips in the area of interest were accessible in aggregated Origin-Destination (OD) form and in centroids of a few city blocks (Oikonomou et al., 2020). Additionally, since the proposed service is an anywhere-to-anywhere on-demand passenger transportation service, the optimization problem to be formulated and solved is a variation of a DARP, which belongs to the broad family of VRPs. However, the available data apart from being aggregated, included no time information, so this DARP variation will not take time constraints into account.

To compensate for the lack of disaggregate trip information, the trips that would be served by the automated shuttle bus service will be disaggregated to individual customer requests. A sensitivity analysis, differentiating important characteristics like shuttle buses' capacity and the parts of the total trip demand they are going to undertake is warranted in order for service representative scenarios to be produced. Afterwards, the DARP variation will be solved so as to create routes for the entire fleet, and for every examined scenario.

Finally, from the optimization and simulation of the chosen scenarios, the service will be analyzed, both in terms of its efficiency and the impacts it is going to induce on the transportation system and the environment. The service will comprise a fleet of an optimized number of automated shuttle buses of varied capacities, deployed from strategic depot locations within the city center that will be optimally assigned and routed to customer requests.

3.1.3.3 Scenario Formulation and impact assessment

While the demand data for the city center of Athens were obtained through an Aimsun Next mobility simulation model and the output data of the optimization process will be fed back into the Aimsun Next simulation, the optimization of the service fleet is achieved externally, through a macroscopic, data driven approach. We first introduce a disaggregation process to go from aggregated OD trip information in the city of Athens to disaggregated ride requests, in order to portray the individuality of the calls both in the assignment stage as well as in the pickup and drop-off stages. The disaggregated information is further considered as customers' requests for the on-demand service.

The service operational efficiency is demonstrated through a set of scenarios that vary in terms of the demand to be served, the fleet size and the vehicle capacity, as shown on Table 3.6. The sensitivity analysis consisted of assigning percentages ranging from 1% to 100% of the total demand to the new service, for shuttle bus fleets with proportionally increased number of vehicles, which had capacities of 1, 4, 8 or 15 passengers. Finally, the scenarios in Table 3.6 were selected to be examined extensively through the AIMSUN's software simulations: 5% and 10% of the total demand to be served by 50 and 100 automated shuttle buses of 8 and 15 people capacities, respectively. In addition, in the traffic simulation model the shuttle bus characteristics were implemented. The dimensions of the first type, with capacity of 8 passengers, were 4.5 meters in length and 2.5 meters in width. The dimensions of the second type, namely the one with capacity of 15 passengers, was 8 meters in length and 2.5 meters in width, respectively. In addition, the maximum operating speed of the buses was 40.0 km/h and the mean speed was 25.0 km/h; these parameters were also inserted in the model. For the on-demand operation scenarios, the existent public transport remained constant since the on demand automated service was considered to be an additional service in the network.

Table 3.6: On demand service scenario specifications

No. of Scenario	Demand to be served from total	Total trips to be served	Initial Shuttle buses provided	Shuttle bus capacity
1	5%	338	50	8 people
2	5%	338	50	15 people
3	10%	909	100	8 people
4	10%	909	100	15 people

The factors that determined the final scenarios were applicability to real world situations, for example 1% of the total demand was merely 26 trips which could not support the existence of an on-demand service and beyond 20% exceeded the scope of this sub-use case. 1 to 4 people capacities produced outcomes similar to taxi services, which again deviated from the objective. Also, the range of different scenarios were limited by the time needed to execute the extensive impact analysis simulation pipeline on the next step of this paper. Finally, the above 4 scenarios were chosen, for being the most descriptive and suitable for the needs of this sub-use case, to be optimized, simulated and investigated in depth.

Furthermore, the number of the starting depot locations, was statically determined beforehand to be 10. This number was assigned as per by the EU guideline of 1 charging point per 10 EVs, considering that the automated shuttle buses in this paper are electric and these depots would be charging locations (Mathieu 2020). The initial shuttle buses that were provided to the optimization algorithm were inflated and evenly distributed to the starting depot locations, in order for feasible initial solutions to be achievable. The optimization process would then minimize the number of shuttle buses used and optimally utilize the vehicles located in each starting depot location.

It is noteworthy, that the demand percentages, given in the OD matrix of the city of Athens, include trips that are located exclusively inside the city center of Athens, as that is the most probable initial step of the implementation of such a service (Maurer et al. 2016). This means that demand inflated centroids from the perimeter of the selected area of interest were omitted from the optimization process.

3.1.3.4 Data preparation

The study network that has been used for the traffic microsimulation in AIMSUN software is the city of Athens. The network is presented in Figure 3.6 and consists of 1,137 nodes and 2,580 sections. In addition, the OD matrices consisted of 290×292 centroids of the study network and a total number of 82,270 car trips and 3,110 truck trips for peak hour.

Figure 3.6 The city of Athens network in AIMSUN software

The Athens transport network includes 170 public transport lines and 1.030 public transport stations. More specifically, there are 95 bus lines, 14 trolley lines, 4 metro lines, 2 tram lines, 5 suburban train lines and 50 intercity bus lines which are presented in Figure 3.7 and were included in the simulation model, as well as their frequencies and waiting times at stops.

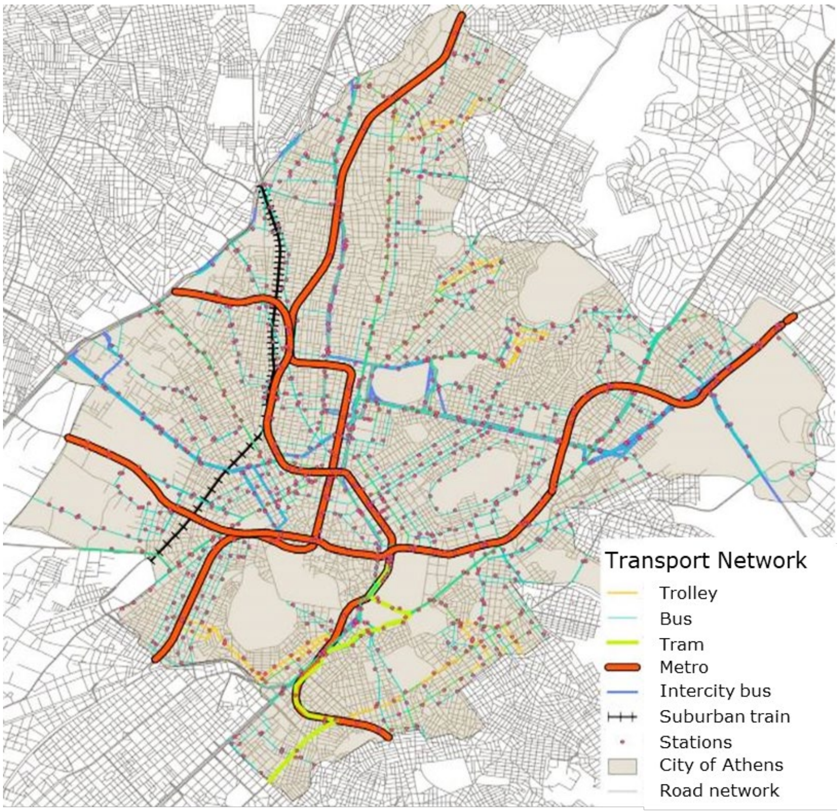


Figure 3.7 The Athens transport network

From the study's network the following files were exported.

- The Origin-Destination (OD) matrix for the city center of Athens, consisting of 82,274 car trips during peak hours.
- A Distance matrix, with values derived from the simulation of the trips of the above OD matrix, using the Aimsun Next software.
- A GIS file and a text file, which hold important spatial data, such as centroid visualization and their exact coordinates.

Furthermore, visualization of any needed information such as centroid locations or examination of produced shuttle routes was available via the Aimsun Next software.

We assume that the demand for the new service will be a subset of the original OD table, meaning that the new service will attract private vehicles users. The new OD matrices, for the proposed service scenarios, contain aggregated travel information that need to be transformed to individual ride requests so that the on-demand service can feasibly operate. To that end, and taking into account that in Google's OR-Tools, a node can be visited only once and can be either a pickup or a delivery location, a two-step process was developed, as seen in Figure 3.8. Firstly, the demand was disaggregated to single trips for every centroid, by creating dummy centroids in the vicinity of the original, with one, at most, trip assigned to each of the dummy centroids but with zero distance from the original. Subsequently, based on the Origins and Destinations of the trips, more dummy centroids were created, again with zero distance from the original centroids, in order to represent distinctive pickup and delivery nodes. The demand was positive in the pickup nodes and negative in the delivery nodes, in order for both actions to be possible.

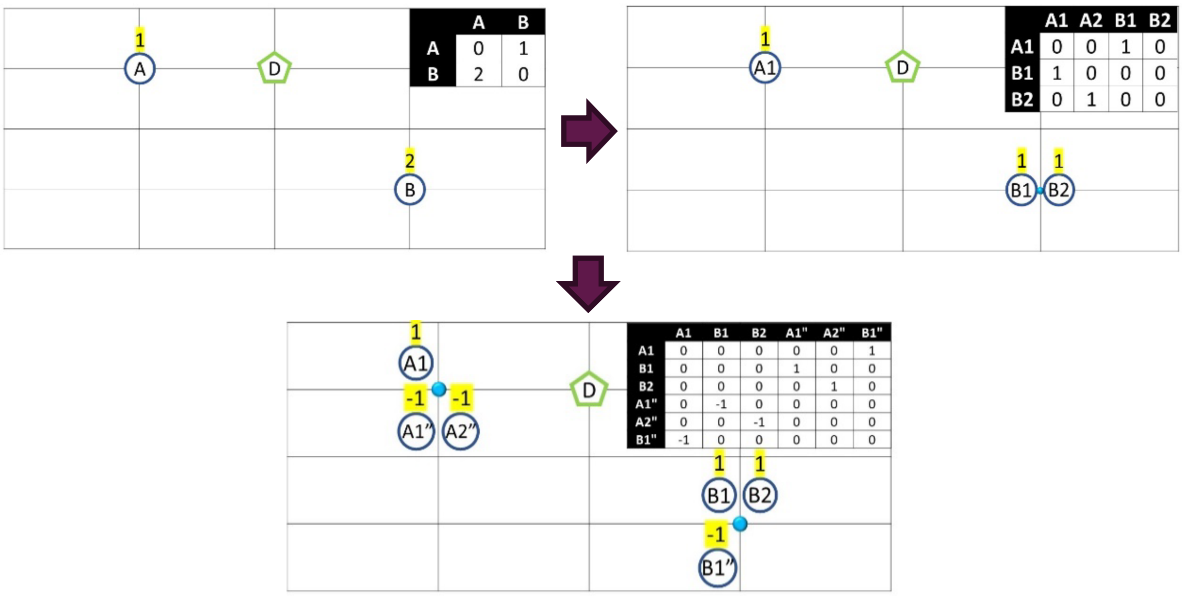


Figure 3.8: Schematic representation of the OD disaggregation process

3.1.3.5 Starting Depots Allocation

Next, a k-Means clustering algorithm, executed with 500 maximum iterations and 10 cluster centroid initializations, was implemented to specify the locations of the starting depots for the new service. The required 10 clusters were provided from the algorithm, based on the exact locations of the centroids in the Athens network and the total trip demand each centroid had in the original OD matrix, and the centers of these clusters were selected as depots for the automated shuttle buses to originate from, at the start of the optimization, as shown on Figure 3.9. The exact location of each depot was assigned to the nearest centroid from the center of each cluster.

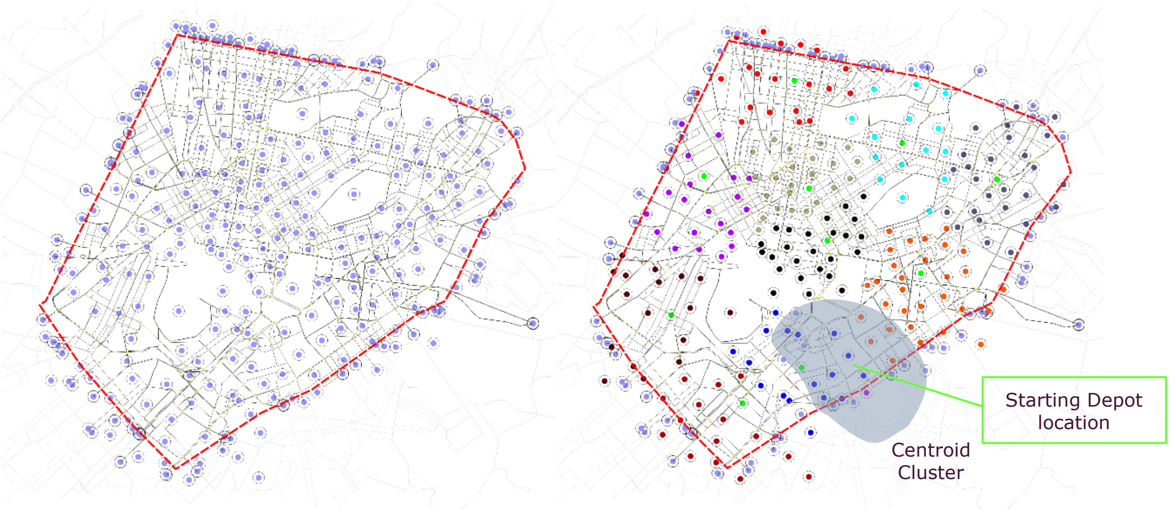


Figure 3.9: Allocation of the shuttle service depots based on k-means clustering. In the left, centroid locations from Athens' network, in the right, the clusters and the depot locations (in green)

The output of the above data preparation process, is a 1D demand array, which contains the positive and negative demands of all the created dummy centroids, a list of all the pickup and delivery pairs, a list of the starting depot locations and a 2D distance array, that contains the distances between every dummy centroid, derived from the centroid distances of the original OD matrix.

3.1.3.6 Optimization problem parameters

The input data in Google's OR-Tools, for the examined DARP variant, are the 2D distance array, the number of vehicles to be used in each scenario, the 1D demand array, the capacities of the shuttle buses of each fleet, the list of the pickup and delivery pairs, the 10 starting depot locations and a single arbitrary ending depot location. The impact analysis will take place in the morning peak hour, so the shuttle buses are not required to return to their depots, but instead they will end their routes at their last delivery location, which is represented by the arbitrary ending depot location, which has zero distance from every other centroid.

The maximum driving distance for every shuttle bus during the considered peak hour, is set to be 10km, so that the shuttle buses are able to finish their optimized routes within the Aimsun Next simulation, while impeded by heavy traffic and delays for picking up and delivering passengers at every stop. Furthermore, a limit of 1000 solutions is set for every scenario, to ensure the solver will not run indefinitely, due to the size of the optimized problems, while sufficient investigation of the solution space will take place.

Finally, for every optimized scenario, the output for meta-analysis and impact analysis included information about the number of shuttle buses used, the driven distance, total and individual for every shuttle bus, depot utilization and centroid succession for every active shuttle bus route.

3.1.3.7 Assumptions and parameters

For the present sub-use case the assumptions made regarding the AVs and their driving profiles are the same as presented in section 3.1.1.2.

The impact assessment of the shuttle bus service is analyzed for each one different simulation set for different autonomous vehicles penetration rate in the prevailing traffic. These market penetration rate scenarios are presented in Table 3.7.

Table 3.7: The CAV market penetration rate scenarios

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Car	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (Aggressive) CAV	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven Truck	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

3.1.3.8 Service optimization

As seen in Figure 3.10, which depicts the total distance that was covered by the entire fleet for every scenario described in Table 1, using higher capacity vehicles greatly reduces the total distance the shuttle buses travel, especially for higher demand.

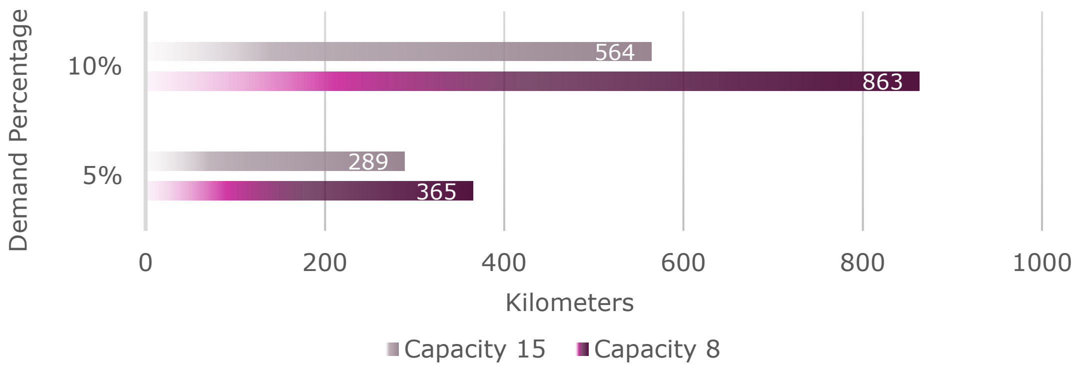


Figure 3.10: Total Distance travelled by the shuttle bus fleet in kilometers

Another important aspect of the service is the number of passengers that were served by the shuttle bus fleet for each scenario. In Figure 3.11, the total passengers that were served for each scenario can be seen, which are 338 passengers for the 5% scenario and 909 passengers for the 10% scenario in total, distributed to the total of shuttle buses that served them. It can be seen that for both 5% and 10% scenarios, fewer vehicles are needed to transport the same number of passengers and that higher capacity shuttle buses server considerably more passengers individually.

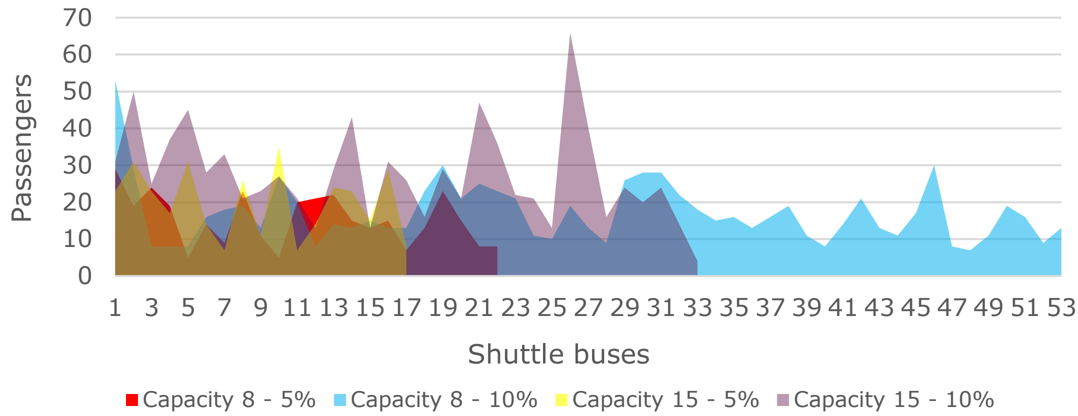


Figure 3.11: Passengers served by shuttle buses for every scenario

Figure 3.12 demonstrates more clearly the number of utilized shuttle buses for every scenario. The significance of higher capacity vehicles in large demands can be observed. While the difference of the number of shuttles buses is not considerable regarding the scenarios with 8 people capacity shuttles buses, that difference is almost doubled for scenarios with 15 people capacity.

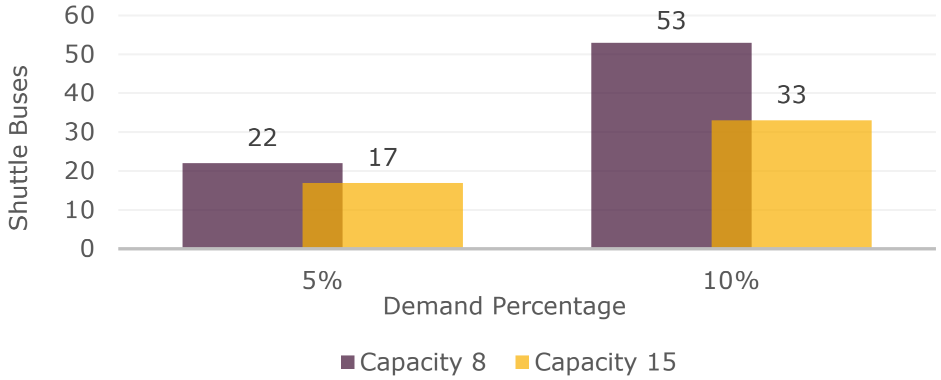


Figure 3.12: Total number of shuttle buses used in each scenarios' fleet

In Figure 3.13, the occupancy of the two shuttle buses that served the most passengers across the scenarios, one for each capacity configuration, can be seen for their entire routes on an event-based sequence. This was calculated by dividing the number of people inside the shuttle buses by the available seats for every event of a pickup or a delivery. The mean occupancies for the entire fleet of every scenario, calculated as the overall mean of the mean occupancies of every vehicle, are 43% and 50%, for the 8-passenger shuttle buses and 51% and 57%, for the 15-passenger shuttle buses, for the 5% and 10% scenarios respectively. The reason 15-passenger shuttle buses appear to have lower occupancy rates than 8-passenger ones due to the fact that the optimization problem that was solved did not include time windows, so the only main constraint defining the route choices was distance and not passenger needs, such as total ride time or time boundaries. This can also be observed again in Figure 3.13, where significant alterations in the occupancy of the vehicles take place, especially for the 15-passenger capacity shuttle buses.

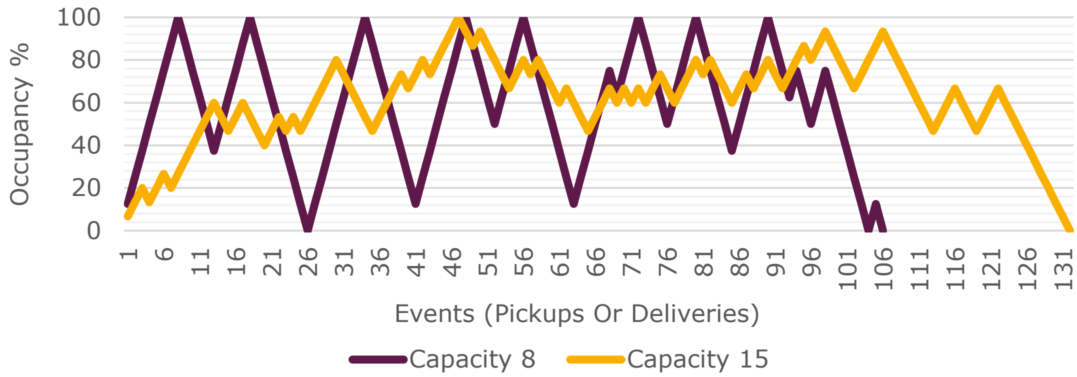


Figure 3.13: Percentile Occupancy for the two vehicles that served the maximum passengers across the examined scenarios for both shuttle bus capacities

The proposed automated shuttle bus service does not have fixed stops, but instead their number and location are shaped by the demand. In Figure 3.14, the average and maximum shuttle bus centroid stops, both for pickup and delivery of passengers, can be observed.

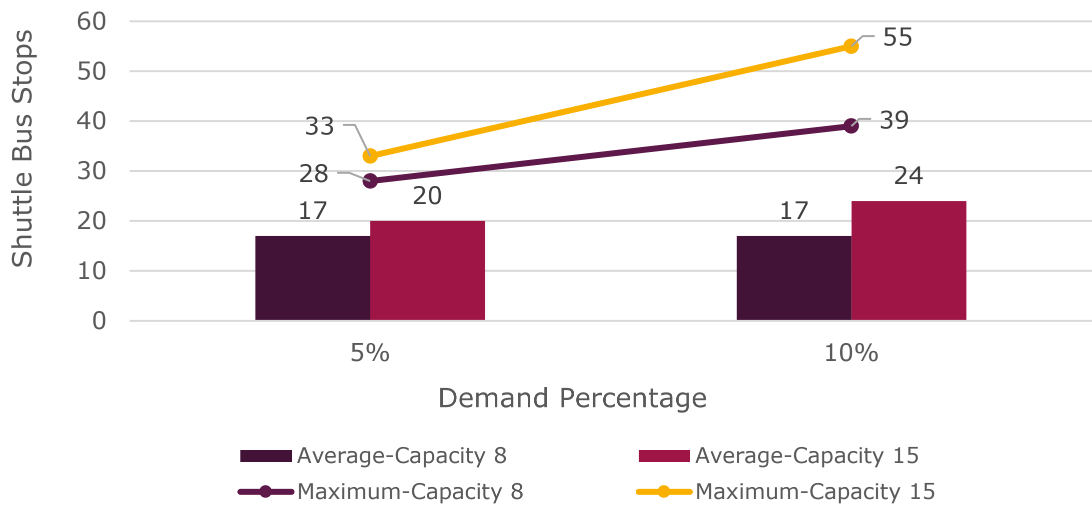


Figure 3.14: Centroid stops

Finally, since in the optimization problem more shuttle buses were fed than they were ultimately used, as shown in Figure 3.15 and Figure 3.16, the utilization of the starting depot locations and the percentile diagram for all 10 depots and with spatial perspective are presented. Obviously, for the 10% scenarios the utilization of the majority of the depot locations is increased for both shuttle buses capacities and decreased between the vehicle capacities, lower being for the 15 people capacity. It is observed that some depots at the edges of the selected area, furthest from the city central areas, are more intensively utilized than innermost depots.

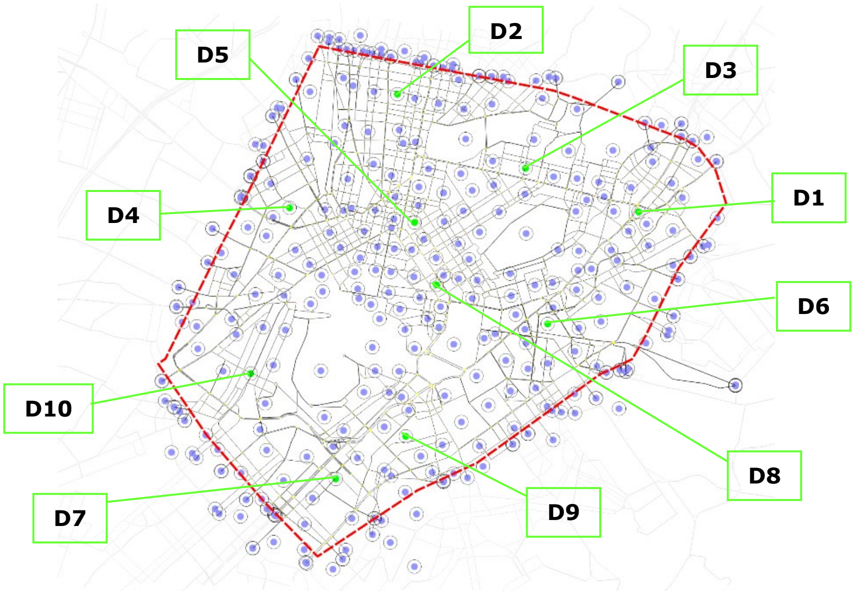


Figure 3.15: Starting Depot Locations

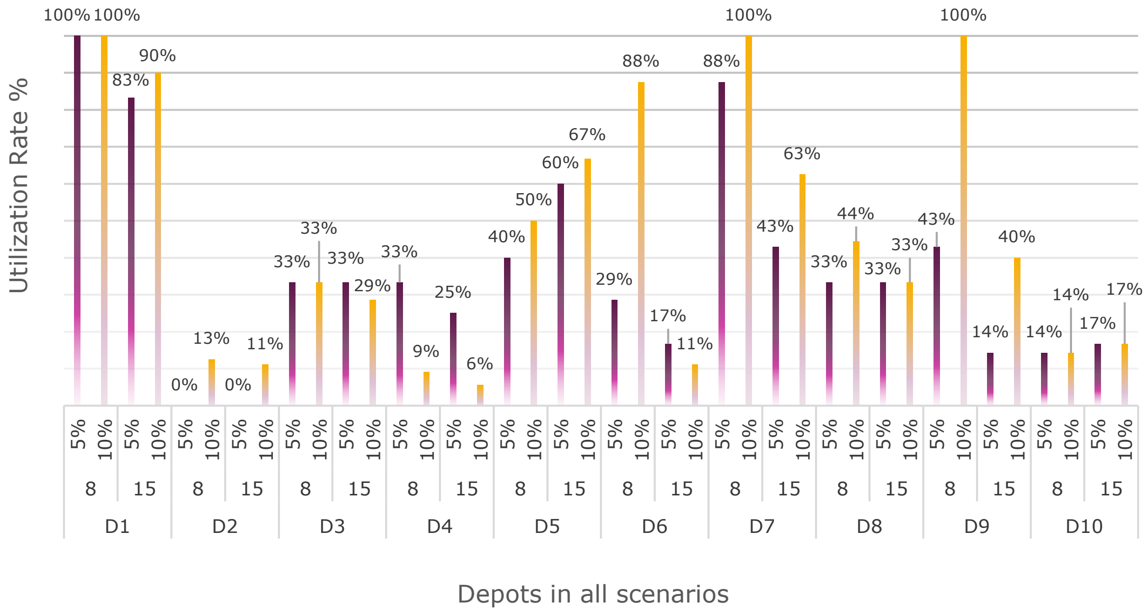


Figure 3.16: Utilization rates for every starting depot location for every examined scenario

3.2 Mesoscopic simulation

The mesoscopic simulation and the setup for the sub-use cases are described in detail in Deliverable 5.2, section 3.1.

3.3 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. Within LEVITATE, the Delphi method is used to determine all impacts that cannot be defined by the other aforementioned quantitative methods (traffic microsimulation, system dynamics, etc.). 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. They were asked to evaluate the potential influence of the proposed interventions on different impact areas. Their answers were then analyzed in order to create anonymized summaries for the different CCAM related interventions, which were sent during the second round of the Delphi, giving the experts the opportunity to change their answer or retain the original. In total, 14 experts participated in the automated urban transport delphi and 9 of them participated in round 2. The complete method and the results analysis are described in detail in Deliverable 5.2, section 3.2.

4 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 CCAM 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. The short-term impacts of CCAM are those described as direct impacts. These impacts refer to changes noticed by each road user on each trip and can be measured directly after the introduction of intervention or technology. Systemic impacts are impacts wide enough to be observed across the entirety of the transport system. These are measured indirectly from direct impacts and are considered medium-term. The medium-term impacts for different sub-use cases are described in the following sub-sections. Wider impacts are even broader changes occurring outside the transport system, such as changes in land use and employment. These are inferred impacts measured at a larger scale and are the result of direct and system wide impacts. Wider impacts are considered to be long-term impacts (presented in Deliverable 5.4).

4.1 Amount of travel

4.1.1 Microscopic simulation

4.1.1.1 Point-to-point AUSS connecting two modes of transport

Figure 4.1 illustrates that, if the shuttle bus drives on a dedicated lane, total distance travelled remain the same during off peak hour for all mobility scenarios. Overall, the existence of the shuttle bus service led to increased total distance travelled for the most of market penetration scenarios. This can be explained by the fact that the service is considered as an additional service complemented the existence public transport. Due to the high traffic volumes during peak hour, the existence of a dedicated lane significantly influences the traffic conditions. More specifically in this scenario, decreased travelled distances are noticed for multiple market penetration rate scenarios. As can be observed, total distance travelled values do not seem to be significant affected when the number of automated vehicles is increased.

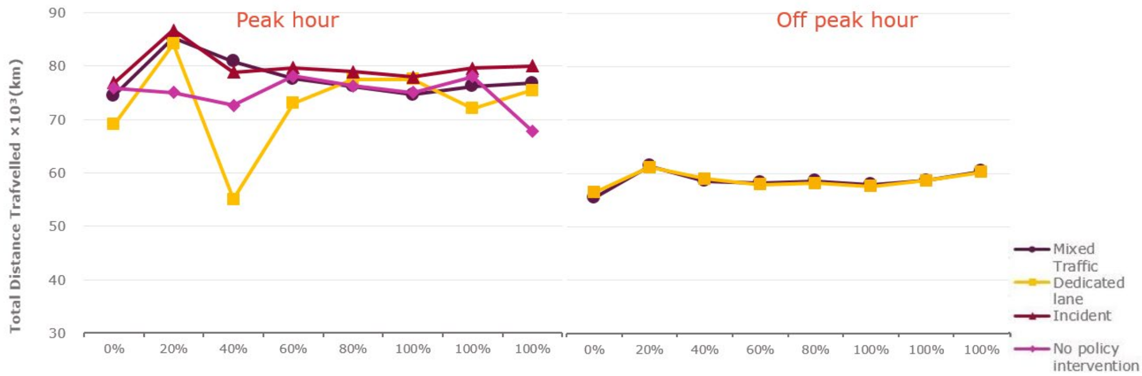


Figure 4.1: Total distance travelled for point-to-point AUSS connecting two modes of transport

4.1.1.2 Point-to-point AUSS in a large-scale network

Figure 4.2 illustrates that, if the shuttle bus drives on a dedicated lane, total distance travelled remain the same for all mobility scenarios. In addition, the existence of the shuttle bus service does not significantly affect total distance travelled for all market penetration scenarios. As can also be observed, total distance travelled values seem to be increased when the number of automated vehicles is increased for the most of the market penetration rate scenarios.

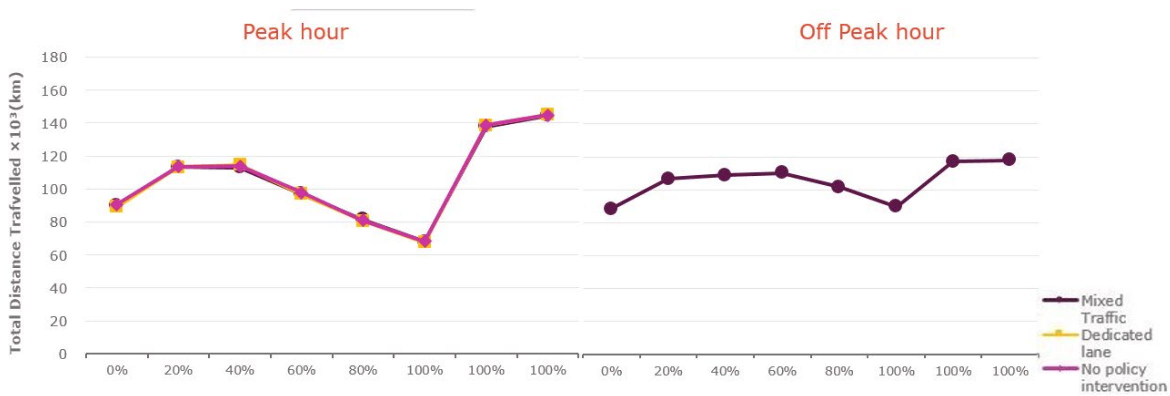


Figure 4.2: Total distance travelled for point-to-point AUSS in a large-scale network

4.1.1.3 On-demand AUSS

Firstly, according to Figure 4.3, it seems that the implementation of the automated service leads to slightly increased values of total distance travelled for the last two scenarios, while for the rest of the scenarios there is a decrease. The on-demand service does not show any significant differences in total distance travelled.

Figure 4.3: Total distance travelled for the on-demand AUSS

4.1.2 Mesoscopic simulation

In the mesoscopic simulation, the agents perform the same activities at the same locations throughout all scenarios. Differences in the amount of travel are therefore only caused by the use of different transportation modes. In Figure 4.4, the annual average trip distances of all agents is shown. The dotted and dashed lines refer to different marginal utilities of money (mUoM) indicating different economic situations of the agents. A higher value (mUoM=1.05) means a worse economic situation with agents reacting more sensitive to high prices for transport whereas agents care less about the price in scenarios with a lower value (mUoM=0.95). This results in slightly longer trips for a lower mUoM since agents use more public transport than active modes resulting in detours compared to direct walk or bicycle routes. The differences are however marginal. The introduction of private CAVs generally reduces the amount of travel which is assumed by more direct routes on less congested roads.

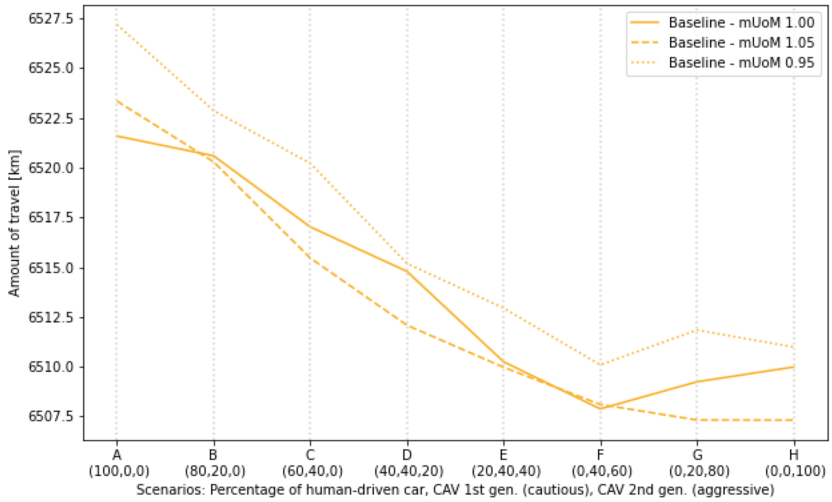


Figure 4.4: Average kilometers traveled per day for all trips in the city area for the anywhere-to-anywhere scenario

4.1.2.1 Anywhere-to-anywhere AUSS

Figure 4.5 shows the relative changes in the amount of travel compared to the baselines. The strongest increase is apparent for the scenarios with private conventional cars only. Once private CAVs are introduced, the amount of travel only slightly increases or there is even no effect visible. The drop in the amount of travel from scenarios in A to scenarios B-H can be explained by the flow capacity factor which leads to a better flow in traffic. The effect is non-linear and affects the amount of travel not that strong anymore when a higher market penetration rate is reached. The larger the AUSS fleet, the more attractive the service. Using the AUSS might lead to detours which is the reason why there is a higher amount of travel visible in the scenarios with a larger fleet size. The different marginal utility of money parameters do not affect the amount of travel.

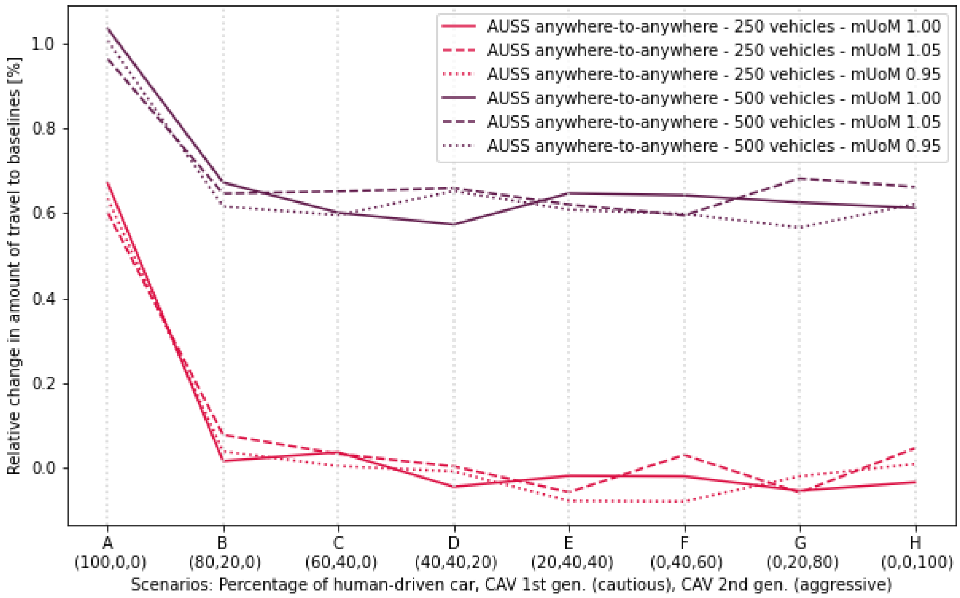


Figure 4.5: Relative change [%] in the amount of travel compared to baselines for all trips in the city area for the anywhere-to-anywhere scenario and different marginal utilities of money (mUoM).

4.1.2.2 Last-mile AUSS

For the last-mile AUSS sub-use case, the drop between scenarios for conventional cars (A) and the introduction of private CAVs (B-H) are not apparent since the AUSS trips are short and not that strongly affected by the different flow capacity factor. The surplus in the amount of travel is with 0.3% to 0.5% between the increase of amount of travel in the anywhere-to-anywhere scenario. A larger fleet size only contributes to a very little increase. Again, the marginal utility of money does not have any effect on the amount of travel in this scenario.

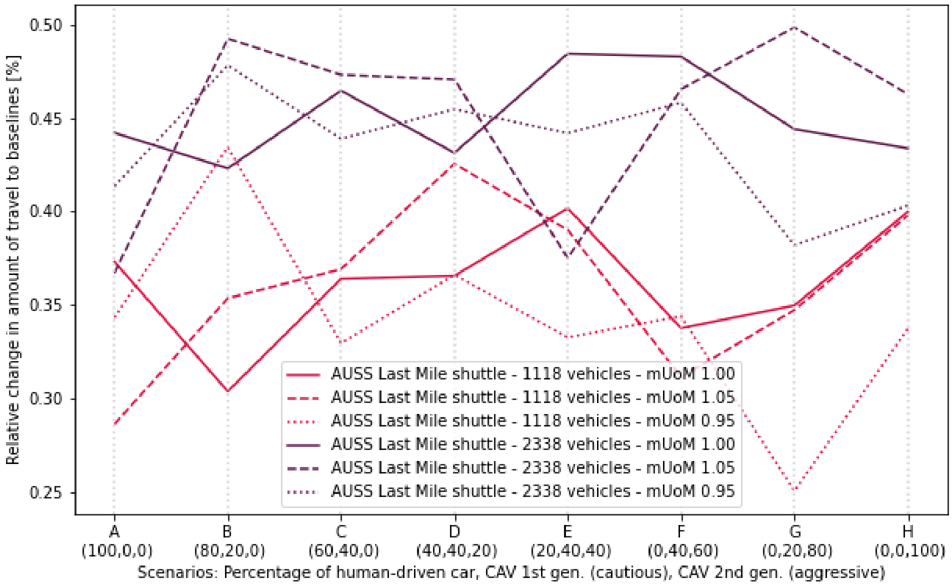


Figure 4.6: Relative change [%] in the amount of travel compared to baselines for all trips in the city area for the last-mile scenario and different marginal utilities of money (mUoM).

4.2 Congestion

4.2.1 Point-to-point AUSS connecting two modes of transport

Figure 4.7 illustrates that, if the shuttle bus drives on a dedicated lane, the delay time remains the same during off peak hour for all mobility scenarios. In general, the existence of the shuttle bus service led to increased delays for the most of market penetration scenarios. This can be explained by the fact that the service is considered as an additional service complemented the existence public transport. Due to the high traffic volumes during peak hour, the existence of a dedicated lane significantly influences the traffic conditions. More specifically in this scenario, increased delays are noticed for multiple market penetration rate scenarios. As can be observed, automation decreases delay time during peak hour while during off peak remain constant.

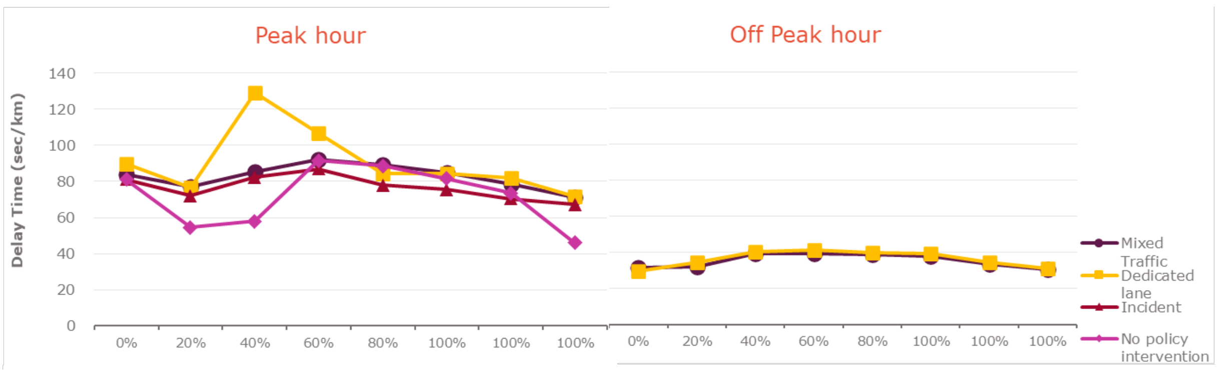


Figure 4.7: Delay time for point-to-point AUSS connecting two modes of transport

4.2.2 Point-to-point AUSS in a large-scale network

Figure 4.8 illustrates that, if the shuttle bus drives on a dedicated lane, the delay time remains the same for all mobility scenarios. In addition, the existence of the shuttle bus service does not significant affect delays for all market penetration scenarios. As can also be observed, automation decreases delay time during both peak hour and off-peak hour conditions for the last two market penetration rate scenarios while for the rest remain constant.

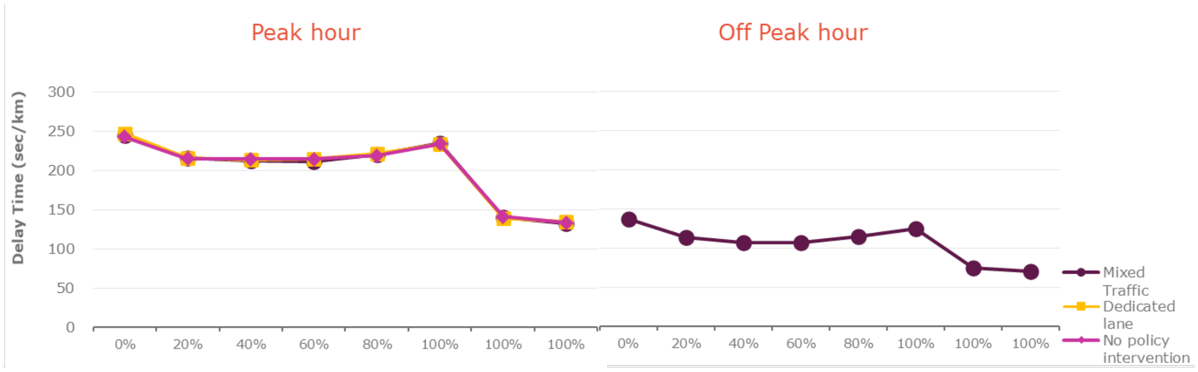


Figure 4.8: Delay time for point-to-point AUSS in a large-scale network

4.2.3 On-demand AUSS

Firstly, according to Figure 4.9, it seems that the implementation of the automated service leads to decreased delay times. More specifically, delay time values of the baseline scenario are higher for all market penetration rates except from the last two, in which delay time is almost the same for all different types of the on-demand service implementation.

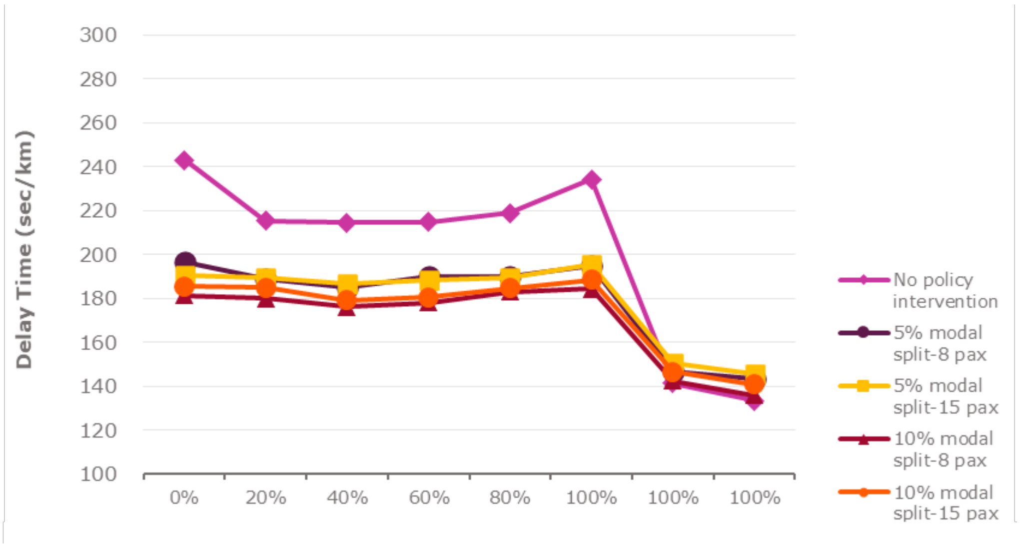


Figure 4.9: Delay time for on-demand AUSS

4.3 Modal split using public transport, modal split using active travel and shared mobility rate

4.3.1 Mesoscopic simulation

In the mesoscopic simulation, agents maintain their activity chains and activity locations across all scenarios. For this reason, general trends of increasing or decreasing travel demand cannot be represented in this simulation. However, the mode that agents may use may change if the new transportation options in the scenarios result in higher individual utility. This is why modal shifts have been analysed for all simulated scenarios.

A sharp increase in AUSS as the longest distance mode is observed for all sub-use cases and fleet sizes when private CAVs are introduced. In Scenario A, AUSSs always have a relatively small share. The additional ridership for AUSSs mainly comes from existing car drivers. When private CAVs are introduced, up to 3.7% of agents no longer use their cars. Interestingly, active modes also increase in the modal split. There is a very weak linear effect at different AV market penetration rates: as the share of conventional cars decreases, the share of AUSS in the modal share increases. Once all private cars are CAVs, the share of AUSS remains at the same level. The reduction in public transport can be considered nearly constant across all fleet splitting rates and appears to be independent of the proportion of cautious and aggressive CAVs.

A higher fleet size leads to a higher share of AUSS. The additional ridership is mainly cannibalized by public transport riders and car users. The increase in active traffic decreases slighlty.

Last-mile AUSS leads to a similar decline in car users as demand-responsive AUSS. However, there are many fewer car drivers who switch to the new mode. In addition, even more people are switching to active modes. The reason for the overall low share of last-mile AUSS is that travel distances are more limited due to the restricted operating area.

For Figures 4.10 to 4.13, the black frame indicates the modal split of the scenarios with no introduction of AUSS shuttle while the numbers show the modal shifts (top: car, middle: pt, bottom: walk and bike).

4.3.1.1 Anywhere-to-anywhere AUSS

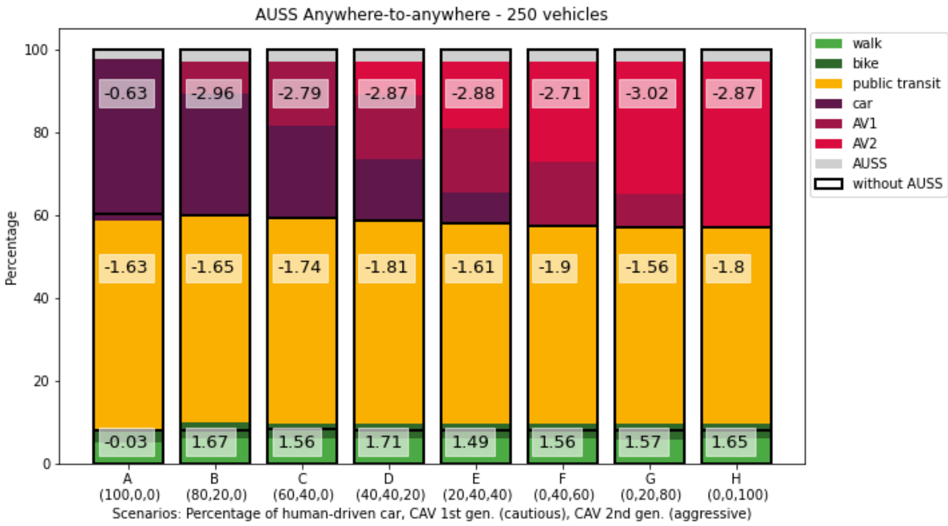


Figure 4.10: Modal Splits of trip distances per longest distance mode for all market penetration rates of the anywhere-to-anywhere AUSS scenarios with a fleet size of 250 vehicles.

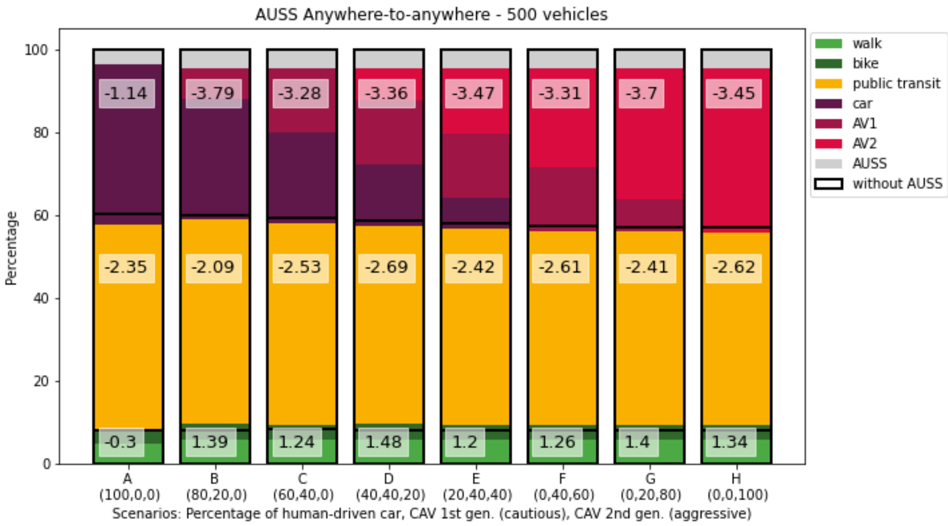


Figure 4.11: Modal Splits of trip distances per longest distance mode for all market penetration rates of the anywhere-to-anywhere AUSS scenarios with a fleet size of 500 vehicles.

4.3.1.2 Last-mile AUSS

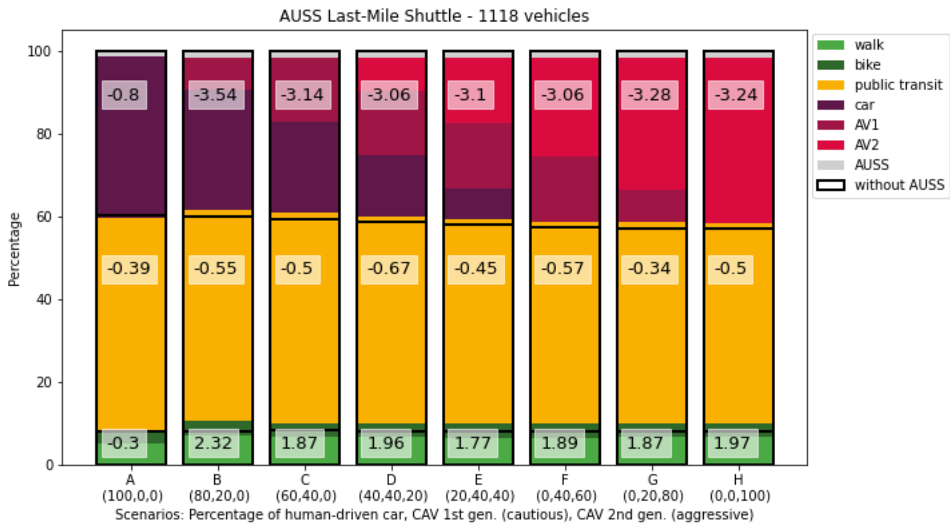


Figure 4.12: Modal Splits of trip distances per longest distance mode for all market penetration rates of the last-mile AUSS scenarios with a fleet size of 1118 vehicles.

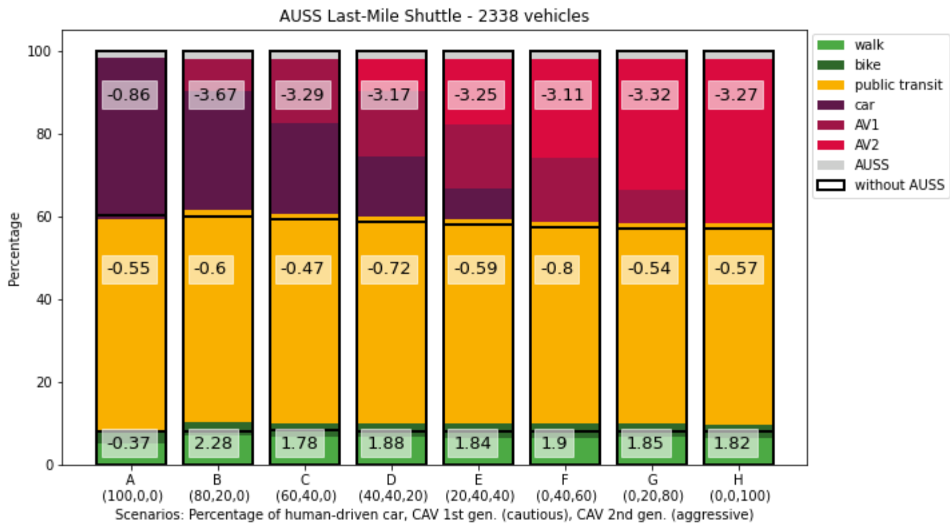


Figure 4.13: Modal Splits of trip distances per longest distance mode for all market penetration rates of the last-mile AUSS scenarios with a fleet size of 2338 vehicles.

4.3.2 Delphi method

The impact of the introduction of automation in urban transport on modal split using public transport (percentage of trip distance made using public transportation) is also estimated by the Delphi method. According to the 1st round replies, point-to-point AUSS and e-hailing will not affect modal split using public transport regardless of the AVs market penetration rates. The baseline scenario (no intervention) leads to a reduction of 32,4% on modal split using public transport since more people will tend to use automated vehicles instead of public transport, given the fact that automation will also increase access to travel (mentioned in deliverable 5.2). The introduction of anywhere-to-anywhere AUSS will also reduce modal split using public transport reaching -18,2% for 100% AVs market penetration rate, according to experts, since more people will prefer to use this automated service instead of the conventional public transport services. On the other hand, the introduction of last-mile AUSS will increase modal split using public transport given the fact that last-mile services will make public transport (buses, metros, trains, etc.) more accessible reaching an increase of 24,6% for 100% AVs market penetration rate.

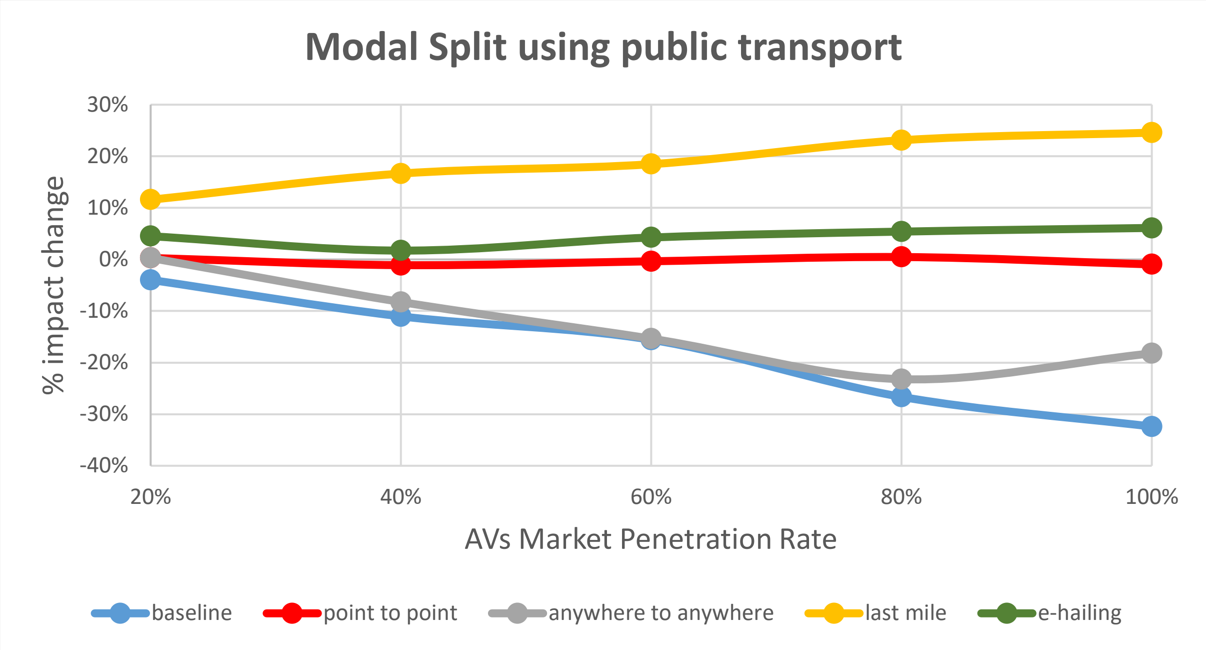


Figure 4.14: 1st round Delphi modal split using public transport results

The majority of the 2nd round participants stated that they agree definitely (33%-56%) or moderately (44%-67%) with the resulted trends. Regarding the 1st round results of the point-to-point AUSS and anywhere to anywhere AUSS 11% of experts suggested that they slightly agree with the curves and proposed an average percentage of 10% and 25% respectively. On the other hand, 11% of experts stated that they do not at all agree with the results of e-hailing and suggested that e-hailing will have a negative impact on modal split using public transport as this intervention will replace more public transport than it supports.

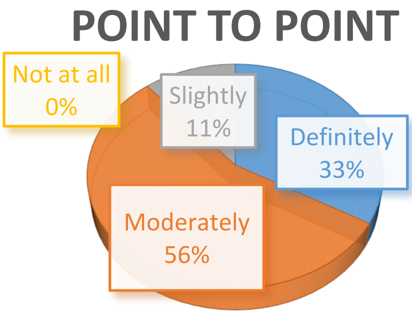


Figure 4.15: 2nd round Delphi results point-to-point AUSS scenario

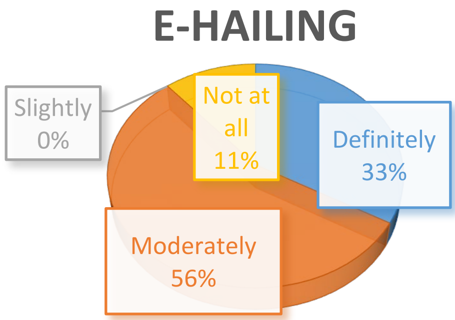


Figure 4.16: 2nd round Delphi results e-hailing scenario

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

Table 4.1: Final PST coefficients for modal split using public transport

	Baseline		Point-to-point AUSS		Anywhere to anywhere AUSS		Last-mile AUSS		E-hailing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	-3,8%	0,962	0,7%	1,007	1,4%	1,014	11,1%	1,111	3,7%	1,037
40%	-10,6%	0,894	-0,6%	0,994	-6,8%	0,932	15,9%	1,159	1,1%	1,011
60%	-14,9%	0,851	0,1%	1,001	-13,6%	0,864	17,7%	1,177	3,4%	1,034
80%	-25,5%	0,745	0,9%	1,009	-21,1%	0,789	22,1%	1,221	4,5%	1,045
100%	-31,0%	0,690	-0,5%	0,995	-16,3%	0,837	23,5%	1,235	5,1%	1,051

The impact of the automated urban transport services on modal split using active travel (% of trip distance made using active transportation (walking, cycling)) has been also estimated using the Delphi method. According to experts, point-to-point AUSS and last-mile AUSS will not affect modal split using public transport. The baseline scenario as well as e-hailing and anywhere to anywhere AUSS will tend to have a negative impact on modal split using active travel especially as the AVs market penetration rate increases, reaching -18,8%, -22,1% and -21,7% respectively for 100% AVs market penetration rate. This reduction of modal split using active travel is explained by the fact that using automated vehicles and the anywhere-to-anywhere services people will not have to walk or cycle to their destination as door-to-door travel will be possible.

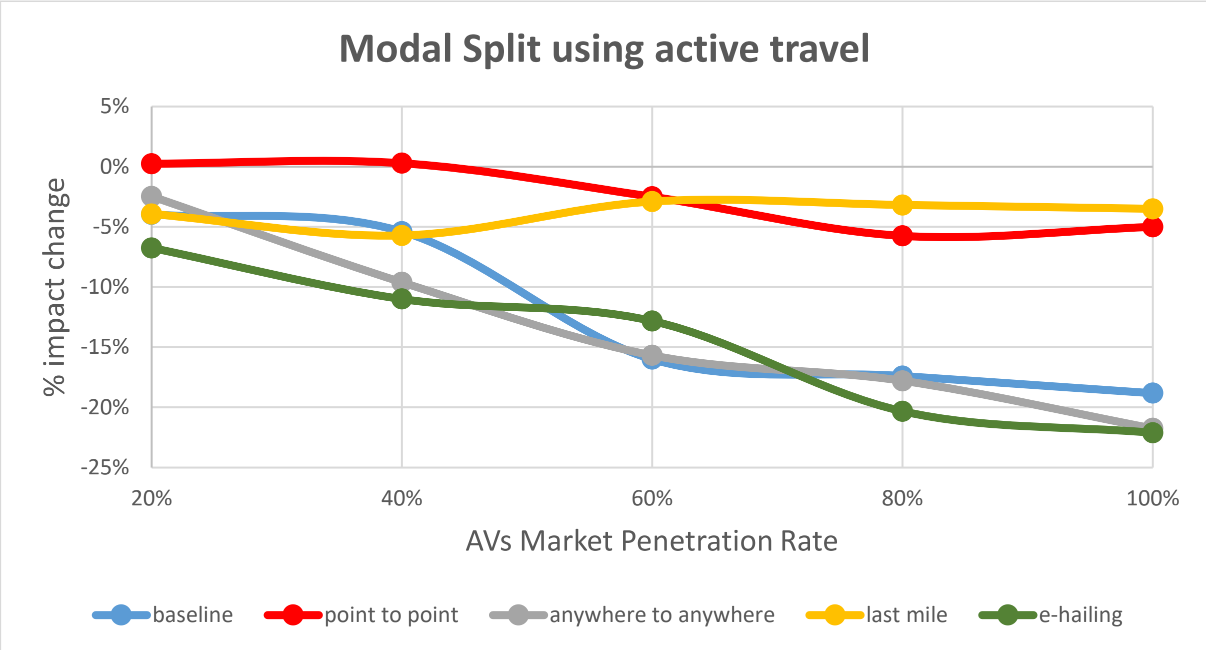


Figure 4.17: 1st round Delphi modal split using active travel results

In the second Delphi round experts stated that they agree definitely (44% & 45%) or moderately (44% & 56%) with the curves of the 1st round. Regarding the point-to-point AUSS and last-mile AUSS trends 11% of experts stated that they slightly agree with the 1st round results and suggested that both SUCs will also affect negatively (-20%) modal split using active travel.

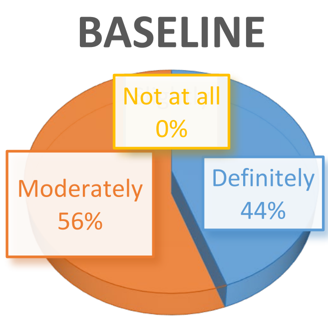


Figure 4.18: 2nd round Delphi results Baseline scenario

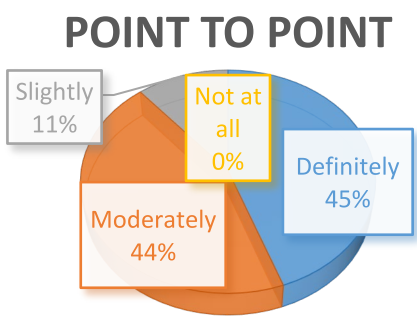


Figure 4.19: 2nd round Delphi results point-to-point AUSS scenario

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

Table 4.2: Final PST coefficients for modal split using active travel

	Baseline		Point-to-point AUSS		Anywhere to anywhere AUSS		Last-mile AUSS		E-hailing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	-3,4%	0,966	-0,6%	0,994	-1,7%	0,983	-4,5%	0,955	-5,6%	0,944
40%	-4,7%	0,953	-0,6%	0,994	-8,5%	0,915	-6,1%	0,939	-9,7%	0,903
60%	-14,9%	0,851	-3,2%	0,968	-14,3%	0,857	-3,5%	0,965	-11,4%	0,886
80%	-16,2%	0,838	-6,1%	0,939	-16,4%	0,836	-3,8%	0,962	-18,6%	0,814
100%	-17,6%	0,824	-5,4%	0,946	-20,2%	0,798	-4,1%	0,959	-20,3%	0,797

Using the Delphi method, the impact of automation on shared mobility rate (% of trips made sharing a vehicle with others) has been estimated. According to experts shared mobility rate will be increased after the introduction of AVs in the baseline scenario, as well as after the implementation of the automated urban transport interventions. More precisely, for 100% AVs market penetration rate shared mobility rate will increase by 26% for the baseline scenario. Point-to-point AUSS will increase shared mobility rate by 24,7% for 100% AVs market penetration rate, anywhere to anywhere AUSS will lead to an increase shared mobility rate by 15,4% for 100% AVs market penetration rate and last-mile AUSS will increase the studied impact by 19,3%. Finally, the e-hailing sub-use case will not affect shared mobility rate based on the experts' answers in the 1st round.

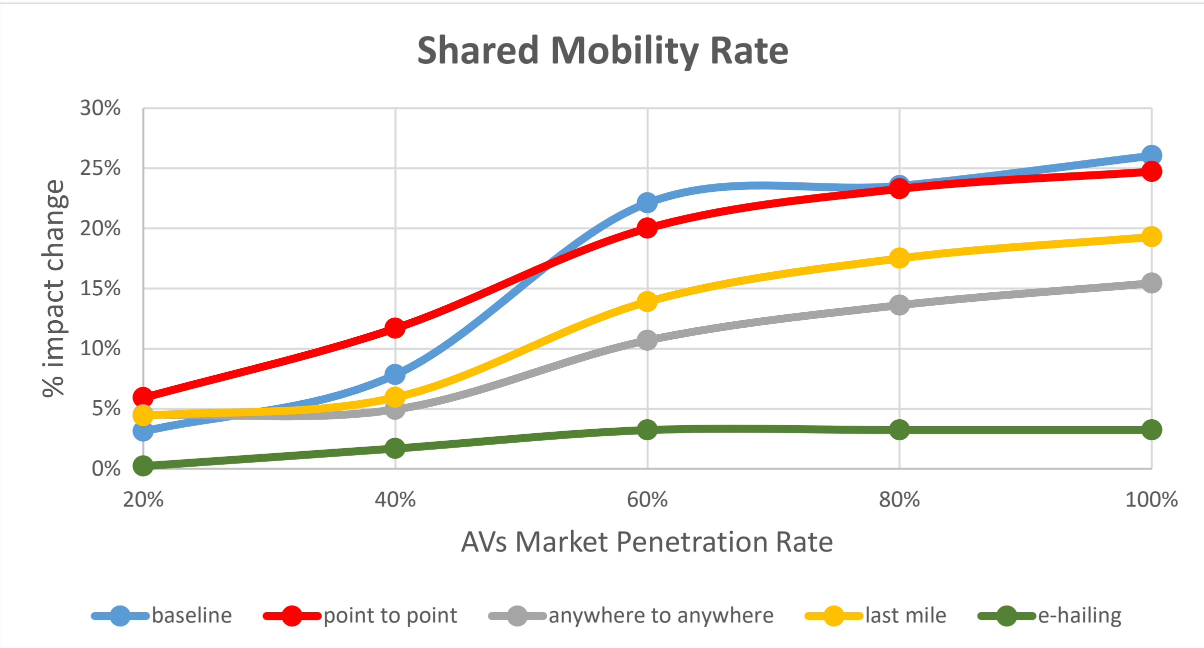


Figure 4.20: 1st round Delphi shared mobility rate results

In the 2nd round questionnaires, the majority of experts agreed definitely (44% & 45%) or moderately (44% & 56%) with the first-round curves. Regarding the baseline scenario, 11% of experts stated that they not at all agree with the proposed trend, commenting that this impact would be negative by 50% since people will not have to share their AV with a driver as well as there will be no more the need to escort kids, the elderly, etc.

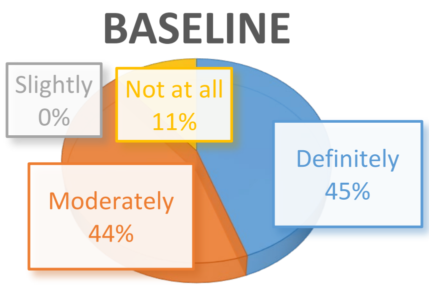


Figure 4.21: 2nd round Delphi results Baseline scenario

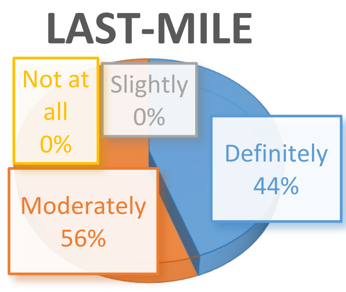


Figure 4.22: 2nd round Delphi results last-mile AUSS scenario

These suggestions have been taken into consideration in order to form the final coefficients to be introduced in the PST.

Table 4.3: Final PST coefficients for shared mobility rate

	Baseline		Point-to-point AUSS		Anywhere to anywhere AUSS		Last-mile AUSS		E-hailing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	0,7%	1,007	5,6%	1,056	4,3%	1,043	4,2%	1,042	0,2%	1,002
40%	5,0%	1,050	11,2%	1,112	4,7%	1,047	5,7%	1,057	1,6%	1,016
60%	18,0%	1,180	19,1%	1,191	10,2%	1,102	13,3%	1,133	3,1%	1,031
80%	19,3%	1,193	22,3%	1,223	13,0%	1,130	16,7%	1,167	3,1%	1,031
100%	21,6%	1,216	23,6%	1,236	14,8%	1,148	18,4%	1,184	3,1%	1,031

4.4 Vehicle utilization rate

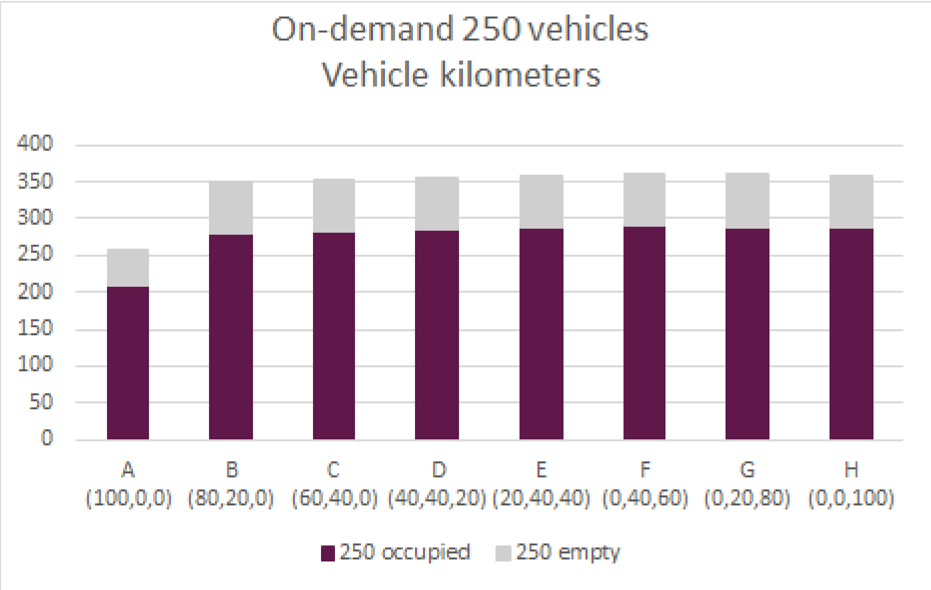
4.4.1 Mesoscopic simulation

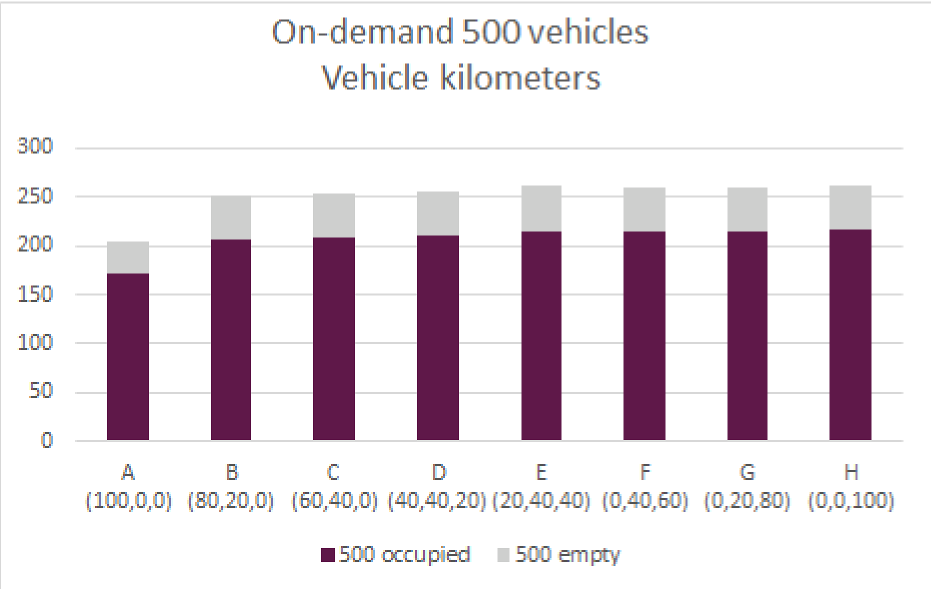
In the mesoscopic simulation, we refer to the vehicle utilization rate as the vehicle kilometers that an AUSS was transporting passengers and performing service trips (empty kilometers).
The fewer AUSS vehicles are available, the higher is the average trip distance per vehicle. In the case of anywhere-to-anywhere AUSS, it ranges from 250 to more than 350 km/vehicle for smaller fleet sizes and from 200 to more than 250 km/vehicle for larger

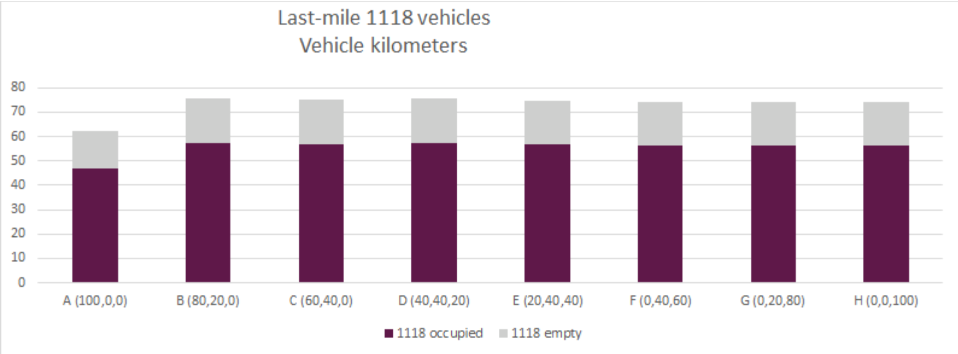
fleet sizes. For the last-mile AUSS, the average distance of a vehicle is only part of that in the anywhere-to-anywhere AUSS. It ranges from 60 to 80 km/vehicle for small fleet sizes and 30 to 40 km/vehicle for larger fleets.

Distances remain nearly the same once private CAVs are introduced and increase only slightly with a higher proportion of aggressive CAVs.

The proportion of empty vehicle miles is lower for smaller fleet sizes. This is due to better availability of AUSS vehicles, which leads to a higher number of service trips. AUSS empty vehicle miles also increase for all sub-use cases with a higher CAV market penetration rate.







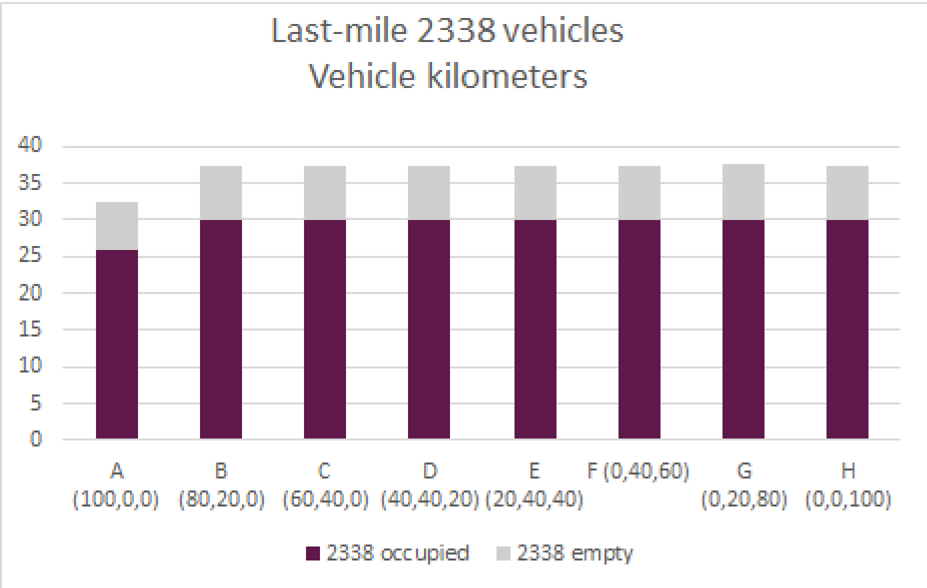


Figure 4.23: Average kilometers driven per vehicle (km/veh) for the different fleet sizes and different scenarios.

4.4.2 Delphi method

Vehicle utilisation rate is considered as the percentage of time a vehicle is in motion (i.e. not parked). The impact of the introduction of automation in urban transport is calculated based on the experts' answers in the Delphi questionnaires. The overall experts' opinion is that the introduction of automation in the urban environment will lead to an increase of vehicle utilisation rate, which is compatible with the resulted impact on access to travel, on the amount of travel (chapter 4.1) and on modal split. More precisely, the baseline scenario (no intervention) will have the biggest impact on vehicle utilisation rate leading to an increase of 43,6% for AVs market penetration of 100%. Regarding the automated urban transport interventions, point-to-point AUSS, anywhere to anywhere AUSS and e-hailing they will lead to an increase of vehicle utilisation rate of 20,8%, 37,5% and 23,2% respectively for 100% AVs market penetration rate.

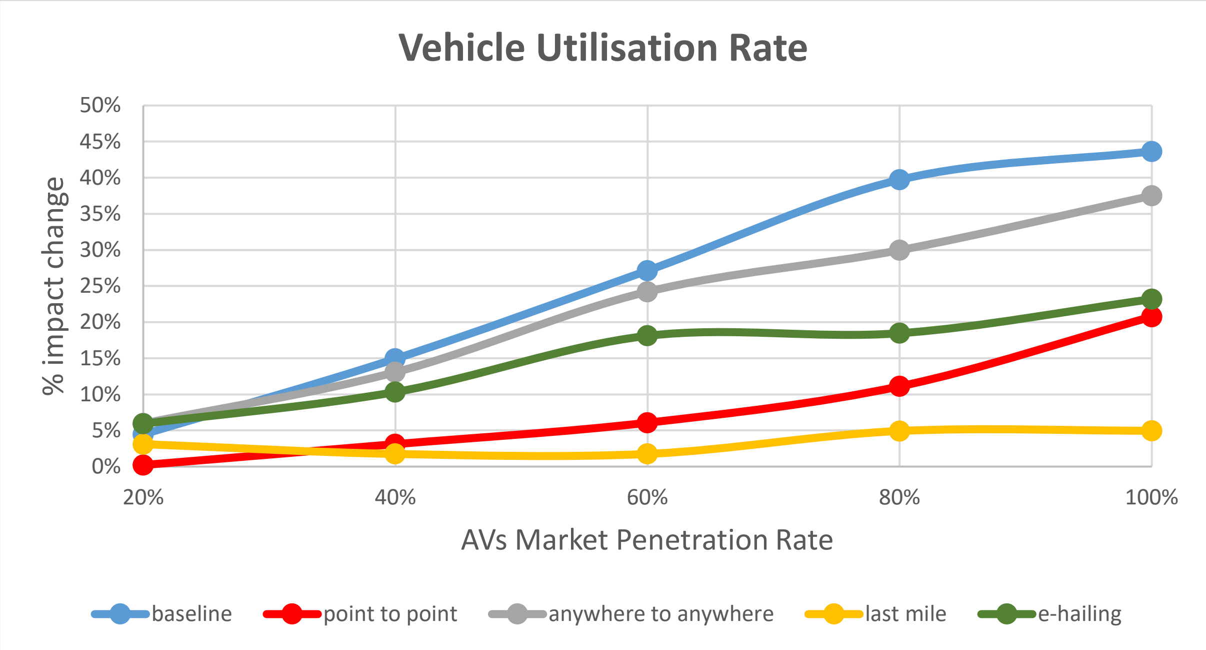


Figure 4.24: 1st round Delphi vehicle utilisation rate results

According to the 1st round results, last-mile AUSS will not affect shared mobility rate, but on the 2nd round questionnaires 11% of experts suggested that this sub-use case would also lead to a 50% increase of vehicle utilisation rate. Regarding the other scenarios the 2nd round results indicated that experts agreed definitely (33%-56%) or moderately (44%-56%) with the resulted trends.

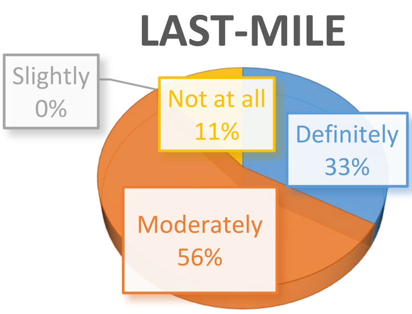


Figure 4.25: 2nd round Delphi results last-mile AUSS scenario

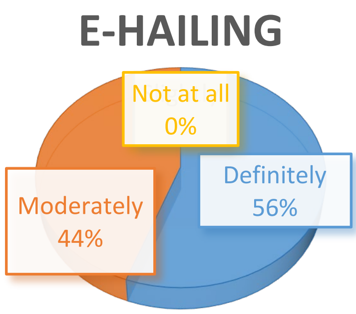


Figure 4.26: 2nd round Delphi results e-hailing scenario

Table 4.4: Final PST coefficients for vehicle utilisation rate

	Baseline		Point-to-point AUSS		Anywhere to anywhere AUSS		Last-mile AUSS		E-hailing	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	4,3%	1,043	0,2%	1,002	5,7%	1,057	5,1%	1,051	5,7%	1,057
40%	14,3%	1,143	3,0%	1,030	12,5%	1,125	3,8%	1,038	9,9%	1,099
60%	26,0%	1,260	5,8%	1,058	23,2%	1,232	3,8%	1,038	17,3%	1,173
80%	38,0%	1,380	10,6%	1,106	28,7%	1,287	6,9%	1,069	17,7%	1,177
100%	41,7%	1,417	19,8%	1,198	35,9%	1,359	6,9%	1,069	22,2%	1,222

4.5 Vehicle occupancy

4.5.1 Mesoscopic simulation

In the mesoscopic simulation, ridesharing for private vehicles is not implemented. Therefore, the vehicle occupancy in the baseline is 1 and cannot be taken as a valid reference for comparison. This is the reason why the presented numbers in following refer to the AUSS only.

Figure 4.27 shows the utilization rate of the demand-driven AUSS which corresponds to the average utilization rate of private vehicles in Austria (1.3, Tomschy et al., 2016). In all scenarios of the last-mile scenario, the utilization rates are lower. The reason is that sharing a vehicle with other passengers is not as useful for these short trips. The larger the AUSS fleet, the higher the vehicle occupancy rate tends to be. There are no significant changes for different CAV market penetration rates.

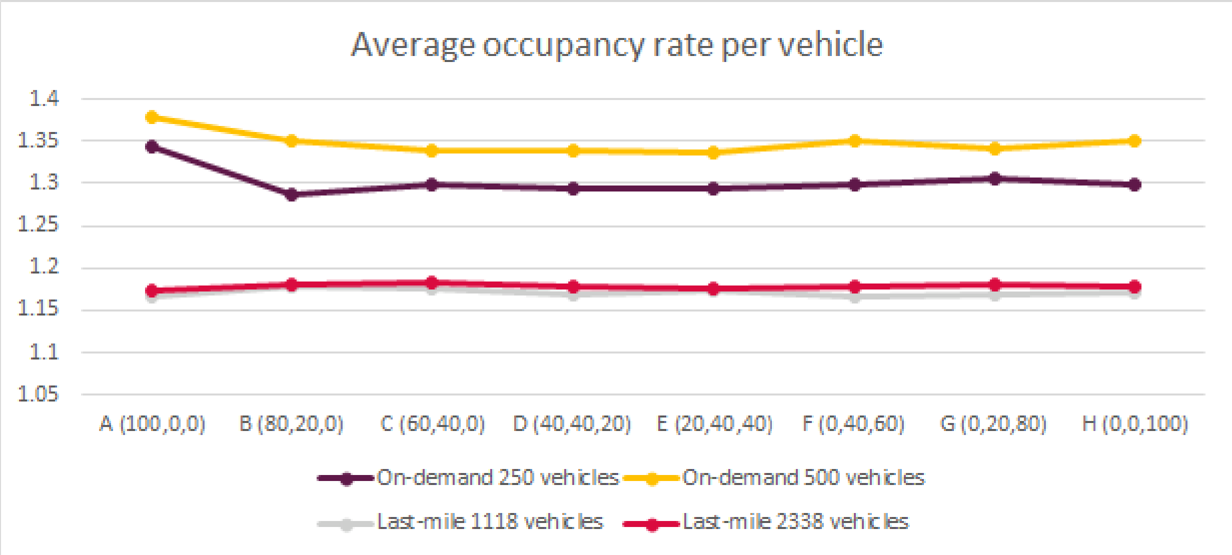


Figure 4.27: Average vehicle occupancy rate [person/vehicle] for AUSS shuttles with a maximum occupancy of 4 people/vehicle.

4.5.2 Delphi method

The Delphi method was also used to estimate the impact of automation on vehicle occupancy (average % of seats in use). According to experts e-hailing and anywhere to anywhere to anywhere AUSS will not affect vehicle occupancy. On the other hand, the introduction of AVs (baseline scenario), point-to-point AUSS and last-mile AUSS will increase progressively vehicle occupancy reaching 20,8%, 20,4% and 16,4% respectively for 100% AVs market penetration rate.

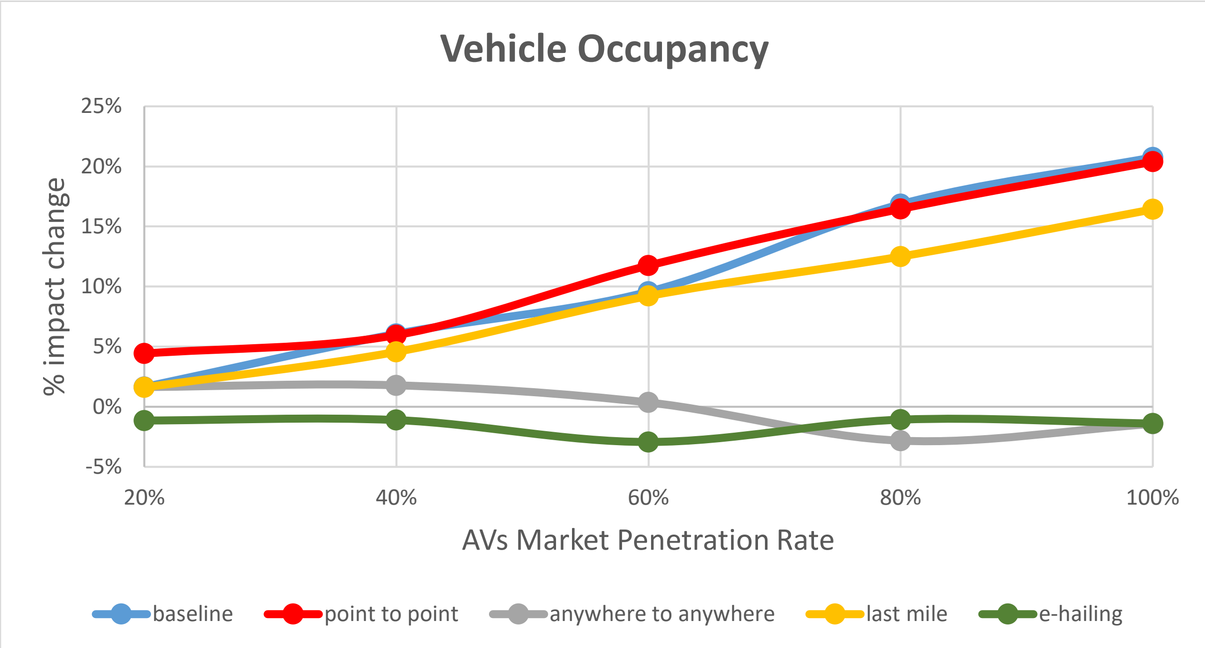


Figure 4.28: 1st round Delphi vehicle occupancy results

In the 2nd round of Delphi questionnaires, the majority of experts stated that they agree definitely (33%-56%) or moderately (with the resulted curves. Regarding point-to-point AUSS 11% of experts suggested that they slightly agree with 1st round results because after implementing this sub-use case vehicle occupancy will be reduced by 30% since more people will use this service instead of the vehicles.

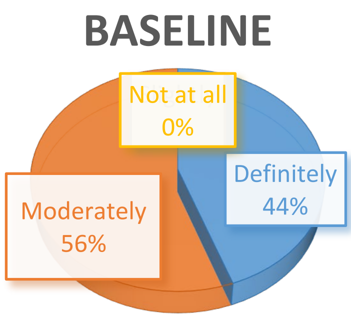


Figure 4.29: 2nd round Delphi results Baseline scenario

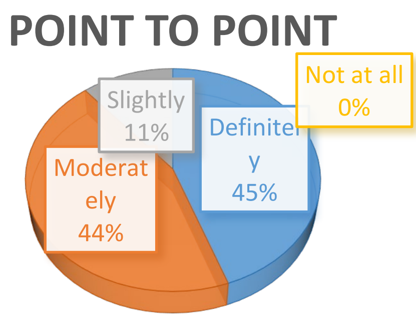


Figure 4.30: 2nd round Delphi results point-to-point AUSS scenario

Table 4.5: Final PST coefficients for vehicle occupancy

	Baseline		**Point-to-point AUSS**		**Anywhere to anywhere AUSS**		**Last-mile AUSS**		**E-hailing**	
AV penetration rates	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients	Aggregate change	PST coefficients
20%	1,6%	1,016	2,9%	1,029	1,6%	1,016	1,5%	1,015	-1,1%	0,989
40%	5,8%	1,058	4,4%	1,044	1,7%	1,017	4,4%	1,044	-1,1%	0,989
60%	9,2%	1,092	9,9%	1,099	0,3%	1,003	8,8%	1,088	-2,8%	0,972
80%	16,1%	1,161	14,4%	1,144	-2,7%	0,973	12,0%	1,120	-1,0%	0,990
100%	19,8%	1,198	18,2%	1,182	-1,4%	0,986	15,7%	1,157	-1,3%	0,987

5 Discussion

Overall, the analyses regarding the medium-term impacts of CCAM in urban transport reveal several interesting findings. Regarding the studied automated urban transport SUCs both methods, mesoscopic and microscopic simulation, suggested that the amount of travel will reduce with the increase of AVs MPRs. Thus, if implemented, the proposed services will contribute to the amelioration of traffic conditions and the reduction of delay times. The mesoscopic simulation indicated that there will be a slight increase of modal split using active travel and a reduction of public transport use, when the anywhere to anywhere and last-mile AUSS are introduced. On the other, the Delphi method, presents different results for modal split depending on the intervention, suggesting that the anywhere-to-anywhere AUSS will have a negative impact on modal split using public transport and active travel, and that the last mile AUSS will enhance the use of public transport and active travel. The point-to-point AUSS will not significantly affect modal split allocations, and e-hailing will lead to the reduction the use of active travel modes. Regarding, the shared mobility rate, experts in the Delphi method agree with the mesoscopic simulation results, that indicate an increase of shared mobility rate with the increase of CAV MPRs and the introduction of the different automated urban shuttle services. Vehicle utilization rate will increase with the increase of AVs MPRs which is compatible with the aforementioned impact on modal split. Vehicle occupancy is expected to increase for all studied scenarios based on the mesoscopic simulation and the Delphi method results.

One of the most important effects that the advent of automation is expected to have in the urban environment is the amelioration of traffic conditions. The results of microscopic and mesoscopic simulation suggesting the reduction of the total distance travelled and of delay time after the introduction of the studied automated urban shuttle services, are also supported by the literature. More precisely, during the transition period when vehicles of various automation levels will share the roads along with conventional vehicles, travel time may increase. In contrast, when the CAV MPR reaches higher levels, the connected systems will self-balance and optimize traffic flow and reduce congestion (Folsom, 2012). The International Transport Forum (2015), simulated different scenarios of automated transport systems, penetration rates and availability of high-capacity public transport. This report stated that automated shuttles could replace conventional vehicles, offering equal levels of mobility with up to 89.6% (65% during rush hour) fewer vehicles on the roads, reducing congestion. Finally, according to the outcomes of hypothetical and realistic simulations in the city of Zurich, one shared automated vehicle could replace approximately 10 to 14 conventional (unshared) vehicles contributing to the amelioration of traffic conditions (Boesch et al., 2016; Zhang et al., 2015).

Regarding modal split and ridesharing the mesoscopic simulation and Delphi method present different results for the different automated shuttle services. These results are also supported by the literature. Studies have shown that the introduction of automation in the urban environment will increase sharing which will lead to a slight overall decline in public transit use and an increase in alternative modes, such as walking, bicycling, and carpooling (Martin & Shaheen, 2011). On the other hand, experts in the Delphi method suggested that the anywhere to anywhere-to-anywhere AUSS will in fact reduce modal split using public transport and active travel since using these services people will not have to walk or cycle to their destination as door-to-door travel will be possible. Studies that investigate impacts on mode share by modelling a competition of CAVs with currently existing modes mostly indicate that AVs lead to a reduction in public transport and slow modes share (Correia & van Arem, 2016; Kim et al., 2015a; Kröger et al., 2018). Additionally, the introduction of automated shuttle services such as the anywhere-to-anywhere AUSS lead to the reduction of the use of public transport and also lower the private car modal split (Boesch et al., 2018). The increase of CAV MPR will also increase the private AV availability for all (even people without driving license, children, elderly and mobility-impaired people), leading to an increase of private car share (Soteropoulos et al., 2019). These studies also support the increased vehicle utilization rate and vehicle occupancy that was indicated by the mesoscopic simulation and the Delphi method. Studies on last-mile AUSS which assume a complete ban of privately owned vehicles and high operating costs of conventional vehicles (Childress et al., 2015; Heilig et al., 2016) report increases in public transport and slow mode shares because of people using these services for short trips to avoid costs. All relevant studies results are strongly dependent on model assumptions, and the same applies to the LEVITATE methodology.

Naturally, the present impact assessment approach adopted within LEVITATE has some limitations. First of all, a certain degree of uncertainty is underlying in every method, while this quantity is inherently different for each method. Additionally, each quantitative method has different parameters and is applied in a different city model, for example the mesoscopic simulation is using the MATSim model for Vienna (presented in LEVITATE D5.2) and the microscopic simulation considers the AIMSUN model for Athens, partly due to the resources in which the LEVITATE partners had access to. Regarding the Delphi method, limitations are posed by the number of experts, and the accuracy of their estimations. Thus, the Delphi results will be used to fill in the PST when no other method can provide outputs. Approaches such as Delphi can be updated when the CCAM reach increased maturity and revisited for future efforts either in projects such as LEVITATE or in broader research. Furthermore, all methods are bound to specific MPR scenarios, with the aim to create a functional PST, and thus the results lack degrees of freedom they might otherwise have. Finally, another limitation of the LEVITATE project is that there was enough capacity to examine only two CAV profiles, even though it is probable that much more granular CAV profiles will function in the future network. Ultimately, the PST user will be informed regarding transferability of results and will be able to receive an educated estimate of how to use these results for CCAM-related predictions or design.

6 Conclusions and future work

6.1 Conclusions

The advent of automation is expected to considerably transform the transport market. For transport researchers, practitioners and stakeholders alike, it is prudent to anticipate and plan for the impacts that the introduction of automation will introduce. For the purposes of this project, short-, medium- and long-term impacts would be those defined by Deliverable 3.1 (Elvik et al., 2019) as direct, systemic and wider impacts, respectively. Based on that taxonomy, seven impacts were considered as medium-term/systemic and presented in this report; namely amount of travel, congestion, modal split using public transport, modal split using active travel, shared mobility rate, vehicle utilization rate and vehicle occupancy. Three methods were used in order to quantify these impacts; microscopic simulation, mesoscopic simulation and the Delphi panel method.

The results demonstrated that the introduction of CCAMs in the urban transport will reduce congestion and the amount of travel, especially for high CAV market penetration rates since more people will use the urban transport services thus reducing traffic. Modal split using public transport is expected to slightly increase since the last-mile AUSS will connect various public transport stations with suburban areas or lower-density areas. On the other hand, active travel may be negatively affected due to the more transport possibilities that will be available. The shared mobility rate, vehicle utilization rate and vehicle occupancy will significantly increase after the implementation of the on demand AUSS since more people will be able to travel using urban transport even if they do not possess a private vehicle. The majority of the Delphi method participants agreed definitely or moderately with the resulted trends for all the impacts and all the studied SUCs, verifying that the obtained results are reasonable, as it was also supported by the literature.

6.2 Future work

Further work to be carried out in WP5 includes the following tasks:

1. Analysis of long-term impacts using appropriate methodologies (Task 5.4).
2. Formulation of policy recommendations (Task 5.5).
3. Provision of input to WP8 for the development of the PST regarding urban transport.

Task 5.4 will assess long-term impacts, as they are presented in Deliverable 3.1 of LEVITATE (Elvik et al., 2019). Each type of impact will be forecasted using the appropriate assessment methods. These methods are microscopic simulations used to identify the medium-term impacts, system dynamics that is a system level analysis providing long-term impacts analysis, and the Delphi method for the impacts that the aforementioned methods cannot quantify. The impact assessment outcomes will be synthetized in Task 5.5 in order to provide a comprehensive overview of the impacts of CCAM in urban transport and produce guidelines and policy recommendations. All the obtained results will inform the PST development and will be integrated into WP8 for the creation of the online dynamic tool.

References

Ararat, O. and Aksun-Guvenc, B. "Development of a collision avoidance algorithm using elastic band theory." Proceedings of the seventeenth IFAC world congress, 2008, p. 8520–5.

Boesch, P. M., Ciari, F., & Axhausen, K. W. (2018). Transport policy optimization with autonomous vehicles. Transportation Research Record, 2672(8), 698-707.

Boesch, P. M., & Ciari, F. (2015). Agent-based simulation of autonomous cars. Proceedings of the American Control Conference, 2015–July, 2588–2592. https://doi.org/10.1109/ACC.2015.7171123

Bootsma G. and Koolen R. "What moves people? evaluation of the application and appreciation of the peoplemover capelle-rivium, the netherlands." In Association for European Transport., 2001.

Cao, Z. and Ceder, A. "Autonomous shuttle bus service timetabling and vehicle scheduling using skip-stop tactic", Transportation Research Part C: Emerging Technologies, Volume 102, 2019, Pages 370-395.

Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. Transportation Research Record, 2493(1), 99-106.

Chong, Z. J., Qin, B., Bandyopadhyay, T., Wongpiromsarn, T., Rebsamen, B., Dai, P., Rankin, E. S. and Ang, M. H. "Autonomy for mobility on demand. In Intelligent Autonomous Systems", 12: Volume 1 Proceedings of the 12th International Conference IAS-12, pages 671–682. Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.

Correia, G., & van Arem, B. (2016). Solving the user optimum privately owned automated vehicles assignment problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. Transportation Research Part B, 87, 64–88. doi: 10.1016/j.trb.2016.03.002

Cybercars project. url: www.2getthere.eu.

Cybercars2 project. url: cybercars2.paris-rocquencourt.inria.fr.

CyberCars2, 2009. Final report. Close Communications for Co-operation Between CyberCars

Diethelm, I., Geiger, L. and Zündorf, A. "Applying Story Driven Modeling to the Paderborn Shuttle System Case Study." In: Leue S., Systä T.J. (eds) Scenarios: Models, Transformations and Tools. Lecture Notes in Computer Science, 2005, vol 3466. Springer, Berlin, Heidelberg

Elvik, R. Quddus, M. Papadoulis, A. Cleij, D. Weijermars, W. A. M. Millonig, A. Vorwagner, A. Hu, and P. B & Nitsche. "LEVITATE Societal Level Impacts of Connected and Automated Vehicles. Deliverable D3. 1 of the H2020 project LEVITATE: A taxonomy of potential impacts of connected and automated vehicles at different levels of implementation." (2019).

European Commission, (2017). Towards clean, competitive and connected mobility: the contribution of Transport Research and Innovation to the Mobility package, SWD (2017) 223 final.

Emirler, M.T., Wang, H. and Aksun-Guvenc, B. "Socially acceptable collision avoidance system for vulnerable road users Istanbul Turkey", IFAC control in transportation systems, May 18-20, 2016.

Firnkorn, J. and Müller, M., (2015). 'Free-Floating Electric Carsharing-Fleets in Smart Cities: The Dawning of a Post-Private Car Era in Urban Environments?', Environmental Science & Policy, Vol. 45, pp. 30-40.

Folsom, T. (2012). Energy and Autonomous Urban Land Vehicles. IEEE Technology and Society Magazine, 31(2), 28–38. https://doi.org/10.1109/MTS.2012.2196339

Gelbal, S., Chandramouli, N., Wang, H., Aksun-Guvenc, B. and Guvenc, L. "A unified architecture for scalable and replicable autonomous shuttles in a smart city.", 2017, 3391-3396.

Giese, H. and Klein, F. "Autonomous Shuttle System Case Study. In: Leue S., Systä T.J. (eds) Scenarios: Models, Transformations and Tools. Lecture Notes in Computer Science, 2005, vol 3466. Springer, Berlin, Heidelberg

Heilig, M., Hilgert, T., Mallig, N., Kagerbauer, M., & Vortisch, P. (2017). Potentials of autonomous vehicles in a changing private transportation system–a case study in the Stuttgart region. Transportation research procedia, 26, 13-21.

Ho, C. Q., Mulley, C., Shiftan, Y., & Hensher, D. A. (2015, September). Value of travel time savings for multiple occupant car: evidence from a group-based modelling approach. In Australasian Transport Research Forum 2015 Proceedings.

Huang, D., Gu, Y., Wang, S., Liu, Z., & Zhang, W. (2020). A two-phase optimization model for the demand-responsive customized bus network design. Transportation Research Part C: Emerging Technologies, 111(March 2019), 1–21. https://doi.org/10.1016/j.trc.2019.12.004

Khendek, F. and Zhang, X.J. "From MSC to SDL: Overview and an Application to the Autonomous Shuttle Transport System.", In: Leue S., Systä T.J. (eds) Scenarios: Models, Transformations and Tools. Lecture Notes in Computer Science, 2005, vol 3466. Springer, Berlin, Heidelberg

Kim, K. H., Yook, D. H., Ko, Y. S., & Kim, D. H. (2015). An analysis of expected effects of the autonomous vehicles on transport and land use in Korea. New York University: New York, NY, USA.

Kröger, L., Kuhnimhof, T., & Trommer, S. (2019). Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. Transportation research part A: policy and practice, 122, 146-161.

Linares, M. P., Barceló, J., Carmona, C., & Montero, L. (2017). Analysis and Operational Challenges of Dynamic Ride Sharing Demand Responsive Transportation Models. Transportation Research Procedia, 21, 110–129. https://doi.org/10.1016/j.trpro.2017.03.082

Liyanage, S., & Dia, H. (2020). An Agent-Based Simulation Approach for Evaluating the Performance of On-Demand Bus Services. Sustainability, 12(10), 4117. https://doi.org/10.3390/su12104117

Lu, Q., Tettamanti, T., Hörcher, D., & Varga, I. (2020). The impact of autonomous vehicles on urban traffic network capacity: an experimental analysis by microscopic traffic simulation. Transportation Letters, 12(8), 540–549. https://doi.org/10.1080/19427867.2019.1662561

Martin E, Shaheen S (2011) The impact of carsharing on public transit and non-motorized travel: an exploration of North American carsharing survey data. Energies 4:2094–2114

Mathieu, L. (2020). Recharge EU: how many charge points will Europe and its Member States need in the 2020s. In Transport and Environment.

Maurer, M., Gerdes, J. C., Lenz, B., & Winner, H. (2016). Autonomous driving: Technical, legal and social aspects. In Autonomous Driving: Technical, Legal and Social Aspects. https://doi.org/10.1007/978-3-662-48847-8

Mourad, A., Puchinger, J., & Chu, C. (2019). A survey of models and algorithms for optimizing shared mobility. Transportation Research Part B: Methodological, 123, 323–346. https://doi.org/10.1016/j.trb.2019.02.003

Müller, J. Straub, M. Naqvi, A. Richter, G. Peer, S. Rudloff, C. (2021) MATSim Model Vienna: Analyzing the Socioeconomic Impacts for Different Fleet Sizes and Pricing Schemes of Shared Autonomous Electric Vehicles. In "Proceedings of the 100th Annual Meeting of the Transportation Research Board" Transportation Research Board, Washington DC, 2021.

Nadimi, N., Amiri, A. M., & Sadri, A. (2021). Introducing novel statistical-based method of screening and combining currently well-known surrogate safety measures. Transportation Letters, 1–11. https://doi.org/10.1080/19427867.2021.1874184

Nesheli, M., Li, L., Palm, M., Shalaby, A. (2021). Driverless shuttle pilots: Lessons for automated transit technology deployment, Case Studies on Transport Policy, Volume 9, Issue 2, Pages 723-742, ISSN 2213-624X, https://doi.org/10.1016/j.cstp.2021.03.010.

OECD/ITF. (2016). Automated and Autonomous Driving: Regulation under Uncertainty.

Ohnemus, M., & Perl, A. (2016). Shared autonomous vehicles: Catalyst of new mobility for the last mile?. Built Environment, 42(4), 589-602.

Oikonomou, M., Orfanou, F., Vlahogianni, E.and G. Yannis, "Impacts of Autonomous Shuttle Services on Traffic, Safety and Environment for Future Mobility Scenarios," 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), Rhodes, Greece, 2020, pp. 1-6, doi: 10.1109/ITSC45102.2020.9294576.

Pakusch, C., & Bossauer, P. (2017). User Acceptance of Fully Autonomous Public Transport Mittelstand 4.0-Kompetenzzentrum Usability View project Einfach Teilen (Easy P2P Carsharing) View project User Acceptance of Fully Autonomous Public Transport. 2(Icete), 52–60. https://doi.org/10.5220/0006472900520060

Panis, I. L., Broekx, S., & Liu, R. (2006). Modelling instantaneous traffic emission and the influence of traffic speed limits. Science of the Total Environment, 371(1–3), 270–285. https://doi.org/10.1016/j.scitotenv.2006.08.017

Papadoulis, A., Quddus, M., & Imprialou, M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. Accident Analysis & Prevention, 124, 12–22. https://doi.org/10.1016/j.aap.2018.12.019

Parent M. and Bleijs, C. "The cycab : an electric vehicle specifically designed for car-free cities.", In EVS 15 Symposium, 2001.

Parsa, A. B., Shabanpour, R., Mohammadian, A. (Kouros), Auld, J., & Stephens, T. (2020). A data-driven approach to characterize the impact of connected and autonomous vehicles on traffic flow. Transportation Letters, 1–9. https://doi.org/10.1080/19427867.2020.1776956

Popham, K. Transportation Electrification. Smart Cities, 2018

Prokos, A. "Rapport marktonderzoek parking hopper (market research report for the parking hopper)", Technical report, Amsterdam Airport Schiphol, Amsterdam, 1998.

Pruis, J.O. "Evaluatie proefproject parkshuttle: Eindrapport exploitative" (vertrouwelijk) (evaluation of the pilot project parkshuttle: Final report operation), Technical report, ANT, Rotterdam, 2000

Ritter, K. "Driverless electric shuttle being tested in downtown Vegas". [Online], 2017, Available: https://phys.org/news/2017-01- driverless-shuttle-thrill-downtown-las.html.

Romero-gelvez, J. I., Garzon-castro, K. A., & Herrera-cuartas, J. A. (2020). A vehicle routing application for retail delivery with open source tools.

Roussou, J., Papazikou, E., Zwart,R.d., Hu, B., Boghani, H.C., Yannis, G., (2019). Defining the future of urban transport, Deliverable D5.1 of the H2020 project LEVITATE.

Roussou, J., Oikonomou, M., Müller, J., Ziakopoulos, A., Yannis, G., (2021). Short-term impacts of CCAM on urban transport, Deliverable D5.2 of the H2020 project LEVITATE.

Roussou, J., Oikonomou, M., Mourtakos, V., Vlahogianni, E., Ziakopoulos, A., Gebhard, S., Mons, C, Zwart, R.d., Weijermars, W., Zach, M., Chaudhry, A., Hu, B., Yannis, G., (2021). Long-term impacts of CCAM on urban transport, Deliverable D5.4 of the H2020 project LEVITATE.

Salazar, M., Rossi, F., Schiffer, M., Onder, C. and Pavone, M. (2018) "On the Interaction between Autonomous Mobility-on-Demand and Public Transportation Systems".

Shen, Y., Zhang, H., & Zhao, J. (2018). Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. Transportation Research Part A: Policy and Practice, 113(June 2017), 125–136. https://doi.org/10.1016/j.tra.2018.04.004

Simpson, C., Kemp, E., Ataii, E., & Zhang, Y. (2019). Mobility 2030: Transforming the mobility landscape. In KPMG International. https://assets.kpmg/content/dam/kpmg/xx/pdf/2019/02/mobility-2030-transforming-the-mobility-landscape.pdf

Sombuntham, P., Kachitvichyanukul, V., Ao, S.-I., Katagir, H., Xu, L., & Chan, A. H.-S. (2010). Multi-depot Vehicle Routing Problem with Pickup and Delivery Requests. AIP Conference Proceedings, 1285(August), 71–85. https://doi.org/10.1063/1.3510581

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. Transport reviews, 39(1), 29-49.

Straub, M Müller, J., Richter, G. Rosenkranz, P. (2021) MATSim Model Vienna: Open Access. https://github.com/ait-energy/matsim-model-vienna

Úbeda, S., Faulin, J., Serrano, A., & Arcelus, F. J. (2014). Solving the green capacitated vehicle routing problem using a tabu search algorithm. Lecture Notes in Management Science, 6(1), 141–149. www.tadbir.ca

Uber. (2020). Uber. https://www.uber.com/gr/en/

Vernier, M., Redmill, K., Ozguner, U., Kurt, A. and Guvenc, B. A., "Osu smooth in a smart city," in Science of Smart City Operations and Platforms Engineering (SCOPE) in partnership with Global City Teams Challenge, 2016 1st International Workshop on. IEEE, 2016, pp. 1–6.

Vidal, T., Battarra, M., Subramanian, A., & Erdog˘an, G. (2015). Hybrid metaheuristics for the Clustered Vehicle Routing Problem. Computers & Operations Research, 58, 87–99. https://doi.org/10.1016/j.cor.2014.10.019

Wang, H., Tota, A., Aksun-Guvenc, B. and Guvenc, L. "Real time implementation of socially acceptable collision avoidance of a low speed autonomous shuttle using the elastic band method", Mechatronics, Volume 50, 2018, Pages 341-355.

Wang, X., Dessouky, M., & Ordonez, F. (2016). A pickup and delivery problem for ridesharing considering congestion. Transportation Letters, 1–11. https://doi.org/10.1179/1942787515Y.0000000023

Winter, K., Cats, O., Correia, G., & van Arem, B. (2018). Performance analysis and fleet requirements of automated demand-responsive transport systems as an urban public transport service. International Journal of Transportation Science and Technology, 7(2), 151–167. https://doi.org/10.1016/j.ijtst.2018.04.004

Xiong, J., Chen, B., Li, X., He, Z., & Chen, Y. (2020). Demand Responsive Service-based Optimization on Flexible Routes and Departure Time of Community Shuttles. Sustainability, 12(3), 897. https://doi.org/10.3390/su12030897

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustainable Cities and Society, 19, 34–45. https://doi.org/10.1016/J.SCS.2015.07.006

Zhang, W., Jenelius, E. and Badia, H.. "Efficiency of Semi-Autonomous and Fully Autonomous Bus Services in Trunk-and-Branches Networks", Journal of Advanced Transportation. 2019. 1-17.