Quantifying the implementation impacts of a point to point Automated Urban Shuttle Service in a large-scale network

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Abstract

Autonomous point-to-point shuttles are an emerging paradigm of a future mobility-on-demand ecosystem. However, the traffic and environmental impacts of their operation are largely under researched especially in relation to influential infrastructure related factors and service-related specifications. The scope of this study is to reveal the factors that may affect the degree and magnitude of the road segment level impacts of an autonomous urban shuttle service (AUSS) operating in a city using microsimulation and structural equation modeling (SEM). For the purposes of this research, a systematic framework is developed and applied in the city center of Athens (Greece), which encompasses different scenarios of operations including: (i) Baseline (no AUSS operation), (ii) AUSS operation with a dedicated lane during peak hour, (iii) AUSS operation mixed with regular traffic during peak hour and (iv) AUSS operation mixed with regular traffic during off-peak hour. Two connected automated vehicle (CAV) profiles were used to model the advent of automation in the overall traffic: a cautious profile is introduced first, followed by a more aggressive profile. SEM findings indicate that the AUSS operation has a significant effect on cumulative travel time per segment and CO_2 emissions per segment only during the scenario of mixed operation with traffic during off-peak hours. Additionally, the influence of the network geometry is correlated with reduced travel time and with increased CO_2 emissions. Road traffic density was found to be positively correlated with both travel time and CO_2 emissions, while the penetration of both cautious and aggressive CAVs was found to be negatively correlated with both indicators.

Keywords: traffic microsimulation, connected and autonomous vehicles, city automated transport systems, automated public transport, automated traffic profiles, structural equation model

1. Introduction

In the coming decades connected autonomous vehicles (CAVs) are expected to progressively circulate on city road networks. The market penetration of level 3-5 automated vehicles is expected to be below 50% by 2030 (Boghani et al. 2019). This innovative technology and all its components are projected to dominate in all transportation sectors such as road, rail, maritime and aviation, while drivers, passengers and all stakeholders (operators, authorities etc.) ought to be prepared for their advent. Several advantages and disadvantages of automation in transport have been highlighted (Ambühl et al., 2016; Moreno et al., 2018; Bahamonde-Birke, 2018; Soteropoulos et al., 2019; Paddeu et al., 2019; Blas et al., 2020; Ivanov et al., 2020). Researchers, engineers and automobile manufacturers are currently and incessantly working on mitigating the drawbacks and possible failures of the automation and on providing comfort and safety to drivers.

The impacts of automation are expected to be in general positive and reflected in a wide range of operational and strategic levels in transportation, yet with a large degree of uncertainty. Regarding interaction with vulnerable road users, it is established that lower automation level (1 and 2) technologies improve road safety, otherwise for higher level (3, 4 and 5) technologies there is a lot of uncertainty and researches seem to focus on methods that mimic human functions (Ziakopoulos et al., 2019). Another projected benefit of automation is the reduction of the fuel consumption (Fagnant & Kockelman, 2015; Gruel & Stanford, 2016). Regarding CAV cost, according to Elvik (2020), the first commercially available autonomous cars will be not affordable to the majority of the customers, nevertheless over the time automated vehicles are consider to become inexpensive to most of the customers. However, these limitations should be considered in a different light in public transport planning, especially if other costs are suppressed (such as reductions in personnel costs or delays).

The introduction of automation in urban areas is expected to overdraw the direct impacts on traffic flow and its usage (Fraedrich et al., 2019). Autonomous vehicles are expected to improve traffic flow by increasing network capacity (Shladover et al., 2012; Litman, 2014; Friedrich, 2016). More specifically, the road capacity will be increased causing less traffic congestion and offering decreased travel time values (Pinjari et al., 2013; Heinrichs & Cyganski, 2015). There are also studies anticipating detrimental effects to network capacity and overall traffic performance, though these projections assume more specific circumstances such as early stages of low-level automation (Calvert et al., 2017) or shared CAVs with short stops operations (Overtoom et al., 2020). In addition, many efforts have been devoted to investigate the assistance of the infrastructure to CAVs. Research conducted by Coll-Perales et al. (2021) illustrated that infrastructure-assisted traffic management solutions could improve road safety as well as traffic disruptions by reducing the distance that CAVs are driving at low speed. Moreover, simulation findings indicated that unmanaged Minimum Risk Manoeuvres (MRMs) can heavily affect traffic operations and induce traffic disruption while, successful Transition of Control (ToCs) can also reduce the traffic flow performance when the number of CAVs is high (Mintsis et al., 2019). In emergency traffic conditions, such as the existence of an obstacle on the road, CAVs might not be able to detect the situation properly without path information provided by ToC or MRM. In a traffic simulation analysis the corresponding information was given to CAVs and the overall traffic efficiency as well as CO2 levels remained constant, while critical events were significantly reduced up to 45% (Maerivoet et al., 2020).

To date, the literature has focused almost exclusively on the impacts of automated passenger cars to traffic operations, whereas the potential impacts of autonomous transit and similar public transport services remain under-researched with a limited focus on a microscopic level. Hence, more effort is required to project the impacts of the introduction of such systems as well as their integration by large-scale operations on a city level. This broad research gap is actively being addressed by the LEVITATE project, which provided the framework for several aspects of the present study.

For this purpose, the present study aims to identify how the introduction of Connected and Automated Transport Systems (CATS) through the implementation of a point-to-point automated urban shuttle service (AUSS) in a large-scale network will impact different aspects of the network, with a focus on the transition towards higher levels of automation. The present study also aims to further enrich the research concerning the implementation impacts of automated transit services by performing statistical analysis on the microsimulation inputs, in the form of structural equation modeling (SEM).

The paper is organized as follows: in the next section the simulation methodology is presented, in which the microsimulation and statistical analysis are described. Afterwards, the methodological framework of structural equation models (SEM) is presented, and a SEM is fitted in the simulated data to investigate the impacts of AUSS operation and automation of overall traffic to cumulative travel time per segment and CO_2 emissions per segment. Results from the SEM statistical analysis are then described and discussed. A summary of the present research results and their comparison with the results extracted from previous studies is included in following section while the key findings, proposals for further research and paper limitations are presented in the last section of the paper.

2. State of the Art

An amount of publications to date has focused on the CAVs infrastructure, while the impacts of CAVs have been already extensively investigated. More specifically, it is revealed that autonomous vehicles favor urban sprawl and may render public transport superfluous except for the dense urban areas (Meyer, 2017). In addition, an urban mobility system leads to increased total volume of travel and depends on the choice of vehicle type, the level of market penetration and the availability of high-capacity public transport to complement the autonomous shared vehicles' fleet. Autonomous vehicles are estimated to decrease 80% greenhouse gas (GHG) emissions. The operations of small and efficient shared AVs, combining on-demand mobility services and AVs impacts improve respectively the GHG emissions using lower energy and achieve their adoption (Greenblat & Shaheen, 2015). Additionally according to Greenblatt & Saxena (2015), as shared AVs are likely to gain rapid early market shares, it is expected that GHG emissions will decrease by 87-94% for autonomous taxis comparing with conventionally driven vehicles in 2030, without including other energy-saving benefits of automation. Therefore, autonomous taxis could enable GHG reductions even if the total distance travelled and average speed are increased.

Nevertheless, for the road sector perspective, automated shuttle services seem be the first in line of large-scale automated passenger transport. Several studies examined the user acceptance of such services; as automation suggests increased levels of trust and comfort for automated shuttle services and a belief that these services will be reliable, enjoyable, easy to use and of high service quality (Eden et al., 2017; Moták et al. 2017; Salonen, 2018; Salonen & Haavisto, 2019, Nordhoff et al., 2018; 2019). The user enjoyment of the system affects the desire of using it again, while the system performance, the resources that support its use and its social popularity are critical factors (Madigan et al., 2017). In addition, user feedback plays a vital role in the quality of the service, which is considered as the most relevant indicator. Moreover, fleet control is also a crucial operational indicator that offers the ability the timetables requirements to be met by ensuring high service quality (Földes et al., 2021).

In addition, autonomous public transport is already a reality in some form in specific regions, for instance the autonomous buses developed by Navya, currently in service in Lyon (France), Michigan (USA) and at the Frankfurt airport (Germany). Moreover, many projects investigated the implementation of an autonomous shuttle service and revealed their attractiveness as many people use them on daily basis. Two shuttle bus lines were added in Netherlands, within Park Shuttles I and II projects, connecting airports with their parking spaces (Prokos, 1998; Pruis, 2000; Bootsma & Koolen, 2001; Ritter, 2017). Similarly, the CityMobil European Project implemented a shuttle service to Heathrow Airport in London. The CyberCars and CyberCars2 projects also designed an on-demand service operating with small automated cars; the Railcab project proposed an autonomous shuttle providing on-demand service as well (Diethelm et al., 2005; Giese & Klein, 2005).

Autonomous taxis and public transit services encourage vehicle sharing, while improving walking and bicycling conditions and reducing parking needs (Lovejoy et al., 2013). According to Arbib, et al. (2017), by 2030 the 95% of all U.S. passenger miles will be served by transport-as-a-service (TaaS) options that will offer higher levels of service, faster rides and increased safety at a cost up to 10 times lower. Shared rides have lower costs but, conversely, provide less convenience and comfort. Since trip duration is increased by stops, shared rides are not able to offer door-to-door service and passengers travel in confined spaces with strangers (Litman, 2020). More than 40% of current ride hailing vehicle travel is deadheading (Henao & Marshall, 2019). If sharing services become common in an area, deadheading will not disappear, for instance in suburban or rural areas where destinations are longer. Automated shuttle transit services could also improve urban mobility and tourism services by implying complex transportation needs that require new mobility technologies (Bucchiarone et al., 2021). In addition, the introduction of autonomous public transit services provoked public reactions, as those that the CityMobil2 project has experienced, but at the end when passengers had the chance to try the service, it regarded so well that even the most enthusiastic comments received from the bus drivers who temporarily hired to be operators for the demonstrator (Alessandrini et al., 2015).

The micro-level influence of automated shuttle buses through interactions with pedestrians have been the focus of few earlier studies, such as that of Gasper et al. (2018). In this study, RoboShuttles simulated in the SUMO software, by modelling a multi modal trip for pedestrians where they walk, board on the nearest RoboShuttle and disembark, and the results showed that there is a reduction in travel times for the pedestrians. In addition, apart from SUMO, multiple models have also been developed and applied for designing and testing autonomous shuttle bus services microscopically (Marczuk et al., 2015; Lima Azevedo et al., 2016; Lam, 2016; Zellner et al., 2016; Scheltes & Correia, 2017; Shen et al., 2018), in terms of waiting and travel times as well as their effect on road capacity and traffic conditions. So far, studies focus on microscopic traffic impact analysis, and considerable knowledge gaps exist in the literature concerning large, city-scale operations of automated public transport as per the purposes of the current study.

3. Methodological Approach

It is clear that considerable impacts can be expected from the advent of automation in regular traffic. However, there are considerable gaps of knowledge regarding the impacts of automated public transport. Thus, the main research question of the present study is formulated as follows: What are the factors that may affect road segment level impacts of a large-scale autonomous urban shuttle service (AUSS), and how are these relationships quantified?

To address this research question, a two stage methodological approach is implemented based on (i) microscopic simulation and (ii) a statistical analysis based on advanced multiparametric modeling. In the first stage of the analysis, future mobility conditions that will be governed by a gradual substitution of conventional vehicles by CAVs are assumed. Several different scenarios of automating a public transit service are established and introduced in a simulation platform; subsequently, they are evaluated in relation to existing system's conditions.

The microscopic simulation method was selected to examine impacts mainly on traffic, environment and energy efficiency and provide insights into the impacts of microscopic flow characteristics of CAVs. More specifically, the main purpose of this methodology is to identify the impacts of the adoption of CATS on traffic, including travel time, traffic volume, and traffic emissions to the environment under several traffic simulation scenarios and to evaluate the influence of different CAV penetration rates on a microscopic level. Traffic microsimulation provides information related to single vehicles, whereas more macroscopic model refers to entire flow streams. The simulation inputs include data from various sources such as the road geometry and design, traffic volume, modal split, origin-destination (O-D) matrices etc.

The data obtained by the microscopic simulation can provide an initial, descriptive estimation of the examined impacts. However, closer examination is required in order to discover and quantify the underlying relationships. To approach this modelling challenge, some assumptions are required regarding the impacts that are induced by automation and AUSS operations. Specifically, we assume with a high degree of realism that several impacts are systemic and complex, and that several of them depend predominantly on user choice. Additionally, secondary and tertiary correlations of impacts such as the amount of generated travel with network characteristics are quite difficult to foresee and measure beforehand. As a consequence, there are no parameters readily measurable that can directly express the impacts of CAV or AUSS operations. In other words, automation, whether as AUSS or as CAVs in the overall traffic, will introduce effects that are not necessarily directly measurable in the network.

In an attempt to overcome this obstacle, an approach involving the introduction of both AUSS and automated traffic being measured by reflection on widely used aggregate indicators was adopted. Two key impacts that can be readily simulated were selected as key performance indicators (dependent variables): Cumulative travel time of all vehicles per segment (utilize to gauge impacts on traffic flow) and CO_2 emissions of all vehicles per segment (utilize to gauge environmental impacts).

Therefore, the key performance indicators can be thought to not only be affected by directly observed variables, but also from unobserved, latent parameters. The effects from the operation of AUSS and CAVs was considered to be a latent, unobserved parameter. The examined structures involved both direct impacts from observed independent variables and impacts of latent variables, after their formulation from directly observed variables.

Within the present study framework, initial candidates for the latent variables representing unobserved effects included: (i) the effects of the introduction of the AUSS, (ii) the combined effects of traffic parameters, such as flow and density, (iii) the effects of network characteristics and (iv) the effects of the advent of CAVs and the transition of conventional traffic to partly automated at first and fully automated at last. Additionally, the two key performance indicators were examined simultaneously. This approach constitutes a multiple-input-multiple-output model, also known as multiple-indicator-multiple-cause (MIMIC). Several structures were examined with varying numbers of latent variables, as the underlying data structure is not unambiguously evident a priori. The observed variables serving as components of latent variables that did not lead to functional models were also examined as directly influencing independent variables.

Statistical tools that can accommodate latent concepts were thus considered. Structural Equation Models (SEMs) are a useful tool and their application can unearth more details about the underlying structure of simulated data, including any unobserved latent variables. As such, they were selected for the statistical analysis of this study and applied in the simulated network with the intent of capturing the influence of several unobserved effects. SEMs have been used on various instances in transport-related research (e.g. Karlaftis et al., 2001; Eboli et al., 2012; Barmpounakis et al., 2016; Song et al., 2016; Cao et al., 2019). Therefore, the approach adopted for this paper is to create a SEM model from simulated data to discover and quantify the underlying relationships of observed variables and unobserved latent variables with each other and, more importantly, with the two indicator variables.

Lastly, it should be mentioned that issues of modal attractiveness and any shifts in demand which would lead to fluctuations in modal split are not presently considered. In this research, the addition of an automated shuttle bus service with four lines in a congested and dense network of 1,137 nodes and 2,580 road sections did not show any changes in the demand regarding to traffic impacts i.e. travel time, distance and delays. Hence, the traffic demand remained the same for all the simulation scenarios. In addition, this kind of analysis requires estimation of parameters that are dependent on too many factors, such as public acceptance, promotion, real-world design and implementation, pricing, and others; however, the measurement and accounting for these factors fall outside of the scope of the present research.

4. Simulating Automated Shuttle Services in a large urban network

The study network comprises the city center of Athens as shown on Figure 1 (left). This network was simulated in the Aimsun Next mobility modelling software as presented on Figure 1 (right) and consists of 1,137 nodes and 2,580 road segments. In addition, the total length of road sections is 348 km and the network size reaches approximately 20 km^2.

The geometry of the study area was exported from the OpenStreetMap digital map platform (Haklay & Weber, 2008) and its accuracy was verified with random sample comparison with additional maps. OpenStreetMap segmentation was retained for both the simulations and the statistical analysis. The data for each road segment concerned geometric as well as functional characteristics namely length, width, number of lanes, directions, free flow speed and capacity. The respective characteristics of nodes that were included in the model network were the following: allowed movements, number of lanes per movement, priority, traffic light control plans, free speed flow and capacity. Furthermore, the Athens transport network includes at present 95 bus and 14 trolley lines and 1,030 public transport stations, which were also included in the simulation model as well as frequencies and waiting times at stops.

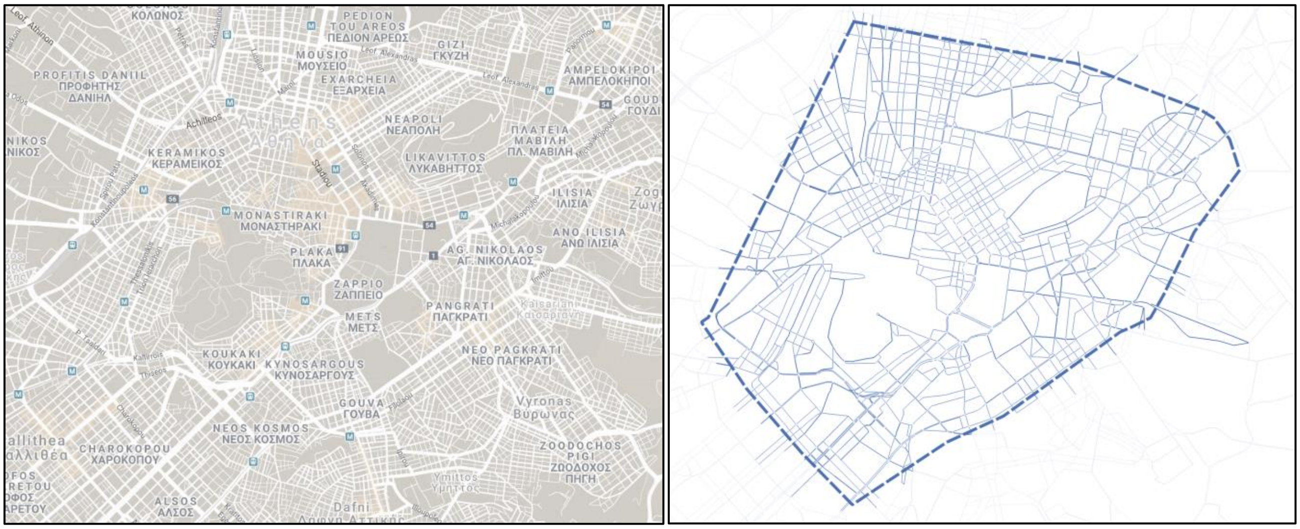

Figure 1: The city of Athens network in a conventional map (left) and in the Aimsun software (right)

In addition, the microscopic model included data that were collected for the year 2019 from 107 detectors, which are recording traffic volume in main roads in Athens network. Additional data of field measurements was also considered. The field measurements were carried out in 2019 and were performed at selected nodes of the study area. At each junction, the number of vehicles in each direction exiting the junction was measured for fifteen minutes for the following vehicle categories: (a) cars and light vehicles, (b) trucks and (c) buses and trolleys. Those data were used in order the network travel demand to be created. More specifically, a scenario was simulated and created the routes that will be followed and the respective OD matrices were extracted. The OD matrices consisted of 358 centroids of the study network and the travel demand was 82,270 trips for cars and 3,110 trips for trucks for peak hour and respectively 49,300 trips for cars and 1,860 trips for trucks for off-peak hour. For all examined automated shuttle service scenarios, the travel demand was inelastic, as it was considered that a few lines would not significantly affect modal split on the city level. Finally for the validation of the model, a verification of estimated average travel times was conducted. For this purpose travel times were obtained using the GoogleMapsAPI application for specific routes within the study area and were compared with the respective travel times extracted of the model.

4.1 The Automation Use Case

For the present research, four point to point automated urban shuttle service (AUSS) bus lines were simulated as implemented in the city of Athens in order to complement the existing public transport as shown in Figure 2. The first AUSS line, Line 1, connects the metro station “Victoria” with the metro station “Panormou”, the second AUSS line, Line 2, connects the National Garden and Greek Parliament with the National Archeological Museum, the third, Line 3, connects Omonoia Square with Acropolis - Parthenon and the fourth, Line 4, connects metro station “Rouf” with metro station “Neos Kosmos” (Points A and points B respectively in Figure 2). 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).

In addition, the shuttle buses of the AUSS were considered to have a total capacity of 10 passengers. Their dimensions were 5 meters in length and 2.5 meters in width. The max operating speed of the buses was 40.0 km/h and the mean speed 25.0 km/h. The frequency of the service for the four bus lines was 15 minutes. The AUSS simulation scenarios included peak and off-peak hour traffic conditions and the use of a dedicated lane by the AUSS buses during peak hour. More specifically, in the second simulation scenario the shuttle buses are operating in mixed traffic conditions during peak hour, as well as in the fourth scenario that respectively concerns off-peak hour conditions. The third simulation scenario includes the shuttle bus service that operates using dedicated lanes in order for the impacts of a different implementation of the shuttle bus service to be captured. This scenario 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. Regarding the dedicated lane scenarios, for each road segment that is included in AUSS bus routes and had a dedicated lane for public transport, the AUSS buses were able to use the existent dedicated lane, in order to evaluate the impact of this service policy without changing road geometry.

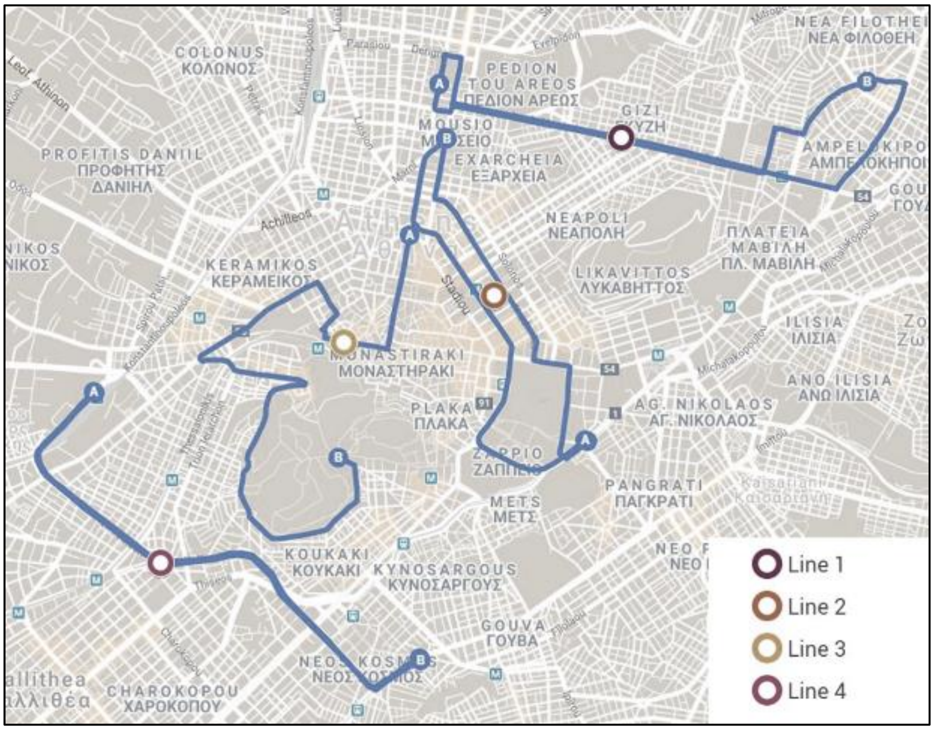

Figure 2: The AUSS bus lines

Overall, the following AUSS implementation scenarios were formulated:

1. Baseline (no AUSS operation)
2. AUSS operation with a dedicated lane during peak hour
3. AUSS operation mixed with regular traffic during peak hour
4. AUSS operation mixed with regular traffic during off-peak hour.

4.2 Modelling Autonomous Vehicles

For the modelling of connected and autonomous vehicles (CAVs) within the present research, two main driving profiles were simulated as in other researches (Sukennik, 2018; Mesionis, 2019) and are presented below:

- Cautious: long clearance in car-following, long anticipation distance for lane selection, long clearance in gap acceptance in lane changing, limited overtaking, long gaps
- Aggressive: short clearance in car-following, short anticipation distance for lane selection, short clearance in gap acceptance in lane changing, limited overtaking, no cooperation, small gaps.

At this point, it is important to note that the cautious driving profile is more aggressive than the human driving, even though it is characterized as cautious. Shuttle buses of the service were simulated as cautious CAVs, as it was assumed that this profile was more appropriate for a public transport mode. In addition, the CAVs and the shuttle buses, as well, in this study were assumed to be exclusively electric.

The behavior of the CAVs modelled by using the Gipps car following model (Gipps, 1981). This model is able to mimic the behavior of real traffic, the parameters involved correspond to obvious driver and vehicle characteristics and affect the behavior of the simulated flow in logically consistent ways. More specifically, the model predicts the response of the following vehicle based on the assumption that drivers set limits to their desired braking and acceleration rates. The Gipps car-following model was originally developed to simulate human-driving and was not able to simulate directly connected CAVs. For this reason, it was assumed that CAV reaction times at traffic lights and stops were 0.1 seconds in order to be simulated as connected vehicles with traffic lights and able to receive information. In addition, in modelling CAVs it was necessary to take into account their lane-changing behavior as it is considered to be different than human driven vehicles behavior. For this reason, the Gipps lane changing model was applied in the present research (Gipps, 1986), as well. This model analyses the decisions that drivers have to make before changing lane and ensures that the simulated drivers behave logically in situations that are similar in real traffic conditions. The vehicle parameters of the car-following and lane-changing behavior that were used in microsimulation are presented in Table 1.

Table 1: Vehicle parameters used in microsimulation

Models	Factors		Human Driven Vehicle	Cautious CAV	Aggressive CAV
Car Following Model	Sensitivity	*Mean*	1.0	0.3	0.1
		Min	1.0	0.7	0.5
		Max	1.0	0.9	0.9
Lane Changing Model	Overtake Speed Threshold		90%	85%	85%
	Cooperate in Creating a Gap		Yes	No	No
	Imprudent Lane change		Yes	No	No
	Distance Zone	*Min*	0.8	1.25	1.25
		Max	1.2	1.5	1.5
	Aggressiveness Level	*Min*	0	0	0
		Max	0	1.0	0.25
	Safety margin	*Min*	1.0	1.25	0.75
		Max	1.0	1.75	1.25
Reaction times	Reaction time in car following		0.8 sec	0.1 sec	0.1 sec
	Reaction time at stop		1.2 sec	0.1 sec	0.1 sec
	Reaction time at traffic light		1.6 sec	0.1 sec	0.1 sec

In the lane changing model, the sensitivity factor controls the clearance distance and the overtake speed threshold is the percentage of the desired speed of a vehicle which decides to overtake. The cooperation in creating gap between the vehicles factor concerns if the vehicle creates a safe gap for another vehicle that change lane to enter. The imprudent lane change factor allows vehicles to enter into gaps that are too short and the distance zone factor determines where vehicles consider their lane choice for a forthcoming. Finally, the aggressiveness level allows vehicles to accept shorter gaps and the safety margin factor determines when a vehicle can move at a priority junction (for more information on the model's structure and parameterization the reader is referred to Mesionis et al., 2019 and Casas et al., 2020).

In order to investigate the implementation of CAVs, different penetration rate scenarios were simulated. These scenarios are presented in Figure 3. The cautious CAVs were considered to be the first generation of this implementation. For this purpose, they appear first in the scenarios and are then followed by aggressive CAVs until the last scenario included only autonomous connected vehicles. For each one of these scenarios, the impact assessment of the AUSS was analyzed for all simulation scenarios. Therefore, 44 scenarios were simulated in total: 11 market penetration scenarios for each of the four AUSS implementation scenarios, with a simulation duration of one hour and simulation time step of extracting data of ten minutes. Each replication had a runtime of approximately 40 minutes on a workstation computer (CPU: Intel Core i7 8700 @ 3.2 GHz; RAM: 32 GB: 2x16 GB DDR4 @ 2400 MHz).

In addition, for each scenario 10 different replications with random seeds were simulated. According to the FHWA (2004), multiple replications of the same scenario are required, because microsimulation results vary depending on the random number seed used in each run. The random number seed is used to select a sequence of random numbers that are used in order to be make decisions throughout the simulation that affect the results obtained by the simulation. The results of each replication are close to the average of all replications, however each one is numerically different from the other.

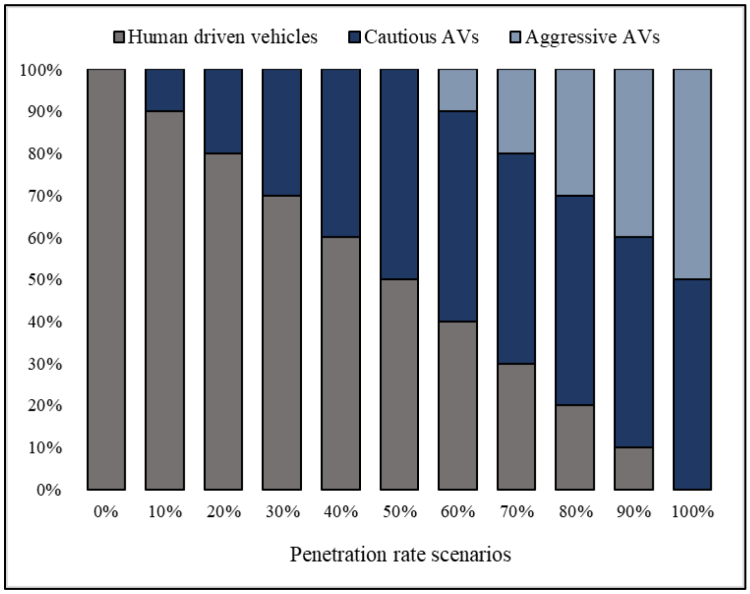

Figure 3: The CAV penetration rate scenarios per profile type

It should be noted that both CAV cautious and aggressive profile parameters and MPR scenario configurations were specifically formulated for the present research. Within the LEVITATE project, several additional configurations are being examined, but fall outside the scope of this paper.

5. Structural Equation Modeling background

The scope of this section is to provide the theoretical background and the results of the application of Structural Equation Models (SEMs) in the simulation data. The target of this approach is to create causal models in order to interpret the dependencies of two critical indicators, which are cumulative on a road segment level: travel time and CO_2 emissions.

Structural Equation Modelling belongs to the model family concerning latent variable analysis. SEMs comprise a widely used array of techniques used to capture effects of parameters that are unavailable or otherwise unable to be observed. In that capacity, SEM techniques serve to illustrate the form of the structure of the examined data and reduce overall model error by incorporating measurement errors into the modeling framework; in addition, they handle endogeneity among variables well (Washington et al., 2020).

The underlying mathematical structure of SEMs can be defined as follows (following Washington et al., 2020):

$$\boldsymbol{\eta} = \boldsymbol{\beta}\,\boldsymbol{\eta} + \boldsymbol{\gamma}\,\boldsymbol{\xi} + \boldsymbol{\varepsilon} \qquad \text{Eq. (1)}$$

Where:

$\boldsymbol{\eta}$ is a vector expressing the dependent variables
$\boldsymbol{\xi}$ is a vector expressing the independent variables
$\boldsymbol{\varepsilon}$ is a vector expressing the regression error term
$\boldsymbol{\beta}$ is a vector expressing the regression coefficients for the dependent variables
$\boldsymbol{\gamma}$ is a vector expressing the regression coefficients for the independent variables

The exogenous factor covariance matrix is expressed as $\boldsymbol{\Phi}$ = COV[$\boldsymbol{\varepsilon}, \boldsymbol{\varepsilon}^T$] and the error covariance matrix is expressed as $\boldsymbol{\psi}$ = COV[$\boldsymbol{\varepsilon}, \boldsymbol{\varepsilon}^T$]. If a parameter vector $\boldsymbol{\theta}$ is considered, which will create a model-based variance–covariance matrix, $\boldsymbol{\Sigma(\theta)}$, the variance–covariance matrix for the model in Equation 1 is:

$$\boldsymbol{\Sigma(\theta)} = \mathbf{G(I\text{-}\beta)^{-1}}\ \boldsymbol{\gamma}\ \boldsymbol{\Phi}\ \boldsymbol{\gamma}^{\mathbf{T}}\ \mathbf{(I\text{-}\beta)^{-1^{T}}}\ \mathbf{G^{T}} \qquad \text{Eq. (2)}$$

Where **G** is a selection matrix containing either 0 or 1 to select the observed variables from all the dependent variables in $\boldsymbol{\eta}$. Further details in the particulars of SEMs can be provided in relevant textbooks by Hoyle (1995) and Arminger et al. (1995).

There are several proposed goodness-of-fit measures regarding SEMs. The topic has been a matter of some debate between experts; indicatively, the reader is referred to Mulaik et al. (1989), Kaplan (1990), MacCallum (1990) and Steiger (1990). Within this study, several of the most widely used metrics are adopted, specifically: (i) the Standardized Root Mean Square Residual (SRMR), (ii) the Root Mean Square Error of Approximation (RMSEA), (iii) the comparative fit index (CFI) and (iv) the Tucker-Lewis Index (TLI). Values less than 0.07 for SRMR and RMSEA and more than 0.95 for CFI and TLI are generally accepted as indications of excellent overall model fit. The Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) are also utilized to aid in the selection of a particular model over others by quantifying the information loss of each examined model structure and variable mix.

As customary in latent variable/path analysis, the proposed model structure and all modelled coefficients and interrelationships can be visualized in a path diagram. Regarding the interpretation of results, SEMs and their respective path diagrams can be typically considered as a multi-stage regression process. Firstly, the coefficients for each independent variable that is a component of the latent variables (also known as factor loadings) are examined to ensure reasonably interpretable results. Afterwards, the influence of the latent variables on the examined indicators is examined with a similar scope. Thus, the components of the latent variables can be thought of as having a direct effect on the latent variables and, through them, an indirect effect on the indicators. Therefore, if an independent variable is (exclusively) positively correlated with a latent variable, and this latent variable is negatively correlated with an indicator variable, the independent variable is negatively correlated with the indicator. In addition to the previous, direct regressions from independent variables can be modelled on the indicators without any intervening latent variable. Lastly, covariances between parameters of the same role (i.e. independent variables, latent variables or indicators) can also be modelled if such correlating effects are included (Washington et al., 2020).

6. Implementation and Findings

6.1 Network Level Impacts

For investigating the impacts of CAVs and the AUSS implementation, forty-four (44) scenarios were simulated. At this point, it is worth examining the simulation extracted results of these scenarios, in order to obtain a first description of this impact before the statistical analysis. The simulation duration of the scenarios was one hour and the simulation time step of extracting data was ten minutes.

Table 2 shows some of the key traffic and environmental measurements on network level for each AUSS implementation and market penetration rate (MPR) scenario, respectively. In addition, the overall CAV MPR rate is distributed between the two CAV profiles in a fixed manner which is also shown on the table.

The environmental measurements that obtained by the simulation, using the Aimsun Next software, were calculated applying the formula developed by Panis et al. (2006). This model computes carbon dioxide (CO_2), nitrogen oxides (NO_X), particulate matter (PM_{10}) and volatile organic compound (VOC) emissions from instantaneous speed and acceleration. The model's parameters for each vehicle type and pollutant were configured for instantaneous emissions calculation and the corresponding emissions were computed for each vehicle trip.

According to Table 2, several insights can be obtained for the network impact changes due to increasing CAV MPR and for each AUSS implementation scenario. Regarding AUSS implementations, all comparisons are made with the baseline (no AUSS across all MPRs). Specifically, for mixed traffic AUSS operation during peak hours, microsimulation results indicate that delay time and CO2 emissions are largely unaffected compared to the baseline across all MPR scenarios. Distance travelled is mostly unaffected as well, but slight increases are detected at the highest MPR levels (about 3km on average) compared to the baseline. For AUSS operation in dedicated lanes during peak hours, the results are almost identical with operation in mixed traffic across all MPR scenarios.

Table 2: Impacts for different simulation scenarios

			Market Penetration Rate Scenarios										
Scenarios		Aggregate	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
		Cautious CAVs	0%	10%	20%	30%	40%	50%	50%	50%	50%	50%	50%
		Aggressive CAVs	0%	0%	0%	0%	0%	0%	10%	20%	30%	40%	50%
		Impacts											
Peak hour	No Shuttle Service	Delay Time (sec/km)	285	275	272	261	254	240	227	208	197	176	161
		Distance Travelled (km)	83.01	86.66	89.42	91.64	96.35	101.05	103.18	108.49	113.87	119.90	120.41
		CO_2 Emissions (kg)	72.11	66.57	60.97	55.22	50.17	44.64	39.23	33.71	28.49	22.76	16.61
	Mixed traffic	Delay Time (sec/km)	282	276	271	262	253	239	225	208	196	176	162
		Distance Travelled (km)	83.78	86.93	89.12	91.99	95.95	100.25	102.42	107.81	115.20	119.98	123.51
		CO_2 Emissions (kg)	72.02	66.69	61.04	55.38	50.13	44.53	39.15	33.70	28.60	22.88	16.84
	Dedicated lane	Delay Time (sec/km)	284	278	272	263	253	241	226	207	196	177	162
		Distance Travelled (km)	83.94	86.93	89.12	91.99	95.95	100.25	102.42	107.81	115.17	120.02	123.39
		CO_2 Emissions (kg)	72.19	66.69	61.04	55.38	50.13	44.53	39.15	33.70	28.58	22.88	16.88
Off Peak	Mixed traffic	Delay Time (sec/km)	177	172	163	156	144	134	123	114	105	96	88
		Distance Travelled (km)	89.73	92.20	94.02	96.36	99.08	101.35	103.61	106.43	108.36	110.67	112.56
		CO_2 Emissions (kg)	47.23	43.81	40.08	36.52	33.07	29.60	26.20	22.79	19.37	15.98	12.60

The underlying cause for this lack of impact is likely the profile of the network of a large, congested metropolis, such as Athens. Due to the high traffic volumes presence during peak hours, a shuttle bus line operating within mix traffic does not influence network capacity at a significant level. Moreover, the existence of a dedicated lane does not significantly influence the outlying traffic conditions on a microsimulation statistics level. This result was contrary to those reported by Talebpour et al. (2017), who also investigated the effects of reserved lanes for CAVs and illustrated that if CAVs use dedicated lanes, congestion levels will be improved as well as their performance over other policies. That was also highlighted by Kyriakidis et al., (2019) who showed that roads which eliminate the interactions between CAVs and other vehicles or pedestrians are more suitable for the CAV deployment. Yet another different finding was reported by Chen et al. (2017), who showed that mixed-condition policies could succeed in providing higher capacity than the segregation of CAVs and conventional vehicles. It should be noted, however, that these studies considered only isolated segments or reported expert responses on generalized questionnaires, and not a large-scale network examination as conducted in the present study.

Contrary to AUSS operation, the effects of the gradual automation of all traffic are considerable and must be underlined. As CAV MPRs increases, delay time was reduced for both peak and off-peak hour scenarios. On the other hand, total distance travelled displays significantly higher values when the number of autonomous vehicles is increased. Finally, increased CAV MPRs were found to reduce CO2 emissions during both peak and off-peak hour conditions. Peak hour conditions lead to higher CO2 levels in comparison with off-peak hours, which is expected due to the lower frequency of stops and conflicts, as well as the reduced size of queues in the off-peak period.

However, as stated previously, the confinement of vehicles in fewer lanes due to the existence of a dedicated lane for the AUSS does not seem to affect emissions caused by total traffic compared to mixed-traffic AUSS operation, again possibly to large degrees of congestion in the system. In other words, based on microsimulation results, it can be concluded that the majority of network impact changes occur due to the advent of CAVs, and the operation of AUSS buses ultimately do not appear to have drastic effects in the network.

The simulation data were then extracted from the simulation environment and statistically analyzed within a Structural Equation Modelling framework. A series of data cleaning and manipulation tasks was essential before the implementation of SEM statistical analysis, which can be briefly outlined as follows:

1. Extraction and compilation of simulation data for all AUSS simulation scenarios.
2. Filtering the values concerning vehicle type selecting those denoting average values of all vehicles and those concerning the time intervals removing the average of all time intervals from the dataset.
3. Screening of incomplete/problematic cases of missing data and removal of such cases from the dataset.

4. Merging of the simulation datasets with the geometric dataset and obtaining a single unified dataset of simulation outputs per segment.
5. Averaging of the numeric values of the ten different replications of each scenario referring to the same segment and for the same temporal intervals. Categorical values were kept constant during this step.
6. Creation of the final dataset to be used for SEM analysis.

The final output of this process appears on Table 3, which serves to provide a snapshot of the data from a descriptive statistics point of view. It should be noted that categorical variables, such as road type, were also processed via one-hot encoding and converted to single category dummy variables before the analysis. The resulting file had 642,845 observations; of these, 343,023 refer to unsignalized streets including on/off ramps and 299,822 refer to signalized streets/arterials.

Table 3: Descriptive statistics of the merged database

	Flow (veh/h)	**Travel time** (sec)	**Delay time** (sec)	**Mean speed** (km/h)	**Flow/ section capacity**	**Density** (veh/km)	**Queue** (veh)	**Virtual queue** (veh)	**Number of stops**	**CO_2 emissions** (g)	**NOx emissions** (g)	**PM emissions** (g)
Min	0.60	0.41	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.18	0.00	0.00
Median	210.00	23.31	8.90	27.98	0.27	9.34	0.27	0.00	0.34	1196.28	5.65	0.21
Mean	355.18	86.94	74.27	25.67	0.30	29.47	2.99	2.42	0.51	2496.08	12.17	0.41
Max	3861.60	3939.84	3930.55	70.36	1.73	246.10	121.81	1404.20	18.82	115536.53	449.40	28.81
St. Dev.	433.12	230.74	229.32	13.26	0.22	45.92	7.36	29.21	0.58	3882.62	18.53	0.67

	Number of lanes	**Number of main lanes**	**Number of public transport lines**	**Number of reserved lanes**	**Number of signals**	**Number of lane changes/ Number of vehicles**	**Road segment free flow travel time**	**Cautious CAV MPR**	**Aggressive CAV MPR**
Min	1.00	1.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Median	1.00	1.00	2.00	0.00	0.00	0.00	224.26	0.50	0.00
Mean	1.73	1.68	4.58	0.12	0.69	0.12	354.55	0.36	0.14
Max	6.00	6.00	61.00	3.00	3.00	6.29	998.43	0.50	0.50
St. Dev.	0.96	0.91	7.34	0.33	0.85	0.22	285.66	0.18	0.18

Based on the descriptive statistics of the SEM input database, the profile of the simulated network and corresponding traffic can be examined in more detail. Firstly, it can be observed that traffic flow (in absolute terms) has a relatively small mean and median values compared to the maximum, and accordingly a large degree of dispersion, provided by the ratio of mean to standard deviation, is present in the measurements. This observation can also be made for travel time and delay speed, which register even larger dispersion, as the aforementioned ratio is lower. A more neutrally dispersed distribution is produced when flow is standardized as the parameter of flow/section capacity or when examining the number of stops per vehicle. The parameters of density and vehicles in queue also display heavily right-skewed distributions, consistent with their dependency on core traffic parameters. CO_2, NO_x and PM_{10} emissions appear to have analogous distributions with traffic flow and travel time as well.

These observations are largely expected, because they include all simulated segments of Athens, smaller to larger. Smaller values typically refer to unsignalized, residential/access or tertiary-type segments on off-peak periods, while larger values typically belong to arterial or collector roads during peak hours, which feature considerably more traffic. In cases of peak hour ‘gridlock’ type congestion, certain densities and queues are expected to persist to higher levels in the simulation, until sufficient headway is available.

Regarding network parameters, it can be determined that the majority of the examined segments feature a single lane functioning as main lane, with no reserved lanes and no signals. A large number of conventional public transport lines operate in the system, with 2 lines per segment as median value. Furthermore, vehicles appear to perform few lane changes on average, however this parameter is also heavily right-skewed, as a large number of lane changes appears to be happening in a select a few of the segments, possibly due to central positioning and/or network geometry. MPR values for the two profiles follow the progression of Figure 3 as per the study design.

6.2 Structural Equation Model Results

The results of SEM analysis are presented in this section, showcasing only the final models. Apart from the previously aforementioned hard goodness-of-fit measures, the produced coefficient estimates were also checked to ensure that reasonable results are obtained based on their interpretation. Furthermore, care was taken to avoid model misspecification based on both the appropriateness of the proposed underlying theoretical structure and on the produced outcomes – for instance, models producing negative variance values for observed and latent variable were discarded as cases of poor/illogical model fit. During the modelling process it became apparent that certain model structures fitted the simulation data much more reasonably than others based on the following criteria; only the best overall models are presented herein. For variations within each different latent variable structure, model attempts were conducted with the backwards elimination technique. All statistical analyses were conducted in R-studio (R Core Team, 2013) and SEM analysis in particular utilized the lavaan R package (Rosseel, 2012).

Ultimately, the proposed SEM structure retained two latent unobserved variables:

1. Network influence, expressing the influence of various network and geometric characteristics, defined from the number of signals per segment (the number of allowed legal movements per signalized segment, when the value is null the segment is unsignalized), the number of lanes per segment, the number of public transport lines per segment, the road type of the segment (arterial/signalized or unsignalized streets including on/off ramps) and the reservation type of the segment (reserved streets for public transport, pedestrian streets, streets with no reservation).
2. Traffic mix influence, expressing the influence of the traffic mix regarding the penetration rates of the two different CAV profiles (cautious and aggressive), defined from the penetration percentages of the profiles and also from traffic density.

Following SEM calibration, the produced model results are presented on Table 4; statistically significant p-values (≤0.05) are shown in bold.

Table 4: SEM model of travel time & emissions per segment

SEM Components		Parameters	Estimate	S.E.	z-value	P(>|z|)
Latent Variables	Network influence	Number of signals	1.000	–	–	–
		Number of lanes	2.777	0.009	305.492	**0.000**
		Number of public transport lines/100	0.158	0.001	293.874	**0.000**
		Road type: Signalized/Arterial [ref: unsignalized street]	1.029	0.004	290.522	**0.000**
		Reservation Type: Public transport [ref: none]	0.351	0.002	232.273	**0.000**
		Reservation Type: Pedestrian Street [ref: none]	0.080	0.001	120.384	**0.000**
	Traffic mix influence	Aggressive CAV MPR	1.000	–	–	–
		Cautious CAV MPR	0.596	0.006	108.131	**0.000**
		Density (veh/km/100)	-0.079	0.003	-24.106	**0.000**
Regressions	Travel Time (s/100)	Intercept	-0.161	0.003	-55.717	**0.000**
		Density (veh/km/100)	3.453	0.005	752.341	**0.000**
		Network influence	-0.739	0.007	-105.167	**0.000**
		Traffic mix influence	-0.203	0.012	-16.967	**0.000**
		AUSS Mixed Off-peak hour [ref: Baseline]	0.038	0.005	7.827	**0.000**
	CO_2 emissions (g/10,000)	Intercept	0.152	0.001	265.747	**0.000**
		Density (veh/km/100)	0.351	0.001	411.962	**0.000**
		Network influence	0.506	0.002	253.255	**0.000**
		Traffic mix influence	-0.323	0.004	-88.152	**0.000**
		AUSS Mixed Off-peak hour [ref: Baseline]	-0.029	0.001	-31.708	**0.000**
Covariances	AUSS Mixed Off-peak hour	Density (veh/km/100)	-0.036	0.000	-141.059	**0.000**
	Reservation Type: Publ.Transp.	Number of public transport lines/100	0.004	0.000	186.564	**0.000**
	Reservation Type: Publ.Transp.	Reservation Type: Pedestrian Street	-0.006	0.000	-112.602	**0.000**
	CO_2 emissions (g/10,000)	Travel time (sec/100)	0.055	0.001	84.435	**0.000**
	Network influence	Traffic mix influence	0.000	0.000	1.190	0.234
Goodness-of-fit measures		CFI	0.988			
		TLI	0.982			
		RMSEA	0.030			1.000
		SRMR	0.014			

All of the four examined goodness of fit measure values and the signs of the parameter estimated coefficients suggest excellent model fit. As an additional verification, the model AIC was the minimum reached within the examined combinations, and no negative variances were calculated by the model, which would suggest misspecification (variance outputs are not shown here for brevity). It is also important to note that several variables were scaled linearly by factors of 10 to reduce variance discrepancies and to allow better model fit without hindering the coefficient interpretation.

Lastly, several covariances of the measured variables have been integrated in the model by an iterative process which involved comparing the observed and fitted covariance correlations. The largest shown differences were then addressed by including the relevant covariance pair in the model, provided that there were no major prohibitions from the underlying theoretical standpoint. This process aided in improving model fit.

The path diagram of the present model is presented on Figure 4; green arrows denote positive correlations, while red arrows denote negative correlations. Several useful insights can be obtained from the produced SEM model results. First and foremost, it appears that AUSS implementation during peak hours does not have a statistically significant influence on the two examined indicators of travel time and CO_2 emissions per segment. The dummy variables referring to these scenarios were not found to be significantly correlated with the indicator variables in any variation of the examined model structure, whether the scenarios were inserted in a latent variable or the indicators were directly regressed on them. This means that the insertion of an AUSS line on a large-scale network, both when a dedicated lane is utilized or when the shuttle buses are mixed with regular traffic, is not enough by itself to reduce travel time or emissions during peak hours, as the network is too congested for any difference to register statistically. This result is a confirmation of the initial intuitive estimates provided by microsimulation outputs, previously shown in Table 2.

This trend does not apply, however, in the scenario when the AUSS operates in off-peak conditions. AUSS operation in mixed traffic conditions is positively correlated with travel time and negatively correlated with CO_2 emissions per segment. The corresponding marginal effects can be considered in order to interpret the effect of a unit change on the dependent variable (Washington et al., 2020). Specifically, implementing AUSS in mixed traffic during off-peak hours increases travel time by 0.038*100 s = 3.8 seconds, and reduces CO_2 emissions by 0.029* 10,000 g = 290 g. Therefore, results indicate that the operation of an AUSS bus line in off-peak conditions does not seem to affect travel time per segment significantly but reduces CO_2 emissions compared to the baseline of no AUSS operation. However, as the baseline scenario concerns peak hour conditions and travel time remains constant in the AUSS implementation during off-peak hours as well, it is possible that the presence of the shuttle buses mixed with regular traffic introduces some delays in the network, which are correlated with lower speeds, which are in turn associated with lower engine workload and thus lower emissions.

It is worth noting that the overall impact of higher traffic density is positively correlated with increases in both indicators (the contribution of density in the latent variable of traffic mix influence is consistently positive as its negative coefficient for the creation of the latent variable is multiplied by the overall negative latent variable coefficient). This is an intuitive and expected result.

The results regarding the latent variable of traffic mix influence are equally interesting. The coefficient signs for travel time and CO_2 are negative, denoting that this latent variable is negatively correlated with both indicators. Within the latent variable, both cautious and aggressive CAV profiles have positive coefficients; when they are multiplied with the overall negative coefficient an overall negative correlation is obtained with travel time and CO_2 emissions. The increased advent of automation, in other words, the gradual substitution of conventional vehicles with CAVs, as modelled in the present study, is hereby shown to reduce both travel time and CO_2 emissions per segment. These results are consistent with the descriptive statistics observations of Table 2.

All network characteristics contribute positively for the creation of the latent variable of network influence. In turn, network influence has opposite effects on each indicator variable: network influence (i.e. the combined effect of the network and geometric characteristics) is found to significantly reduce travel time but on the contrary increase CO_2 emissions. In order to interpret the coefficients, it should be kept in mind that a large amount of predictor variance is interpreted by density and CAV MPR, as per the aforementioned.

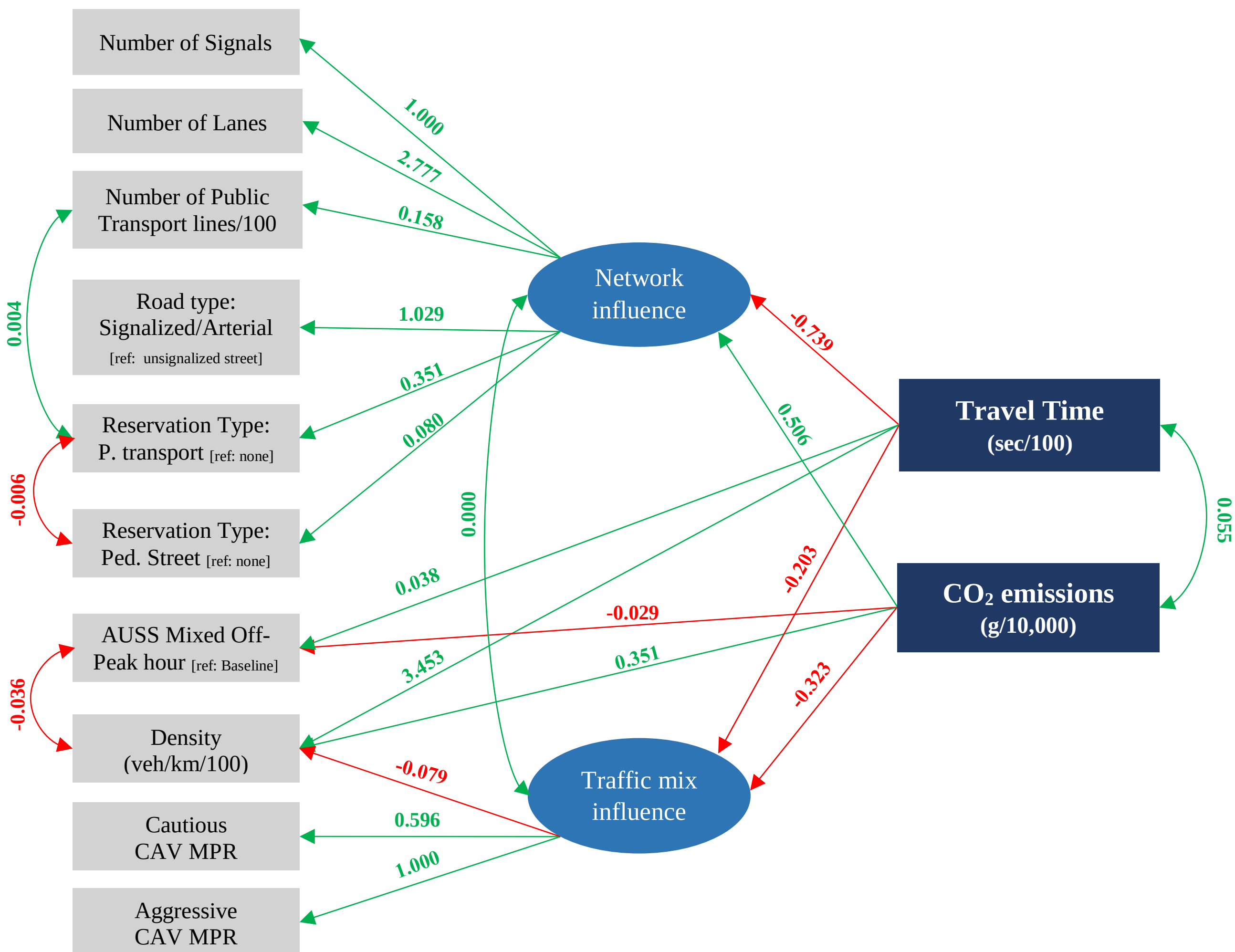

Figure 4: Path diagram of SEM model for travel time & CO_2 emissions

Additionally, one can also consider the direct interpretation of latent variable components based on coefficient signs, as explained in Section 5. Larger numbers of signals, lanes, or public transport lines, arterial road type (compared to unsignalized roads) and road reservation type for pedestrians or public transport (compared to no reservation) all essentially decrease travel time. Larger numbers of signals denote a larger road class, with more regulated and optimized flows, while reserved segments also facilitate travel by reducing traffic conflicts between different transport modes. Conversely, direct interpretation of CAV MPR rates yields the fact that higher rates essentially reduce CO_2 emissions.

The model structures that were explored but ultimately discarded are of interest as well. The inclusion of traffic flow instead of density was found to lead to considerably worse performing model metrics, while the simultaneous inclusion of both traffic flow and density led to over-correlations and misspecified SEM models. The same outcome was obtained when attempting to create latent variables based on traffic flow and density. Likewise, the formulation of a latent variable formulated by the AUSS scenario dummy variables did not lead to viable model structures. An alternative model configuration involved creating latent indicator variables from the combination of travel time and CO_2 emissions, but due to poor model performance was ultimately discarded.

Finally, it is important to note that the projections and forecasting conducted in this research by the simulation and the SEM remains dependent on the assumptions regarding (i) the network, (ii) the automated operation of public transport and (iii) the automation profiles of the overall traffic. Naturally, any value changes in parameters such as sensitivity or safety margins of driving profiles will have an effect on estimated impacts, though the SEM appears robust enough to outline the general expected trends.

7. Conclusions

7.1 Present research

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. The present research contributed to this effort by quantifying the impacts of implementing an Automated Urban Shuttle Service (AUSS) in a large-scale network regarding traffic conditions environment. To that end, shuttle bus routes were designed to operate in the road network of the city of Athens, in order to complement the existing public transport network. Different operating scenarios were established; peak and off-peak hour, existence of a dedicated lane for the shuttle bus and different penetration rates and profiles of autonomous vehicles. Furthermore, the advent of automation is modelled within the network by the examination of two connected automated vehicle (CAV) profiles: a cautious profile, projected to be introduced firstly, and an aggressive profile, projected to be introduced secondly. These profiles were considered to be gradually substituting conventional vehicles, until only CAVs are in the network in a 50% cautious and 50% aggressive ratio. Forty-four (44) scenarios were simulated in total: 11 market penetration scenarios for each of the four AUSS implementation scenarios, with a simulation duration of one hour and simulation time step of extracting data of ten minutes. The simulated data were then processed and modelled with a Structural Equation Model (SEM) approach. Travel time and CO_2 emissions per segment were selected as key indicators in order to measure the impacts of automation.

In order to shed more light into the statistical significance of the relationships and the underlying structure, SEM modelling examined an array of latent and observed variable combinations. The structure of the best performing SEM included two latent variables, one expressing the network influence, including road geometry and segment characteristics and one expressing the influence of CAV traffic mix and density. SEM findings indicate that the AUSS operation has a significant effect on travel time and CO_2 emissions per segment only during the scenario of mixed operation with traffic during off-peak hours. Specifically, AUSS operation was found to statistically increase travel time per segment by 3.8 seconds and reduce CO_2 emissions by 290 g per segment.

Additionally, results indicate that the network influence is correlated with reduced travel time and with increased CO_2 emissions. Road traffic density was found to be positively correlated with both travel time and CO_2 emissions, while the penetration of both cautious and aggressive CAVs was found to be negatively correlated with both indicators. The SEM goodness-of-fit measures indicate excellent model fit, thus supporting the qualitative conclusions as well as the quantifications provided by the model.

7.2 Broader issues of AUSS implementation

The outcomes of the microsimulations and SEM conducted in this study reveal several interesting lessons on AUSS implementation conditions and their respective limitations. The introduction and design of a new AUSS system in a large city should take into consideration several issues.

Firstly, the inelastic behavior of delay time, distance travelled and emissions should be a guide on not to expect spectacular improvements from isolated public transport lines. AUSS services ought to be implemented intensely and in tandem, with precisely calculated optimization for operation, embarking and connection of passengers to other lines to be more attractive, more accepted and ultimately, popular with the public. This inelasticity can work both ways, however. It can provide an incentive to automate existing lanes one at a time with limited adverse impacts on a metropolitan scale. Once a bold decision has been taken to create dedicated AUSS lanes in a congested network, the transport planner can take advantage of the space by aiming for a high utilization rate, in other words increasing the number AUSS lines operating in the dedicated lane, without noticeable adverse effects to the network, compared to general traffic.

Naturally, the timing of the implementation of AUSS lines is critical, considering the state of automation and its market penetration on the general traffic. A critical factor for emissions and travel time is traffic density, as defined by the SEM. Traffic density, among other things, may be largely affected by driving culture, in the form of headway selection by drivers and overall driving aggressiveness. The smooth operation of an automated shuttle service will require education, and, to an extent, enforcement. The overall integration will occur with fewer resources in higher CAV MPRs, as road users will be more familiar with CAV operation, and may unlock hidden capabilities, such as the slight increase of distance travelled discovered in the present microsimulations. On the other hand, this implementation delay might offset the respective gains for the city, so careful cost-benefit analysis will be required on a case-study basis.

The present results provide evidence that automation will work towards beneficially improving traffic and environmental conditions in cities. It is evident that automating a single AUSS public transport service is not panacea for congestion or environmental issues; critical indicators are not affected de facto, as the surrounding congestion continues to play the most crucial role. Nonetheless, the gradual increase in the penetration of automated transit services appears to have the capabilities of reducing travel time and CO2 emissions per segment, as simulated within the current research.

7.3 Future research

This research was carried out within the wider framework of the LEVITATE project. LEVITATE will endeavor to provide a new holistic impact assessment framework for CATS, by incorporating several methods (including the presented microsimulation method) within a freely available web-based policy support tool to enable city and other authorities to forecast impacts of CATS.

Nonetheless, there is a plethora of pending issues for future research to focus on. Indicatively, the creation of a holistic approach for the impact assessment of automated transport on-demand mobility is a broad and ambitious research venue. There are several open questions regarding safety and security (including cybersecurity) issues on automated public transport. Transportation resilience issues, and the degrees of readiness of the various existing urban infrastructure measures should be explored as well. Finally, the critical role of connectivity and its various impacts in relation to simple automated services needs to be further investigated, taking into account the particularities of different areas, vehicle types, transport culture and modal split issues.

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