Autonomous Vehicles in Urban Networks: A simulation-based Assessment

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Word Count: 7483words

Submitted [1 August 2021]

ABSTRACT

The paper proposes a general framework for the assessment of the impacts of the introduction of Connected and Automated Transport Systems (CATS) on traffic. The main objective is to address the question of scalability and transferability of the identified impacts of Autonomous Vehicles (AVs) in particular, focusing on network performance of urban areas. A combination of microscopic and macroscopic simulations as well as statistical methods are applied. Microscopic simulation is conducted to measure the changes in network capacities by utilizing the concept of the Macroscopic Fundamental Diagram (MFD), under different AV penetration rates. The resulting capacities are used to estimate the effects on the Passenger Car Units (PCU) under different AV penetration rates and derive functional relationships, which are further introduced to travel demand models to forecast the macroscopic impacts on network performance. The results indicate a positive impact in terms of capacity changes due to the presence of AVs which vary with penetration rate. Analysis of three different urban networks, Barcelona, Bilbao (Spain) and Athens (Greece), reveals consistent trends. However, notable differences are observed on the estimated PCUs for Athens, potentially due to the different mixed-traffic composition. Further exploration of the critical AV modeling specifications and network characteristics is therefore required for deriving transferable PCU functional relationships across networks. Nevertheless, the static assignment results verify the expected trends in network performance impacts in relation to the applied PCU relationships. Finally, the transferability of the proposed methodology across networks is demonstrated.

Keywords: Connected and Automated Transport Systems (CATS), Traffic simulation, Urban traffic, Macroscopic Fundamental Diagram (MFD), Statistical analysis

INTRODUCTION

During the last decade, there have been numerous studies regarding the development of tools and modeling concepts for Connected and Automated Transport systems (CATs) as well as analyses to understand and quantify their expected implications for the transport system. CATs aim to introduce and integrate new technologies and services (e.g., driverless vehicles, autonomous ride-sharing, public transport) to improve transport system performance, safety, and environmental implications. Such systems will have a major impact on traffic flow and mobility as they consist of vehicles with automation and connectivity capabilities that will communicate with each other and the infrastructure. As empirical data is not yet available, the modeling of Connected and Automated Vehicles (CAVs, a subset of CATs) has had to be based on a number of assumptions regarding their technological characteristics and properties. Depending on the type of impacts and level of detail to be evaluated, different traffic flow resolution models can be utilised. Microscopic models enable the identification of direct impacts on road traffic efficiency (e.g., traffic stability, safety) caused by different AV technologies, since vehicle characteristics are modeled at a disaggregated level. For instance, these models can be used in order to investigate the stability of traffic flow at differing vehicle automation levels and cooperative environments, as well as identify traffic safety implications and design effective traffic management. Many cities utilise macroscopic demand models for the strategic planning of their transport system and assessment of various policies and interventions. These can also be used in CAV modeling and are particularly useful for evaluating and forecasting the long-term impacts on travel demand behavior as well as wider impacts such as changes in land use (area attractiveness, employment, parking spaces, etc.).

As the expected implications of (C)AVs concern various impact areas spanning these two methods *(1)*, there is clearly a need to develop methods for the systematic evaluation of their impacts that can be scalable and transferable across different traffic flow resolutions, network topologies and characteristics, control and traffic patterns *(2)*. In this context, ongoing research within the Horizon 2020 LEVITATE project has established a multi-disciplinary impact assessment methodology for incorporation into an innovative web-based policy support tool to enable cities and other authorities to forecast and evaluate impacts of CATS on urban areas and eventually establish the most effective policy for their city *(3)*. In line with this objective, this work aims to address the question of scalability and transferability of the identified impacts of (C)AVs under various automated transport applications.

A recent study *(4)* proposed a modeling framework for the integration of AV impacts, focusing on network capacity, into existing macroscopic travel demand models. The methodology involves extensive combinatorial analysis on disaggregated network elements (i.e., type of road, intersection) as well as different demand and supply interactions to quantify capacities in passenger car units (PCU). This approach may be time cosuming and complex for the transferability to other networks, demand distributions and vehicle type compositions, hence, it is not adequate for this study.

The remainder of the paper is organised as follows. In the next section a review of the most relevant research studies is presented focusing on the impacts of (C)AV on traffic flow efficiency. The following section introduces the proposed framework for assessing the impacts of AV on urban networks. Next, the methodology is applied to the networks of Barcelona, Bilbao and Athens. Finally, the results are presented and discussed.

LITERATURE REVIEW

One approach being used in order to assess network impacts, combines microscopic simulation, statistical analysis as well as macroscopic simulation and this builds on a number of earlier works. A common assumption in the literature is that CAV are expected to improve traffic flow efficiency due to their advanced operative characteristics. In particular, they can achieve reduced reaction times, hence, smaller headway between vehicles (*5, 6*).

Recent studies investigate and highlight the potential effects of CAV on network capacity and overall traffic performance (*7, 8*). In *(7)*, simulation experiments were performed on a corridor network assuming low-level automation vehicles in mixed traffic that showed a small negative effect on traffic flow and road capacities. The results indicated improvement in traffic flow only at penetration rates above 70%.

For example, in *(8)* the authors analyse and distinguish the effects of connected and autonomous vehicles on a highway driving environment, using microscopic simulation to assess the effects of CAVs on traffic flow stability and throughput, using the traffic flow fundamental diagram. The results show that throughput increases as CAV market penetration rate increases. Moreover, AVs result in higher throughput compared to connected vehicles, without automation capabilities, at similar penetration rates. In (*5*) the authors quantify through simulation experiments on a freeway segment the headway distributions and variations in the fundamental diagram across different CAV penetration rates. They observed that the average headway is reduced at higher traffic flow and larger CAV penetration rates. In (*9*) the potential benefits of platooning of 100% penetration of connected vehicles on intersection capacities are investigated in urban roads. The results suggest that intersection capacity can be doubled or tripled by platooning, while the travel times remain the same despite the increase of demand. This gain in performance may be reduced in the case of short urban links, where queue spillback can propagate quickly at upstream intersections. In (*11*) the authors proposed a microscopic traffic simulation framework for assessing the impacts of AVs on the capacities of highway systems by incorporating the behavior of AV technologies into the car-following and lane-changing models. The results indicate that cooperative AVs significantly increase the maximum lane capacity (300% improvement) for 100% penetration rate. Nevertheless, it was found that AVs without cooperation have a small impact on highway capacity, irrespective of the penetration rate.

Another approach for observing network capacities is through the Macroscopic Fundamental Diagram (MFD). The MFD is viewed as the basis of traffic flow theory and has various applications in transportation. It can demonstrate, under certain conditions, at a network-level a functional relationship between the macroscopic variables of the network, i.e., traffic flow (throughput), vehicle density, and speed *(12)*. It has been shown in the literature *(12)* that the network-level MFD is a property of the network itself as well as the network capacity derived from the MFD is independent of the demand patterns in space and time. Hence, the MFD is considered a suitable and easily transferable tool for analysing the network capacities, compared to the approach applied in *(4)*, as it implies the relation between capacities and network characteristics. A brief overview of the MFD properties as well as its recent developments in traffic flow modeling and applications (such as network-wide control strategies, network performance evaluation, and road pricing) are presented in *(13)*, which also summarises the factors that are found to influence the existence and a well-defined shape of MFD, including traffic demand, network and signal settings, and route choices.

The concept of the network MFD or Network Fundamental Diagram (NFD) is not new and has been used in various studies, such as in perimeter traffic control *(14-17)*, modeling and control of urban traffic emissions *(18)* as well as validation of microscopic simulation models *(19)*. While several studies have utilised the MFD to express the traffic dynamics of large-scale urban transport networks, only a few have applied it for the identification of capacity implications of AVs. The capacities for (C)AVs and for mixed traffic composed of both AV and conventional vehicles can be easily derived from the network MFD, independently of the specific modeling assumptions of AVs and network characteristics. In *(17)* microscopic simulation is used to investigate how AVs affect the network performance on urban networks. It is demonstrated, using the network MFD obtained from simulation experiments, that the network throughput increases and the traffic conditions improve as the penetration rate of AVs in the traffic demand increases. In *(20)* the authors point out that most of the studies in the literature consider connected AVs (CAVs) and address the impacts on highway capacity and only few of them focus on urban transportation. In their study they investigate the possible impacts of AVs without connectivity on the MFD. Simulation investigations in SUMO are performed for a real-world traffic network and a virtual grid road network considering different penetration rates. The authors conclude that AV penetration rate has a positive impact on improving the network capacity in a quasi-linear way. In particular, the maximum traffic flows (for 100% AVs penetration) are 16-23% larger than that of all conventional vehicles' scenario. This improvement is attributed to shorter headway and less reaction time of AVs.

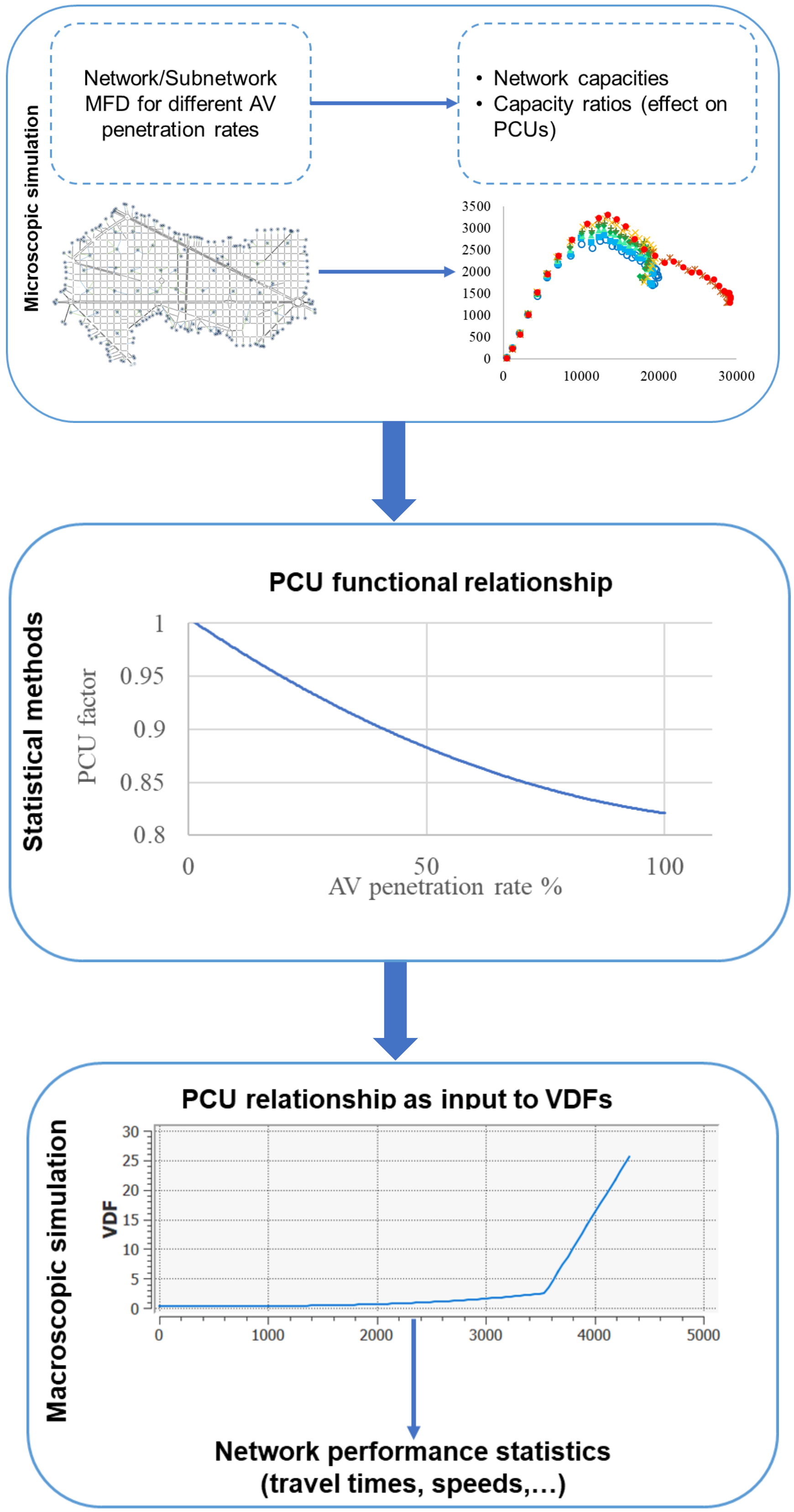
This paper adopts the utilization of the network MDF to evaluate the impacts of (C)AVs on the network supply as a functional relationship between the network capacities and AV penetrations rates. Macroscopic route choice and assignment models apply VDFs (Volume Delay Functions) to model the travel time or the cost on a section as a function of different parameters such as the section volume, capacity, length, etc. VDFs further use the concept of Passenger Car Unit (PCU) to convert the capacity and volumes into passenger car equivalents for each vehicle type. The microscopic simulation outcome can be a characterization of the impacts in terms of macroscopic variables, such as capacity. Subsequently, the PCU factors are estimated from the derived capacities and can be used to adjust the VDFs for the macroscopic models. The feasibility and transferability of the proposed method is explored through microscopic simulations for the city networks of Barcelona and Bilbao (Spain) as well as Athens (Greece), which have different size and topology. The microscopic simulation software Aimsun Next *(21)* is used for conducting the experiments. Subsequently, a statistical analysis is performed to estimate the PCU factors based on the derived capacities for various AV penetration rates. Finally, the estimated functional relationship between the PCUs and AV penetration rates is used as input to the VDFs to forecast the implications of AVs on the network performance.

METHODOLOGY

The approach for assessing and quantifying the impacts of (C)AVs with respect to the network performance includes the following steps:

1. Microscopic simulation-based experiments to derive the network capacities for scenarios with mixed traffic flow consisting of conventional vehicles and AVs.
2. Statistical analysis for the identification of the effects on the PCUs as a relative change of capacities between different AV penetration rates and conventional vehicles. A functional relationship between the PCU factors and AV penetration rates is estimated.
3. Finally, the PCU relationship is provided as input to the VDFs of macroscopic demand models to forecast the potential macroscopic implications on the network performance induced by different AV penetration rates.

The proposed methodology is intended to be general and used with different networks, AV modeling assumptions. The estimated PCU relationship as a function of the AV penetration rate is expected to be robust and transferable to different networks, under similar AV modeling parameters. Nevertheless, the macroscopic network performance impacts should be evaluated through travel demand models for the specific network of interest. **Figure 1** summarises the steps of the proposed approach. The framework can be used as a complete process from microscopic simulation to macroscopic analysis or different levels of the method can be performed. For example, if a microscopic simulation model of a city is not available, the generalised PCU functional relationship estimated from a different network could be used as input into a travel demand model to forecast the macroscopic impacts.



1 **Figure 1 Framework for AV impact analysis on macroscopic network performance.**

Microscopic simulation analysis

The microscopic simulation analysis explores the implications of AVs on the network efficiency. The MFD of a city is utilized in order to derive the network capacities for different simulation scenarios with various AV penetration rates. One approach to represent the network MFD, which is adopted here, considers the total number of vehicles passing through the network (completing their trip) versus the total number of vehicles inside the network (which equals the density divided by the sum of all link lengths of the road network), within a specified interval. Alternatively, the total network production (veh · distance traveled per unit time) and accumulation (veh) can be calculated from loop detectors on links, where flows and densities are weighted by the length of the link *(12, 17)*. The first approach is preferred in homogeneously congested networks, while the second can be more accurate for the estimation of the average network speeds and densities in less homogeneously congested networks. Three different networks are examined in this analysis using microscopic simulation; the cities of Barcelona, Bilbao and Athens. The networks differ with respect to their size, infrastructure characteristics and topology as well as their mixed-traffic compositions. The demand profiles are constructed to contain a mix of free-flow and congested traffic conditions.

Parameter configuration and experimental design

In this study no vehicle connectivity is assumed, hence, the impacts of AV are assessed with respect to modified parameter values in the car-following, lane-changing and gap acceptance models. A modified Gipps car-following model *(22)* is used in Aimsun Next, which consists of the acceleration and deceleration components. Vehicles accelerate to achieve a certain desired speed, while the preceding vehicle imposes limitations when trying to drive at the desired speed. Hence, the maximum speed to which a vehicle (n) can accelerate during a time period (t, t+T) is given by **Equation 1**:

$$V_a(n,t+T) = V(n,t) + 2.5a(n)T\left(1-\frac{V(n,t)}{V^*(n)}\right)\sqrt{0.025+\frac{V(n,t)}{V^*(n)}} \qquad (1)$$

Where, $V_a(n,t)$ is the speed of vehicle n at time t, $V^*(n)$ is the desired speed of the vehicle (n) for current section, $a(n)$ is the maximum acceleration for vehicle n, and T is the reaction time.

The maximum speed of a vehicle is also influenced by the limitations imposed by the presence of the lead vehicle (vehicle $n-1$) (**Equation 2**):

$$V_b(n,t+T) = d(n)T + \sqrt{d(n)^2T^2 - d(n)\left[2\left\{x(n-1,t) - s(n-1) - x(n,t)\right\} - V(n,t)T - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \qquad (2)$$

Where:

- d(n) is the maximum deceleration desired by vehicle n;
- x(n, t) is position of vehicle n at time t;
- x(n-1, t) is position of preceding vehicle (n-1) at time t;
- s(n-1) is the effective length of vehicle (n-1);
- d'(n-1) is an estimate of desired deceleration of vehicle (n-1).

The speed for vehicle n during time interval $(t, t+T)$ is then the minimum of these two speeds (i.e., **Equations 1** and **2**). The estimation of the leader's deceleration is a function of the "Sensitivity Factor" parameter α defined per vehicle type. The model desired deceleration becomes:

$$d'(n-1) = d(n-1) * \alpha \qquad (3)$$

When α is < 1, the vehicle underestimates the deceleration of the leader and therefore the vehicle becomes more aggressive by decreasing the gap ahead of it. While when α is greater than 1, the vehicle overestimates the deceleration of the leader, hence, the vehicle becomes more cautious by increasing the gap ahead of it.

Due to the enhanced technological capabilities of AVs, the headway between vehicles can be reduced, which in turn is expected to increase the capacity. In order to model these behaviors, the appropriate reaction time factors can be modified for AVs in the simulation. In particular, the reaction times in the Gipps car-following model (**Equations 1** and **2**), at stops as well as at traffic lights are modified to be 0.8 seconds for conventional cars and 50% lower for autonomous vehicles (0.4 seconds). Lower reaction times (0.1s) were also tested, however, no significant difference was observed in the results. Another parameter that is modified in this analysis for AVs is the sensitivity factor in the car-following model (**Equation 3**), which is used to estimate the leader´s deceleration. The value of this factor is reduced to 0.5 for AVs, in order to impose shorter gap between AVs, while for conventional vehicles is kept to its standard value (1.0).

In the lane-changing model, the distributions for the distance zone factor and aggressiveness level are modified for AVs. The distance zone factor is used to determine the zones where vehicles consider their lane choice for a forthcoming turn. The factor range for AVs is chosen [1.0, 1.25], while a common range for regular vehicles is lower [0.8, 1.20]. Hence, longer anticipation distance is implied for AVs. The aggressiveness level controls the sensitivity of a vehicle to the deceleration of the leader with respect to determining how short the gap can be to make a lane change. The higher the level, the smaller the gap the vehicle will accept. A level of 1 corresponds to the vehicle's own length. For AVs small aggressiveness level is assumed, with a distribution range [0.0, 0.25], compared to conventional vehicles which is usually set from 0.0 to 1.0. This implies that AVs will keep longer clearance with the leader during lane changing. The overtake speed threshold, which expresses the percentage of the desired speed of a vehicle below which the vehicle may decide to overtake, is also modified for AVs. The threshold is reduced to 85% for AVs compared to 90%, for conventional vehicles. Finally, the safety margin factor is a give way behavior parameter in the gap acceptance model. It is used as a multiplier, by vehicle type, to the turn safety margin values that determine the time spent by a vehicle waiting for a gap to move at a priority junction. In this study the AV type is assumed to have different detection technologies, hence, AVs can be either cautious and keep waiting for a high safety gap or less conservative with low safety gap. Here we assume a safety margin range [0.75, 1.25] for AVs. A common factor for conventional cars is 1.0. Based on the selected parameter values for AVs, the AV type can be characterized as aggressive. For a detailed description of the aforementioned models and parameters, see (*23*).

As mentioned earlier in the paper, this study aims to develop a general impact assessment method that can be used under any AV modeling assumptions. Hence, the optimization of the parameter values to model AV behaviors and characteristics is beyond the scope of this work. In this study, the same route choice behavior is considered for both AVs and conventional vehicles. Nevertheless, this aspect can be investigated in future work. Moreover, vehicle connectivity is not considered, however, the applicability of the proposed methodology is independent of the AV modeling assumptions.

Eight (8) simulation scenarios are performed with various penetration rates of AV in the traffic demand (0% - 100%), with a 10% step increase. A few penetration rate scenarios are excluded to be used for the validation of the estimated PCU functional relationships. For each simulated scenario 10 replications with different random seeds have been performed in order to account for the inherent stochasticity in the microscopic simulation results. The simulation time-step is set at 0.4 seconds. The scenario with only conventional cars in the traffic flow is considered the base-case scenario throughout this analysis.

Estimation of PCU factors

Passenger car units measure the impact of a transport mode (cars, heavy vehicles, buses, etc.), as a function of vehicle dimensions and operating capabilities, on the traffic flow efficiency compared to a standard unit of passenger car. Hence, a PCU is the number of passenger cars a single vehicle is equivalent to. Traditionally, PCUs have been used for freeway design and operations analysis, such as to represent the effects of different vehicle types on the saturation flow at traffic signals junctions and the effect of large vehicles on road capacity. Several methods have been proposed to measure and/or calibrate the PCUs mainly for heavy trucks and buses. Most of them are simulation-based, with only a few field measurements to validate the relevant simulated values. Depending on the road facility type, PCU equivalents are derived based on different performance measures for each vehicle type, such as flow rates and densities, headways (time or space), queue discharge flow, travel times, capacities, etc. *(24, 25)*. In the case of AVs, as field data is not yet available, the estimation of the PCUs can only be based on simulation output data. Depending on the percentage of AVs in the demand, different capacity levels are expected to occur, hence, the PCUs will vary accordingly. One approach to derive the equivalence in PCUs is to calculate the proportion of capacity reached by vehicles of different types (e.g., bus, truck) with respect to conventional vehicles (reference vehicles). Subsequently, in order to express capacity in macroscopic models, the resulting PCU is used for the VDF calculations. AVs are expected to have lower PCU factors compared to conventional cars, as their enhanced capabilities are expected to increase the network capacity. Nevertheless, the factors are anticipated to differ depending on the AV penetration rate.

Based on the microscopic simulation results, a fitted function (in this case a polynomial function) is used as an example to derive the PCUs given the capacities obtained from the network MFD. In future work, the function can be better approximated and refined to include the standard deviation of the simulated results. The function is described in **Equation 4**:

$$PCU_{AV} = \beta_0 + \beta_1 p_{AV} + \beta_2 {p_{AV}}^2 \qquad (4)$$

where p_{AV} are the AV penetration rates and PCU_{AV} the estimated PCU factors. The PCUs are derived by the capacity ratio of conventional vehicles (CV) and AVs using **Equation 5**:

$$PCU_{AV} = PCU_{CV} \frac{capacity_{CV}}{capacity_{AV}} \qquad (5)$$

In this study the same PCU value for conventional vehicles is considered fixed independently of the vehicle types in the demand composition. However, the PCU estimation can be refined to consider different PCU values for conventional vehicles, depending on the vehicle type, in order to reflect more realistically the impact of mixed-traffic on the traffic conditions.

A parallel study (*26*) applied the proposed framework to the Athens model with the objective to identify the network characteristics (e.g., topology, size, number of signalized intersections, dedicated lanes, etc.) that affect the estimation of the PCU values in the presence of (C)AVs. The MFD concept is also adopted, however, the capacity analysis is conducted both at link and network levels. Preliminary results indicate the impact of specific network characteristics on the capacities and subsequently on the (C)AVs PCU variability. The expected outcome would provide robust PCU functional relationships that can be directly applied to macroscopic demand models of new networks to forecast the impacts, without the need to conduct a microscopic simulation analysis.

Static traffic assignment analysis

Macroscopic demand models apply VDFs, which represent the relationship between link flows and delays, to calculate travel time between origins and destinations. The VDF developed by the US Bureau Public Roads (BPR) is one of the most common functions to determine the travel time on each section as shown in **Equation 6** *(27)*:

$$t = t_{ff}\left(1 + \alpha \cdot \left(\frac{v}{c}\right)^b\right) \qquad (6)$$

Where travel time is a function of free-flow travel time t_{ff}, volume-to-capacity ratio $\frac{v}{c}$, and two parameters α and b. VDF further use the concept of PCU where the volumes and capacities are converted into passenger car equivalents (PCU/hour). In this study a constant value is assumed for the capacity in the VDF of the macroscopic models, while the volume (demand) is adapted using the estimated PCU factors for AVs. This is one of the approaches adopted also in (*4*). Hence, in order to incorporate the impact of heterogeneous traffic with different vehicle types, such as AV, a PCU equivalent can be multiplied with the traffic volume. For the purpose of this analysis, the estimated PCU functions in relation to different AV penetration rates are included in the VDFs. **Equation 6** becomes **Equation 7**:

$$t = t_{ff}\left(1 + \alpha \cdot \left(\frac{v \cdot f_{PCU}(p_{AV})}{c}\right)^{b}\right) \tag{7}$$

where $f_{PCU}(p_{AV})$ is the PCU function dependent on the AV penetration rate p_{AV}.

Different VDFs are expected to result in similar impact trends, as most of them are expressed proportionally to the assigned traffic volume, the constant link capacity and free-flow travel times. Hence, the obtained impact on PCU factors can be easily introduced in any VDF.

To investigate the macroscopic network performance implications of AVs under different scenarios, static traffic assignments are performed. In each assignment, given the specific AV penetration rate, the VDFs are updated based on the derived PCU relationships, using **Equation 4**.

APPLICATION OF THE PROPOSED FRAMEWORK TO THREE NETWORKS

Network description

Three networks were used as testbed to demonstrate the feasibility of the proposed framework. The first network has been used in an earlier study *(17)* and corresponds to a part of the Cental Business District (CBD) of Barcelona in Spain (**Figure 2a**). It consists of 1570 sections and 565 signalized intersections. The traffic demand is represented by a 261 x 261 Origin-Destination (OD) matrix with 115,151 trips. The demand duration is 1 hour. The second network examined is the city of Bilbao, Spain (**Figure 2b)**, consisting of 1264 sections and 63 signalized intersections. The traffic demand is represented by a 37 x 37 OD matrix with 44,068 trips. The demand duration is 1.5 hours.

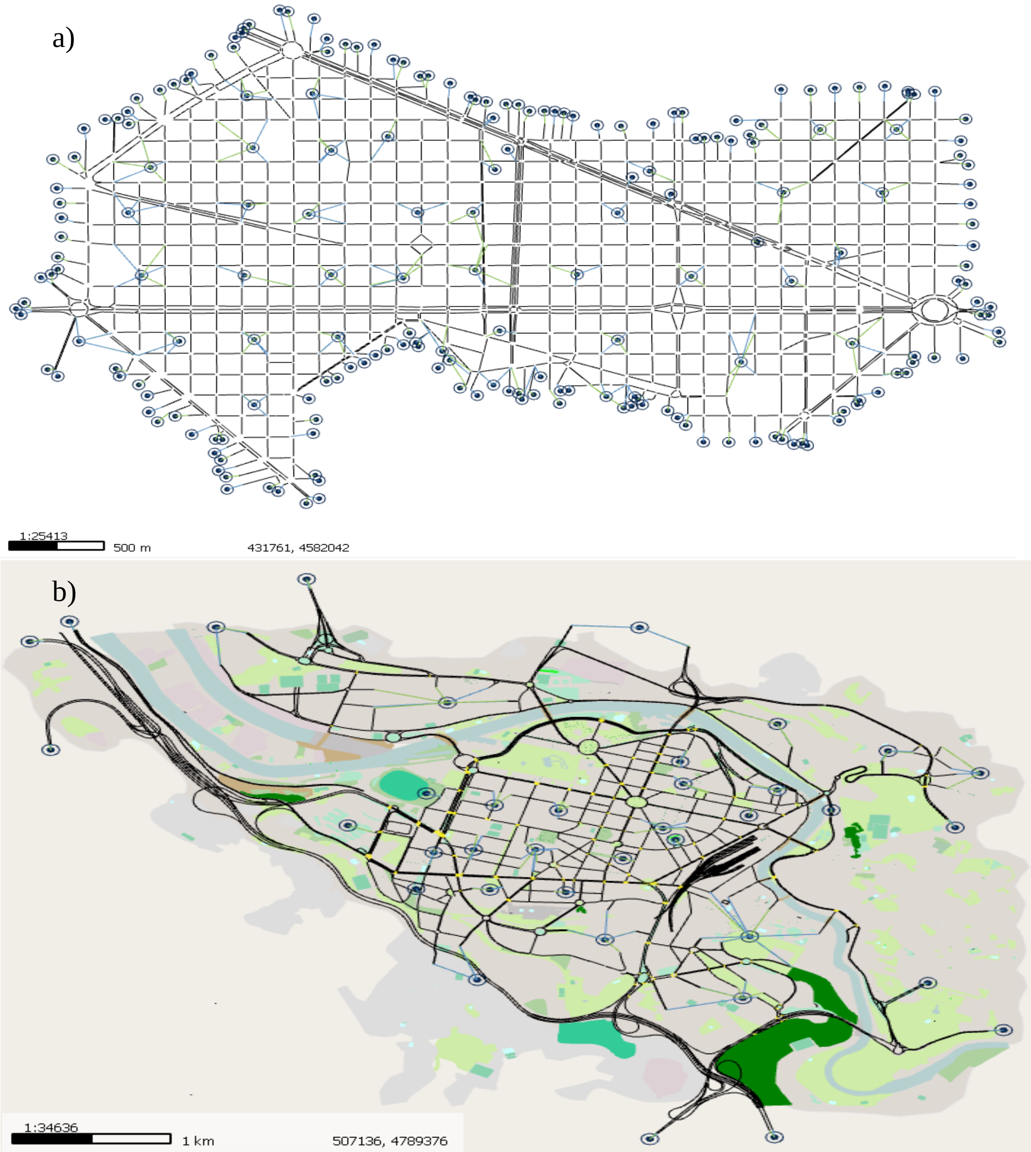


Figure 2 a) Barcelona CBD and b) Bilbao simulation models in the Aimsun Next software.

The third study network that has been simulated is the city center of Athens (**Figure 3**). The network consists of 2,580 road segments (1,424 secondary streets, 1,033 signalized streets and on/off ramps and 123 arterials). The total length of road sections is 348 km and the network size is approximately 20 km2.

Figure 3 The city of Athens network in the Aimsun Next software.

The microscopic model was calibrated using traffic volume data that were collected for year 2019 from 107 detectors in main roads in Athens network. Additional field measurements were also considered. The OD matrices consisted of 290×292 centroids and a total number of 82,270 car trips and 3,110 truck trips for the morning peak hour. Furthermore, the Athens model included public transport namely 95 bus and 14 trolley lines as well as their 1,030 public transport stations, the service frequencies and the waiting times at stops.

It should be noted that the Barcelona and Bilbao traffic models are used as testbed for the implementation and demonstration of the feasibility of the proposed framework, hence, the accuracy of the demand matrices in replicating real traffic conditions was not critical for the scope of this study. Nevertheless, the Athens model is the most realistic model in terms of demand representation (OD matrices) and traffic control plans.

Microscopic simulation results

Microscopic simulations are performed for all three network models. However, they assume different demand fleet compositions. The Barcelona and Bilbao models were initially used in order to demonstrate the feasibility of the proposed approach in deriving the network-wide impacts in the presence of AVs. For this purpose, a hypothetical demand profile was created to bring the network to its capacity and the demand fleet was limited to include only passenger cars (modeled as conventional and autonomous). The investigation of other influencing factors, such as demand fleet and network characteristics, were not considered in the preliminary investigations. The proposed framework was further applied to the Athens network model, which is recently calibrated and the traffic demand is realistically represented by heterogeneous vehicle types (cars, trucks, buses). Furthermore, public transport lines are included and simulated in the Athens network. The MFD-based analysis is flexible and can be applied to multimodal transport systems *(28)* as well.

The microscopic simulation results and statistical analyses are presented and compared mainly for the Barcelona and Bilbao models focusing on demonstrating the contribution and usability of the proposed framework. The corresponding results from the Athens model are used in order to examine the transferability of the proposed method across different networks.

Figure 4a illustrates the impact of different AV penetration rates on the network MFD, which is represented as the vehicles outside (which completed their trip) vs. total number of vehicles inside the network. Hence, the network MFD is derived from the total network outputs, considering all the links in the network. The results represent the average from 10 replications. **Figure 4b** presents the relationship between network average space-mean speed (veh/h) vs. density (veh/km) with each point representing 2 minutes. It is clearly shown that different AV penetration rates can increase the network capacity (**Figure 4a**). It is noteworthy to mention that this conclusion is consistent with the results presented in (*15*), which used same network, although with different AV parameter values. The highest increase in capacity is observed for 100% AV share and is 21% compared to the baseline capacity (2727 veh). However, for high AV rates (90% and 100%), the density increases, hence, the network experiences more congestion. Nevertheless, the average space-mean speed for high density values, induced by the capacity increase, resemble the speeds obtained for lower penetration rates at lower densities (**Figure 4b**).

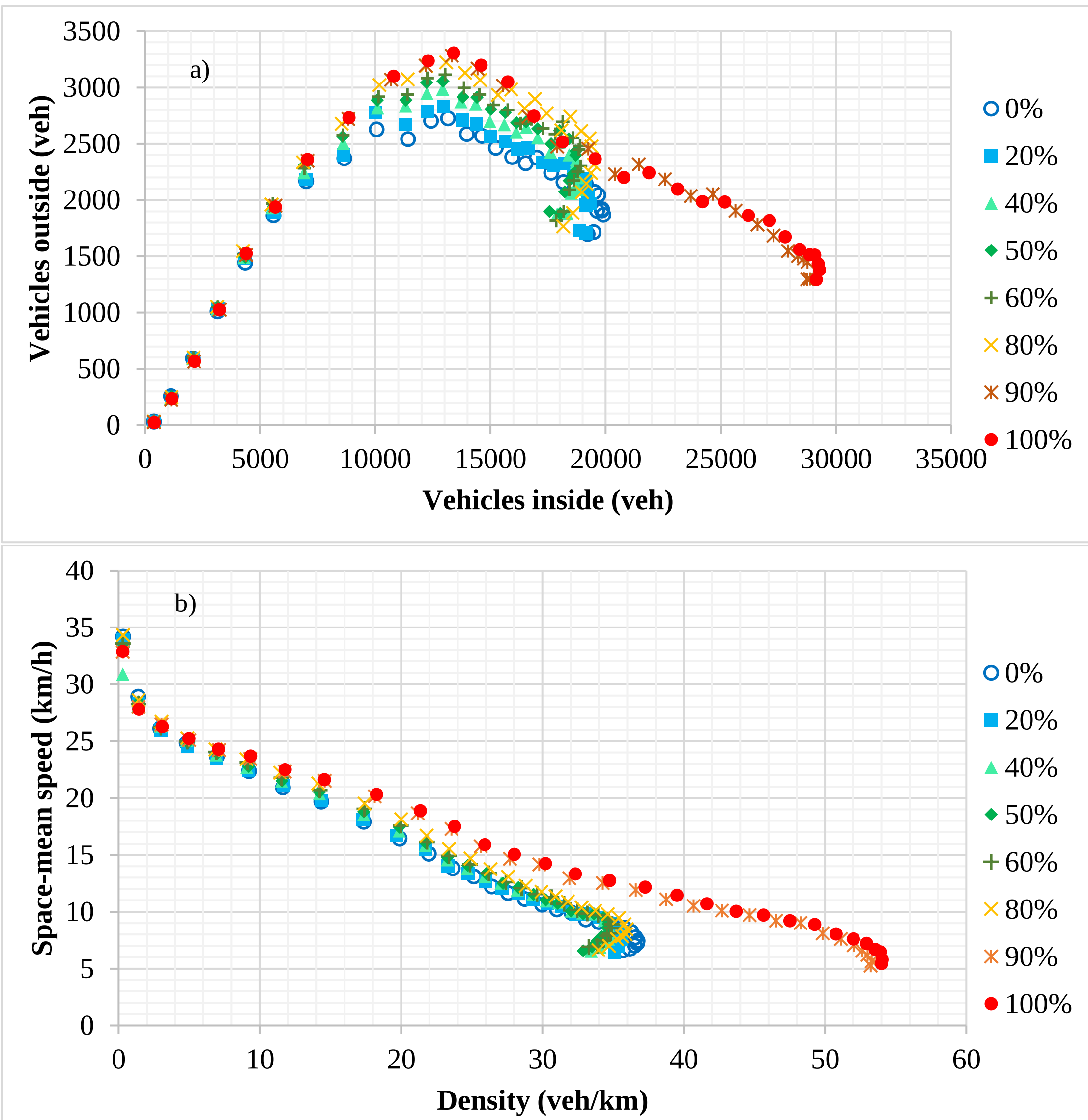


Figure 4 a) Total vehicles outside vs. vehicles inside the network and b) Average network space-mean speed vs. average density for different AV penetration rates.

Figure 5 illustrates the impact of different AV penetration rates on the network MFD for the Bilbao network. This MFD is relatively well-defined during the free-flow and peak period. It can be seen that different AV rates increase the network capacity (**Figure 5a**). The highest increase is 17% compared to the base-case scenario capacity (1167 veh) and is observed around 60% AV share and stabilizes above this rate. No significant variations in average speeds and densities are indicated (**Figure 5b**).

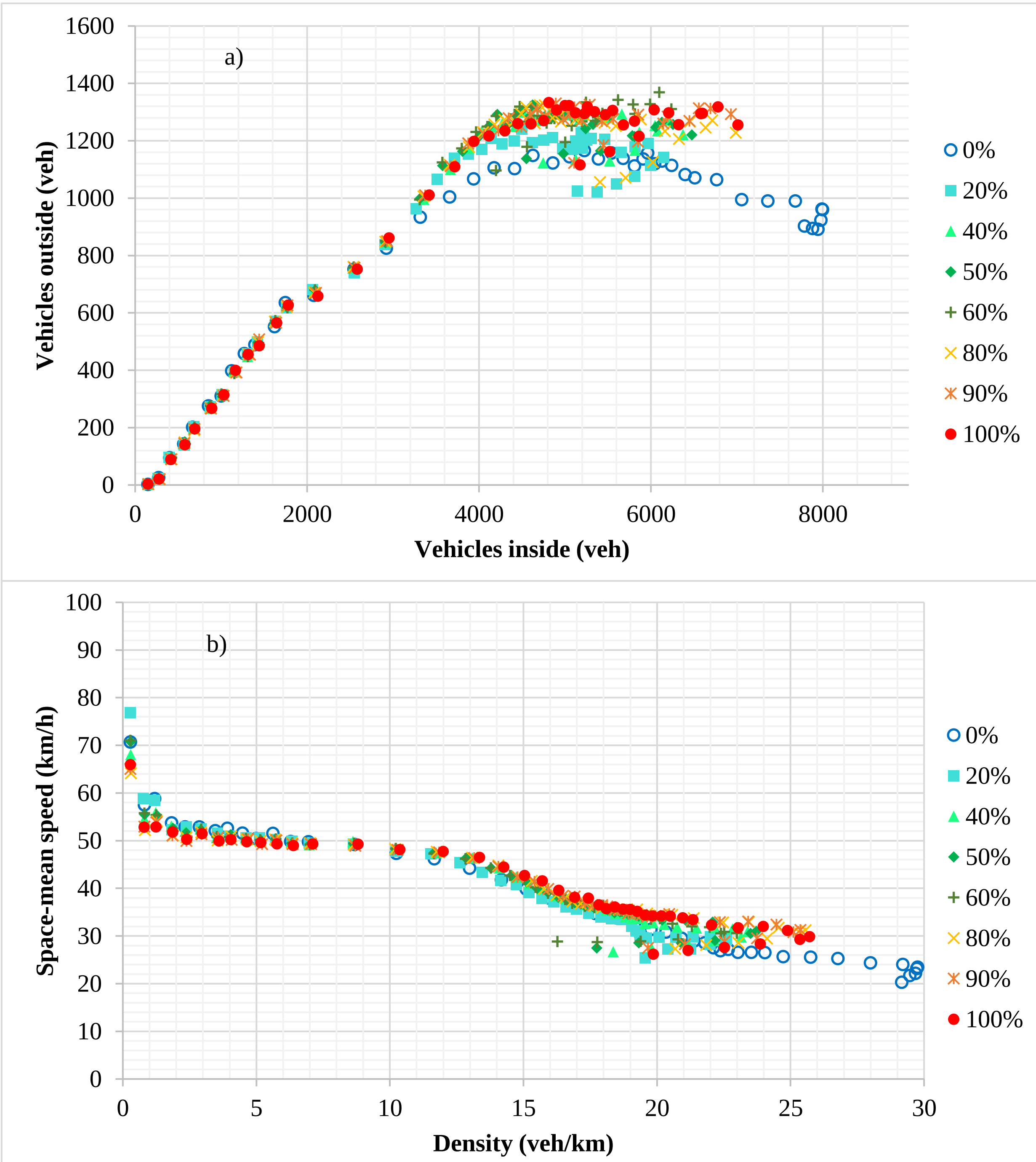


Figure 5 a) Total vehicles outside vs. vehicles inside the network and b) Average network space-mean speed vs. average density for different AV penetration rates.

The confidence intervals for the network average capacities (from 10 replications) across different AV penetration rates are computed at a 95% confidence level (**Figure 6**). The intervals are narrow for both networks; hence, low uncertainty is expected in the results.

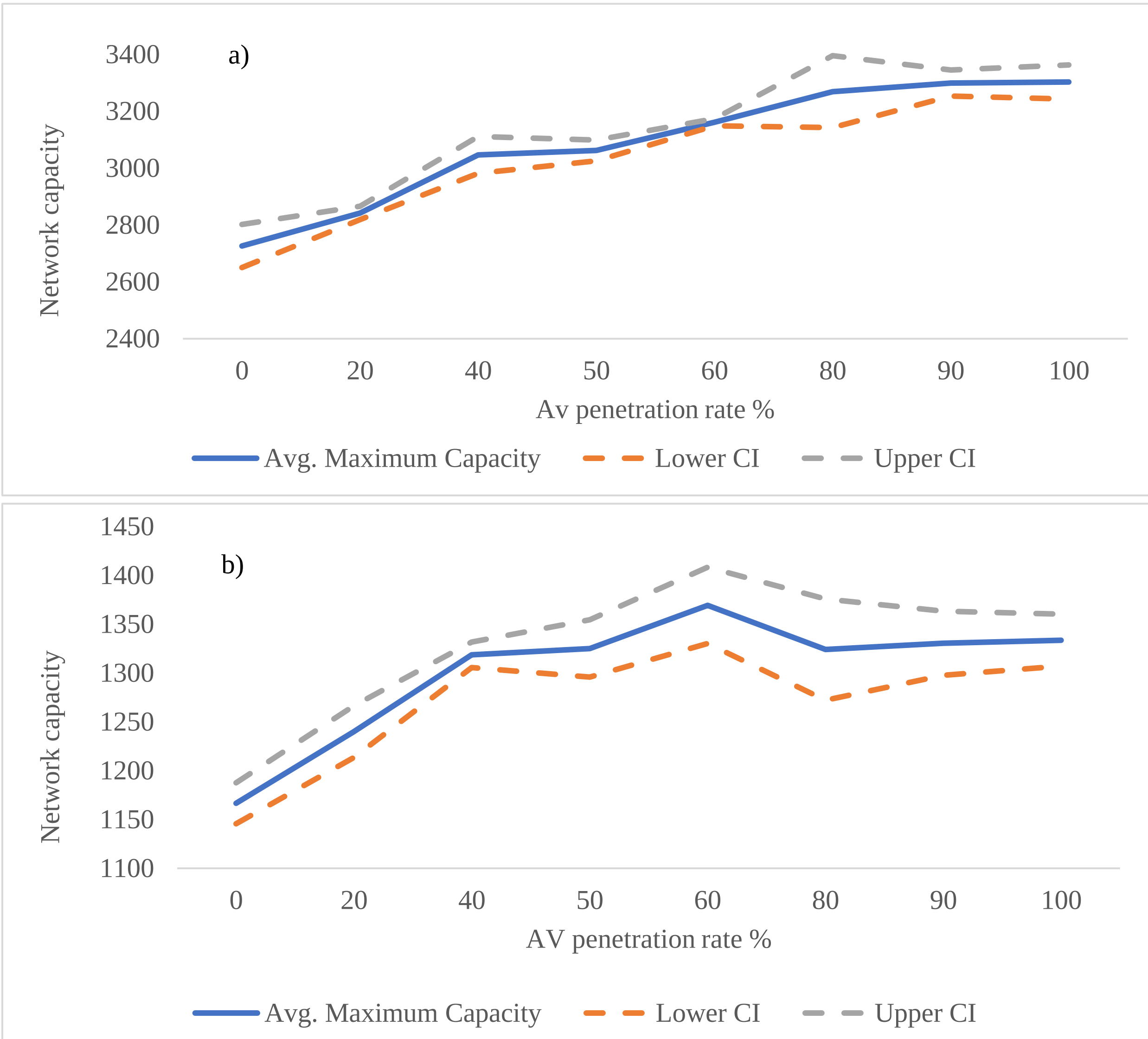


Figure 6 Confidence intervals at a 95% significance level for the average network capacity of 10 replications across AV penetration rates for the a) Barcelona and b) Bilbao networks.

Estimation of PCU factors

Figure 7 illustrates the estimated PCU factors based on the derived capacity ratios for the Barcelona network. The bars indicate the standard deviation, calculated based on the capacity uncertainty as a result of the 10 simulation replications. A PCU factor of 1 is used as the unit for conventional cars. As expected, a decreasing trend is observed as the AV penetration rate increases. For 50% AV penetration rate the PCU factor decreases by 12% (0.89), while the highest decrease (17%) is reached for 100% AV share. It is notable that above 60% AV share there is only slight variation in the PCU factor. Hence, no further capacity gain is obtained for higher penetration rates. The estimated regression line and the $R^2$are also presented on the plot. $R^2$is over 0.99, which indicates a good model fit.

In order to validate the PCU functional relationship derived from the Barcelona simulation network, external validation is performed against the Bilbao network. In particular, the PCU factors for new AV penetration rates are predicted using the Barcelona PCU function and compared against the corresponding values obtained through simulation for the Bilbao network. The additional rates are 2%, 5%, 10%, and 70% with predicted PCU factors 1.0, 0.99, 0.98, and 0.86, respectively. The new points are marked as squares on the regression line on **Figure 7**. The obtained simulation values are 1.0, 0.99, 0.97, and 0.87, respectively, which are very close to the estimated values. Hence, the transferability of the PCU functional relationship to other networks can be justified.

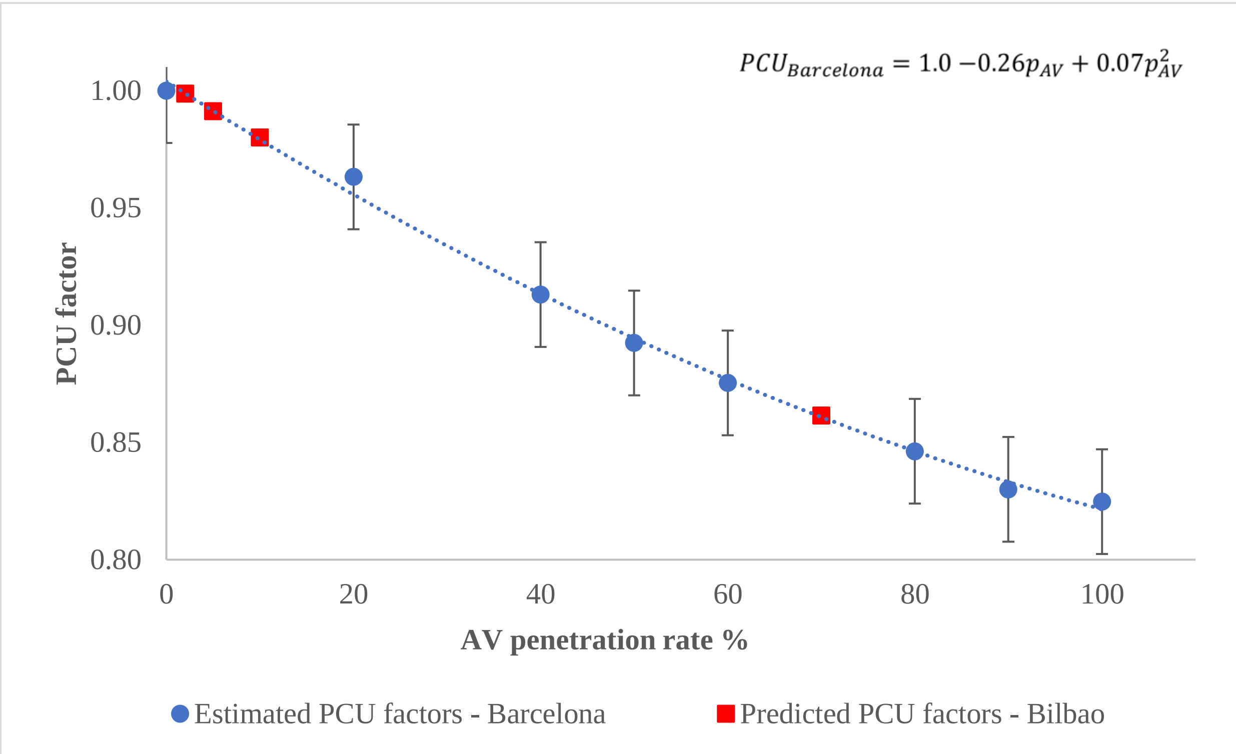


Figure 7 Estimated PCU functional relationship for different AV penetration rates for the Barcelona network.

Figure 8 illustrates the estimated PCU functional relationships as a function of the AV penetration rates (p_{AV}) for the Bilbao network. The estimated functional relationship for the Barcelona network is also displayed for comparison. Similar trends, in line with the derived capacities, are observed for both curves, with decreasing PCU values as the AV penetration rate increases. The PCU values decrease the most up to 50% AV penetration rate. In particular, the lowest PCU factor is obtained for 60% rate and is 0.85. Above 60% AV shares the PCU stabilises around 0.88. The reason why the trend for higher penetration rates does not continue to have a decreasing trend above 80% rates for Bilbao, as in the Barcelona results, may be related to a combination of the specific network characteristics and the high AV presence (e.g., spillback effects or no coordination of signalized intersections). Nevertheless, the standard deviation, indicated by the error bars, is higher for the PCU values derived for the Bilbao network.

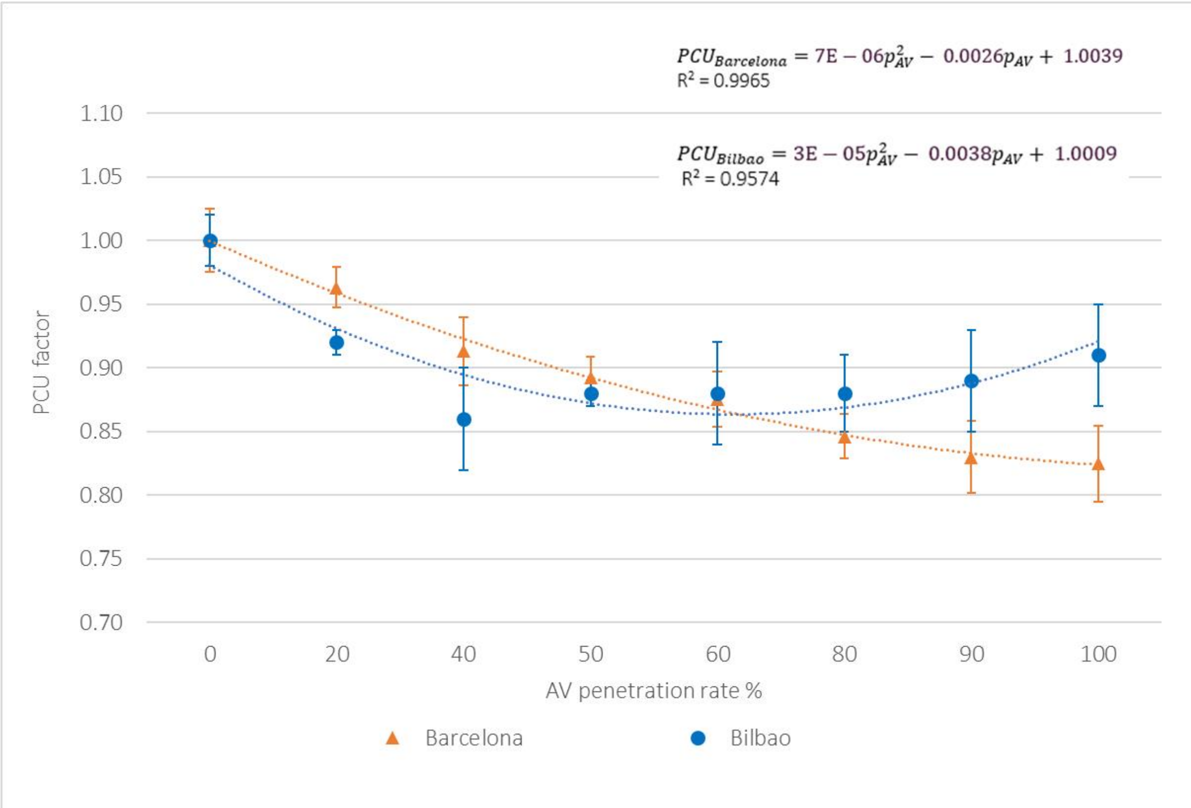


Figure 8 Estimated PCU functions for the Bilbao and Barcelona networks.

Figure 9 shows the estimated PCU functional relationship for the Athens network. A similar trend is observed to the ones for the Barcelona and Bilbao networks across different AV penetration rated. However, the range of the derived PCU values differs. This variation is expected due to the heterogeneous demand fleet in the Athens model as well as the presence of dedicated public transport lanes. Further analysis will be performed to compare the effect on PCUs. The t-statistics and p-values demonstrate that all three estimated models, namely for Barcelona, Bilbao and Athens, are statistically significant at a 95% confidence level ($H_0: \beta_1, \beta_2 = 0$).

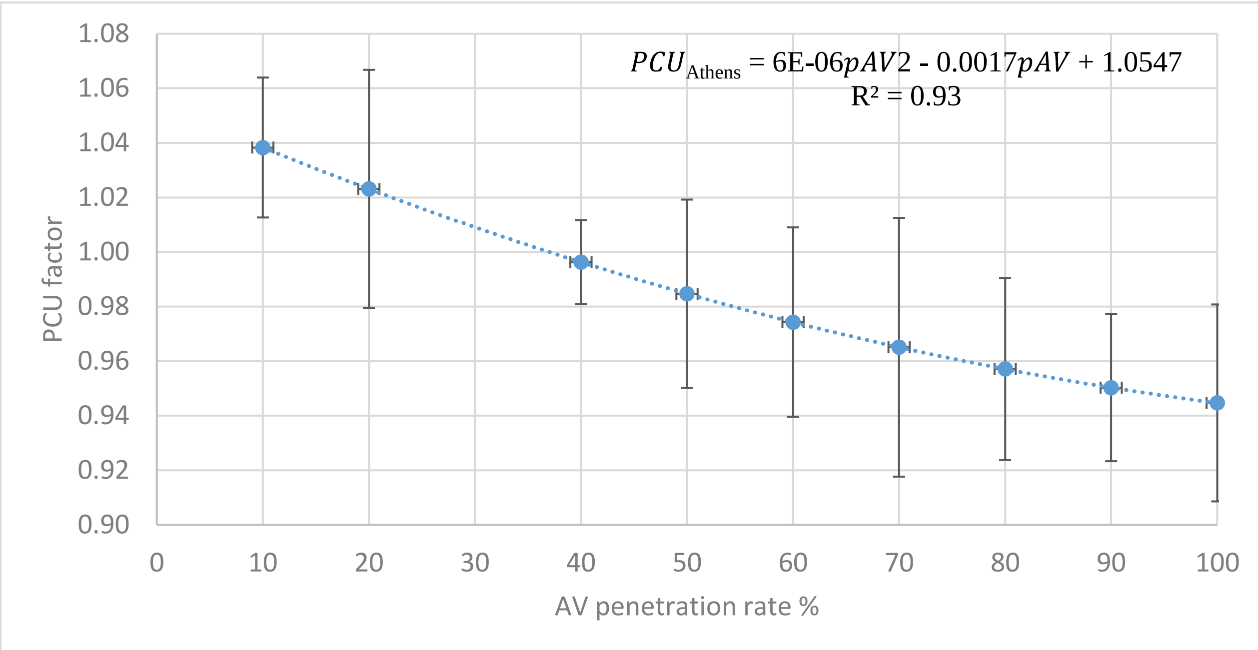


Figure 9 Estimated PCU functions for the Athens network.

Macroscopic simulation results

The third level of the proposed method involves macroscopic simulation analysis to forecast the network performance impacts depending on the PCU factors for different AV penetration rates. Static traffic assignment scenarios are conducted for different AV penetration rates. In particular, the effect of AVs is modeled through the VDFs using the PCU functional relationships obtained from the statistical analysis presented in the previous subsection.

The VDFs in the macroscopic simulation model are updated with the new PCU factors by applying the three different functional relationships estimated in the previous subsection. Hence, a sensitivity analysis is performed with respect to the impact of different PCU factors on the total network performance. The results from the macroscopic simulation analysis are first illustrated for the Barcelona and Bilbao networks on **Figure 10**. The baseline scenario corresponds to a demand with only conventional cars. The network travel time reduction across various AV penetration rates is presented for the two PCU functional relationships that are applied to each network. The Barcelona relationship is denoted as PCU function 1 and the Bilbao relationship as PCU function 2 (**Figure 8**).

The results indicate a consistent trend in terms of total network cost (here travel time) reduction for both networks, with respect to the PCU relationship that is used. Nevertheless, the absolute values of travel time reduction depend on the network itself (route choice options, demand, etc.). Furthermore, the non-parametric Mann-Whitney U test is performed to compare the difference between the two curves after applying them to each examined network. Namely, to examine statistically whether the two independent PCU functional relationships result in different impacts on the same network. The test indicates no statistically significant difference at a 95% confidence level. This verifies that the effect of the AV penetration rate on the PCUs is similar for both networks that are investigated. Defining as null hypothesis that the two curves are equal; the test indicates no statistically significant difference at a 95% confidence level. This verifies that the effect of the AV penetration rate on the PCUs is similar for both investigated networks.

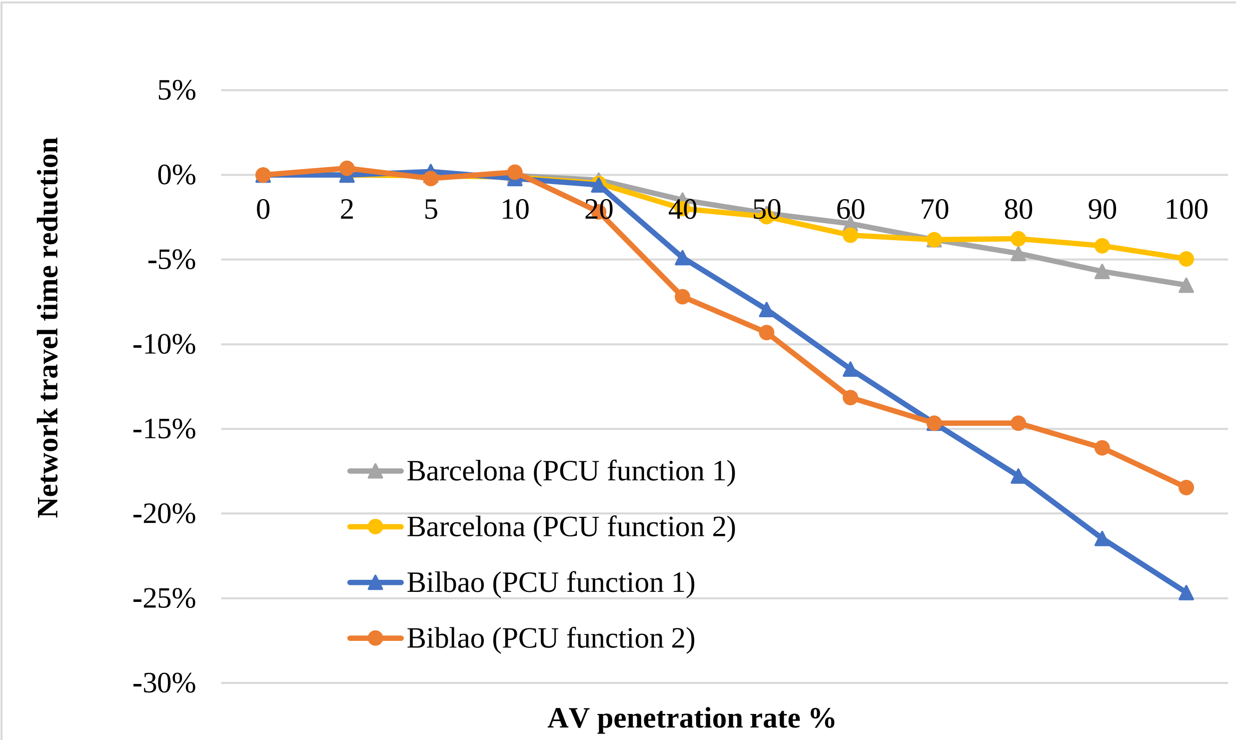


Figure 10 Total network cost change for Barcelona and Bilbao networks across different AV penetration rates for two PCU functional relationships.

Finally, the derived PCU values from the Athens model are applied to the Barcelona and Bilbao networks. **Figure 11** compares the derived curves in terms of network travel time reduction. The results indicate differences with respect to the network performance impacts using the PCU functional relationship (PCU function 3 on **Figure 11**) from the Athens model, compared to the other two functions. The Mann-Whitney U test verifies that PCU function 3 is significantly different from functions 1 and 2, respectively, at 95% confidence level.

Although there are many uncertainties to be able to clearly identify the reason for the observed differences, one potential influencing factor, as reported in *(7)*, is the heterogeneity in traffic flow that can reduce traffic flow capacity due to the larger time headways that can appear between vehicles. In particular, this difference can be justified due to the heterogenous demand fleet in the Athens model. Furthermore, the impact of dedicated public transport lanes as well as the network topology are influencing factors in determining the PCU values. These observations are used as the basis for more extensive investigation of the most critical factors in determining the PCU values in relation to the AV penetration rates as well as the transferability of macroscopic implications across networks.

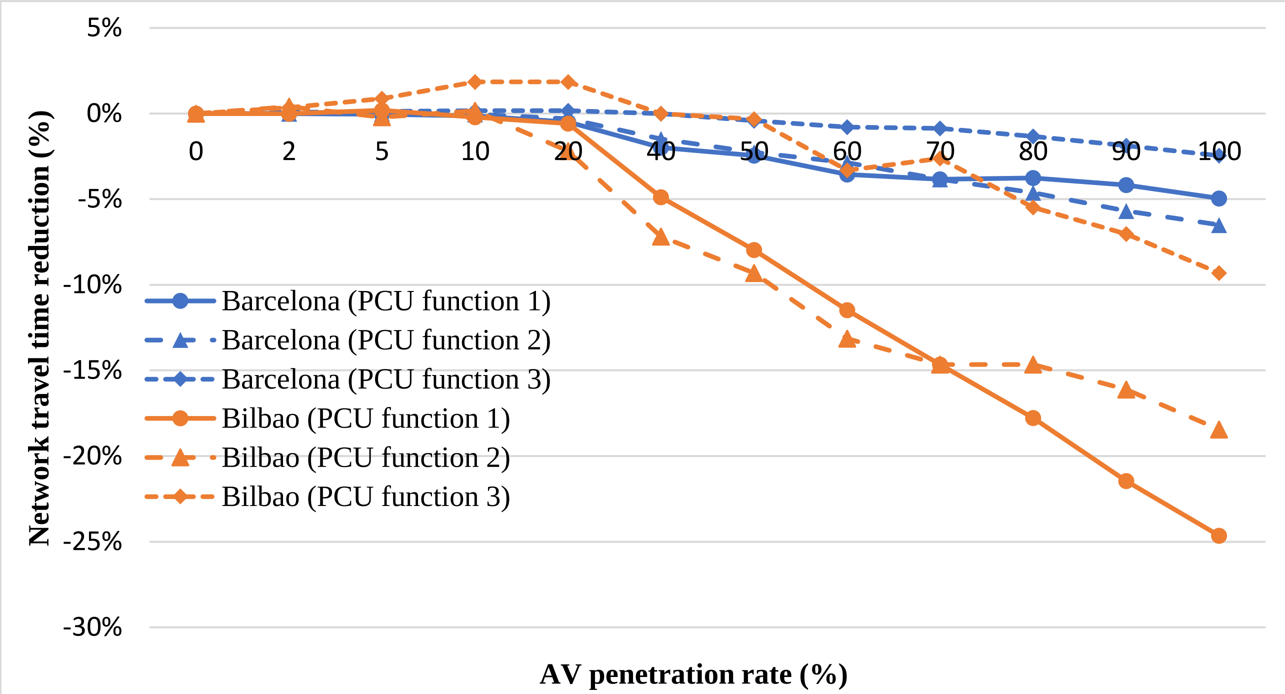


Figure 11 Comparison of total network cost reduction between Barcelona, Bilbao, and Athens networks across different AV penetration rates for two PCU functional relationships.

CONCLUSIONS

The paper presented a general framework for evaluating macroscopic implications of (C)AVs in urban networks. The objective of this work was two-fold: 1. To propose an impact assessment approach that can be adopted for any modeling assumptions regarding connected and automated vehicles, 2. To investigate the potential transferability and upscaling of the identified impacts across different networks. The impacts are investigated with a focus on the changes in the network performance and capacity. The proposed approach consists of three levels of analysis. Microscopic simulation experiments were first conducted for the identification and measurement of the impacts of AVs on network performance as a function of the penetrations rates. The network MFD was used to derive the network capacities. Statistical analysis was then used to provide equivalent modeling relationships for the upscaling of the microscopic results to a macroscopic level. In particular, the capacities were translated into PCU factors for each of the investigated AV penetration rates. Static assignments were performed to forecast the macroscopic network performance impacts (e.g., total network travel times) given the estimated PCU functional relationships. The main contribution of this work is the applicability and transferability of the proposed method to other networks.

The approach was used for the study of three urban networks, which have different size and topology. However, the transferability of the method could be examined on different network areas (e.g., a city centre or a metropolitan area). The results demonstrated positive effects of AVs on the traffic characteristics, specifically, the network capacity and traffic stability increase as the AV penetration rate increases, most notably above 10-20% in penetration. The capacity increase can be attributed to the lower reaction times that (C)AVs can achieve due to their enhanced capabilities compared to conventional vehicles. Another important outcome of the performed analysis is the consistency in the trend of the effect of AVs on the PCU factors as a function of the AV penetration rates. The results are consistent for all three examined networks. The derived effects on the PCUs were further validated by applying the estimated PCU values into the VDFs of a macroscopic demand model to forecast the network performance implications as a function of the AV penetration rate. The static assignment results showed consistency in terms of total network cost reduction with the PCU functional relationships derived from the Barcelona and Bilbao networks. However, the effect of the estimated PCU function for the Athens network is statistically different compared to the other two functions. An intuitive explanation is the different demand fleet composition in the Athens network. Further examination is needed for the transferability and robustness of the presented results on more networks as well as mixed-traffic compositions. Moreover, for heterogenous networks, partitioning can be considered in order to obtain well-defined MFDs (*29*). Nevertheless, the results obtained from the Barcelona and Bilbao networks that have the same demand fleet composition, but differ in size and topology, indicate the potential of the proposed approach to derive robust conclusions.

Ongoing work applies the methodology to more networks in order to validate the robustness of the findings presented in this paper. Furthermore, while capacities are obtained through the MFDs based on microscopic simulation outputs, mesoscopic simulation can also be used to obtain the macroscopic fundamental variables. Future work will address the determination of the set of parameters required to model (C)AVs and systematically derive the equivalent vehicle behavior and characteristics, and hence impacts, for the integration of mesoscopic flow resolution models. Finally, the proposed methodology was applied and demonstrated with respect to one dimension of the potential implications of AVs, namely the transport network efficiency. A similar approach could be developed in order to identify and analyse the other dimensions, such as traffic safety and environmental impacts.

ACKNOWLEDGMENTS

This research has been supported by European Union´s Horizon 2020 research and innovation programme under grant agreement No 824361 (LEVITATE - Societal Level Impacts of Connected and Automated Vehicles).

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Tympakianaki, Nogues, Casas, Brackstone, Oikonomou, Vlahogianni, Djukic and Yannis; data collection: Tympakianaki, Nogues and Oikonomou; analysis and interpretation of results: Tympakianaki, Nogues, Casas, Brackstone, Oikonomou, Vlahogianni, Djukic and Yannis; draft manuscript preparation: Tympakianaki, Nogues. All authors reviewed the results and approved the final version of the manuscript.

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