Impacts of Connected Automated Vehicles on Large Urban Road Network

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Abstract: As an essential component of the Cooperative Intelligent Transportation System (C-ITS), Connected Automated Vehicles (CAVs) are anticipated to play a significant role in the development of the future mobility service. This paper investigates the impacts of different penetration of CAVs on the urban road network. The investigation is carried out in a vast urban network with Simulation of Urban MObility (SUMO), a microscopic traffic simulator. The estimated factors of the network are network maximum flow, critical density, average speed, congestion duration, and roadway over-saturation degree. The Macroscopic Fundamental Diagram (MFD) has been used to estimate the maximum flow and critical density. In a simulation way, it substantiated that a road network could have less scattered MFDs, even if the traffic flow is distributed heterogeneously. The congestion duration and over-saturation degree are used to check traffic congestion. The simulation results show that applying 100% CAVs can contribute about a 13.55% increase in maximum flow. A similar trend can be found in the critical density for different CAV penetration rates. In a similar congestion situation, the network with 100% CAV driving in can carry more than 130% of the original travel demand. In terms of congestion level, even a low CAV penetration rate may significantly improve the traffic condition.

1 INTRODUCTION

Nowadays, researchers support Connected Automated Vehicles (CAVs) improvements in traffic safety and efficiency. However, quantifying the impacts of CAVs is highly challenging. The challenge comes from the uncertainty of how automated vehicles will be introduced into our lives. For example, how will the CAVs drive actually? Moreover, how will the current traffic management methods change with the CAVs, how will the road authorities minimize the infrastructure required for the mixed traffic of manual vehicles and automated vehicles, and the uncertainty of CAV behaviors from different CAV companies, etc.? Thus, the impacts of CAVs on traffic should be first studied extensively. In the absence of precise and massive amounts of data, a common way to achieve this aim in current research is to perform studies based on microscopic traffic simulation tools (Raju and Farah, 2021).

CAV microscopic simulation studies were conducted on many traffic topics, including ramp metering(Liu et al., 2018; Xie et al., 2017), car following (Milanés and Shladover, 2014; Wang et al., 2015), traffic signals (Goodall et al., 2013), emissions (Mersky and Samaras, 2016), road safety (Papadoulis et al., 2019), and mixed traffic (Ye and Yamamoto, 2018). Most studies have differentiated CAVs and human-driven vehicles (HDVs) by assuming that the CAV driving behavior is less stochastic and consistent. Simultaneously, CAVs have good lane discipline.

Researchers used two main ways to model CAVs: modifying the traditional car following and lane changing models by adapting their parameters to the supposed CAVs behavior (Lu et al., 2020), or by defining some novel models directly to mimic CAVs behavior (Treiber et al., 2000; Van Arem et al., 2006). Some researchers modeled CAVs by changing the parameters of the inbuilt car-following models. However, the simulated CAVs were less realistic in comparison to the field behavior. The other researchers applied numerous external algorithms to model the CAVs. The main aim of the algorithms was to induce communication among the vehicles. The CAVs were governed by various models, including the Intelligent Driver Model (IDM) (Treiber and Kesting, 2013),

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the Optimum Velocity Model (OVM) (Maske et al., 2019), Adaptive Cruise Control (ACC) (Van Arem et al., 2006), Cooperative Adaptive Cruise Control CACC.

Of course, the presence of CAVs, once seen aggregately, alters the performance of supply elements, such as link cost functions and network performances. The impacts of CAVs have been investigated recently. For instance, several researchers have investigated the CAV's impacts on the freeway capacity (Ghiasi et al., 2017; Chen et al., 2017). Shi and Li (2021) proposed a method to construct a freeway Fundamental Diagram for traffic flow mixed with AVs. They analyzed 3 data sets related to different time headway values for CAVs. They concluded that different headway settings would mainly affect road capacity. Hu et al. (2021) analyzed the changes in the Macroscopic Fundamental Diagram (MFD) of an urban corridor with the HDVs and CAVs mixed traffic flow. The majority of the simulation results demonstrate that the road capacity has been improved with the growth of the CAVs penetration rate, the increase of CAVs platoon intensity, and the reduction of headway time. However, the conclusions are also different due to the different settings of the time headway for CAVs. Lu et al. (2020) had investigated the impacts of AVs on the MFDs of urban road networks. The paper assumed that AVs have a shorter time headway and concluded that AVs' popularization would enlarge the network capacity. Mavromatis et al. (2020) investigated the impact of AVs and CAVs on five large urban networks (about 3 km $\times$ 3 km). They found CAVs can significantly enlarge the traffic flow, decrease the average trip time and reduce congestion. However, they have yet to investigate the change in travel demand that the road network can afford with the application of CAVs. Tympakianaki et al. (2022) proposed a framework to estimate the impacts of CAVs on urban network performance. They investigated the effects of the different penetration rates of CAVs on network capacities. They found positive effects on capacities with the deployment of CAVs. Nevertheless, the demand durations of the research on the impacts of CAVs on large urban networks were only 1 hour (Mavromatis et al., 2020; Tympakianaki et al., 2022). There is a lack of research on the effects of CAVs on network MFD curve and congestion level with proportional increasing whole day travel demands.

In this regard, this research seeks to close this gap by providing a thorough performance analysis of different CAVs penetration in a vast urban network with daily travel demand. This paper defines congestion duration and over-saturation degree as the key performance indicators (KPIs) to evaluate the congestion level of daily traffics. In particular, this paper quantifies the impacts in terms of MFD, congestion level, and accommodated travel demand. Specifically, the objectives are:

- doing sensitivity analysis on CAV's penetration to see the impacts of CAV on urban MFD and congestion level;
- proportionally scaling the demand to investigate the change of travel demand that the road network can carry.

The remainder of this paper is organized as follows: Section 2 presents the simulation setup and assumptions of HDVs and CAVs. Section 3 discusses the KPIs used to evaluate the impacts of CAVs. Section 4 describes the numerical analysis and simulation results. Finally, the findings and discussion are presented in section 5.

2 METHODOLOGY

This section describes the CAV modeling and simulation network.

2.1 CAV Modeling

In this work, a fully connected automated vehicle is modeled based on microscopic traffic modeling. The movements of a car are the result of both longitudinal and lateral motions. The car-following model reproduces the vehicle's longitudinal actions, while the lane-changing model dominates the lateral movements. The parameters of car-following and lane-changing models allow for fine-tuning of vehicle behaviors. These models have been demonstrated to be useful for simulating traffic behavior and flow instabilities (Treiber and Kesting, 2013).

Table 1: Vehicle models.

Parameters	HDV (car)	HDV (HGV)	CAV (car)	CAV (HGV)
Car-following model	Krauss		IDM	
Speed factor	normal (1, 0.1)	normal (1, 0.1)	normal (1, 0.05)	normal (1, 0.05)
Time headway (s)	1.2	1.5	0.6	0.6
Lane-changing model	LC2013			
Cooperation	0.5	0.5	1	1
Strategic	0.5	0.5	1	1

Adopting a specific model for each type of vehicle is not universally agreed upon in the literature. Table 1 shows the modelings of HDVs and CAVs in this work. The HDVs, including private cars and Heavy Goods Vehicles (HGVs), are modeled with Krauss car-following model and LC2013 lane-changing model because most vehicle features of HDVs rely on these models (Lopez et al., 2018). The Intelligent Driver Model (IDM) car-following model and LC2013 lane-changing model are used to mimic the behaviors of CAVs. The choice of parameters is influenced by recent relevant works. Time headway values have been adjusted to meet the related works (Mahmud et al., 2017; Xie et al., 2019; Lücken et al., 2019; Guériau and Dusparic, 2020). The speed factor of HDVs is assumed to follow a normal distribution with a mean of 1 and a deviation of 0.1. While CAVs are supposed to obey a normal distribution with minor deviation. Lane-changing parameters also vary for different types of vehicles. CAVs are assumed to be connected with each other and the infrastructures with Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communications. This enabled CAVs to show more excellent anticipatory behavior in their routing strategy, leading to earlier strategic lane changes when joining or leaving main streets. Therefore, CAVs have higher values in cooperation and strategic parameters.

2.2 Simulated Urban Road Network

This work investigates a huge-scale urban network, represented in Fig. 1.

The simulated network is the Dublin city center, covering 5 km × 3.5 km area, consisting of 483.4 km of road with a typical daily demand. The daily traffic demand pattern and volumes are generated from real data. Several months of traffic data, excluding holidays and weekends, are averaged to get a typical workday traffic demand with 417997 trips (Guériau and Dusparic, 2020). A typical traffic demand should consist of different traffic conditions, from free-flow traffic via saturated traffic to congested traffic. The free flow traffic demand is from 00:00 to 07:00. From 8:00 to 10:00, the simulation performs the morning rush hours. From 17:00 to 19:00, the afternoon rush hours occur. As the results show that the high CAV penetration improves the network capacity. In order to investigate the over-congested situation for the higher level of CAV penetration scenarios, the original demands are scaled up to guarantee enough congestion in the simulation, since a high CAVs penetration rate could improve the network capacity.

2.3 Performed Scenarios

As shown in Table 2, six different deployments of CAVs have been simulated to reveal the impacts of different percentages of CAVs on the urban road network. The first scenario A was run without CAV inside the simulated network. The scenario A had been used as a baseline for the comparison. Other scenarios had a 20% increasing percentage of CAVs deployments from 20% to 100%.

Figure 1: Dublin city center network.

Table 2: Simulated scenarios with different CAV penetration rates.

Scenarios	HDV	CAV
A	100%	0%
B	80%	20%
C	60%	40%
D	40%	60%
E	20%	80%
F	0%	100%

One wants to remark that all scenarios were simulated with a set of varying traffic demands to obtain a congested traffic situation in each scenario in order to explore a complete empirical network MFD. The traffic demand had been increased to the final value of 130%, with a 10% constant increment applied to the original one.

3 NETWORK PERFORMANCE METRICS

Many indicators can indicate the level of congestion on the roadway. Some indicators are based on roadway performance, such as average speed, flow, density, duration, etc. Others focus on a quantification of the measurements into values that can then be used to inform policy through cost-benefit analysis. In this paper, maximum flow, critical density, average speed, simulation statistics values, congested duration, and roadway over-saturation degree have been used to reflect the traffic condition in the road network.

3.1 Macroscopic Fundamental Diagram (MFD)

MFD reveals the relationship between space-mean flow, vehicle density, and average speed of a road network. The concept of an MFD with an optimal accumulated vehicle number was first proposed by Godfrey (1969). Similar approaches were introduced later by Herman and Prigogine (1979), and Daganzo (2007). Geroliminis and Daganzo (2008) firstly verified its existence with the field experiment data collected in downtown Yokohama. They proved that MFDs could exist in urban neighborhoods, revealing the relationship between space-mean flow and vehicle accumulation in the network. They also stated that there is a linear relationship between the network's average flow and its total outflow. They also found that the MFD's properties are related to the network infrastructure and its control strategy, but not to the traffic demand.

While, Geroliminis and Sun (2011) relaxed the conditions for the existence of less scattered MFDs for urban networks. They found that a strict homogeneous traffic is unnecessary to obtain well-defined MFDs for a metropolitan area. However, the network's spatial distribution of car density is one of the crucial factors affecting an MFD's scatter and shape.

The MFD relates vehicle density in an urban network to travel production (traffic flow). Denoted by i are road edge segments between intersections. l_i, q_i, and k_i represent, respectively, the length, flow, and density of the segment i. Then, one can calculate the weighted average flow (q) and the weighted average density (k) as

$$q = \frac{\Sigma_i q_i l_i}{\Sigma_i l_i}; \tag{1}$$

$$k = \frac{\Sigma_i k_i l_i}{\Sigma_i l_i}. \tag{2}$$

The maximum of the production (q_c) represents the overall urban network capacity at the critical vehicle density (k_c). Consequently, (k_c, q_c) is the critical point on the urban MFD (Geroliminis and Daganzo, 2008; Loder et al., 2019).

Therefore, the weighted average speed is $v = \frac{q}{k}$. It is the average space mean speed within the reported interval.

3.2 Congestion Duration and Roadway Over-Saturation Degree

Congestion duration (in minutes) estimates how long the congested traffic condition exists. We call it Δ in this paper, which can be evaluated with the following equation (3):

$$\Delta = |t_1 - t_2|, \tag{3}$$

where t_1 and t_2 are the moments when the density begins and ends with exceeding the critical density, respectively.

Roadway over-saturation degree ($S\%$) is the ratio of observed maximum density to the critical density of the roadway. It can be calculated with the equation (4).

$$S\% = \frac{k_{max} - k_c}{k_c} \times 100\%, \tag{4}$$

where k_{max} is the maximum vehicle density during the simulation.

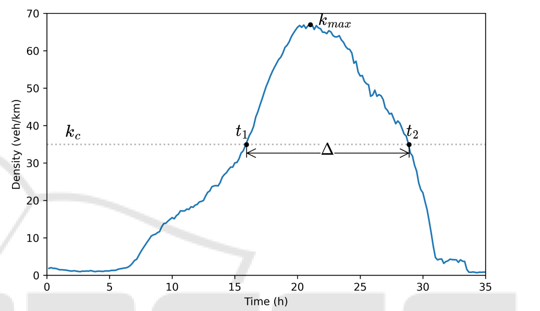

Figure 2: Congestion duration and over-saturation degree.

All the parameters mentioned above are illustrated in Fig. 2.

4 RESULTS

In this section, the simulation results have been presented and discussed in different scenarios.

4.1 Maximum Flow

As shown in Fig. 3, the scatter points are the data collected from the simulation of different scenarios. The MFD in this paper only considers the points when the congestion forms, the dissipation of congestion is not considered. This work aims to investigate the maximum flow for different scenarios. The legend of Fig. 3 shows the color and shape of different scenarios points. The demands of 80% and 100% CAVs scenario are 130% of the original demand to get over congested traffic. Other scenarios get over congested only with a demand of 120% of the original demand. From Fig. 3, one can conclude that the achieved maximum flow increases with the increase in CAVs penetration rate. As the proportion

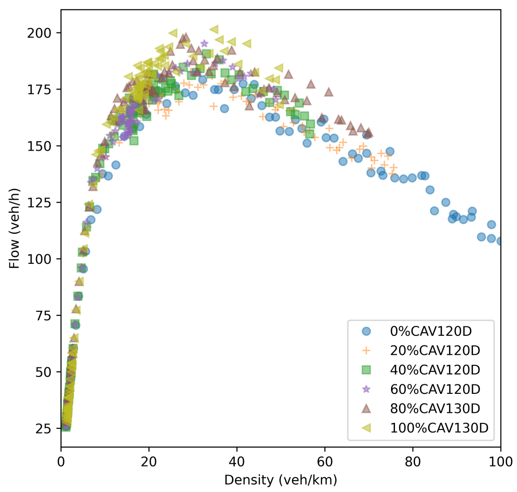

Figure 3: Flow density relationship.

of CAVs increases from 0% to 100%, the maximum traffic flow of the Dublin road network increases by approximately 13.6%, from around 176 vehicles/h to 200 vehicles/h. The critical density varies between 30 to 40 vehicles/km, as similarly happens in Tympakianaki et al. (2022). This work estimated the critical densities for different scenarios to calculate the congestion duration (Δ) and over-saturation degree ($S\%$). With the available data, MFD curves are fitted for each scenario to find the exact critical density and maximum flow. As shown in Fig. 4, the curves are plotted with an upper bound MFD (uMFD) introduced by Ambühl et al. (2020).

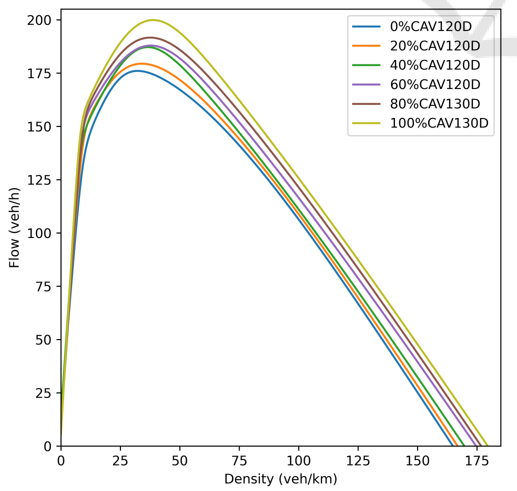

Figure 4: Fitted flow density relationship.

4.2 Speed

In Fig. 5, the empirical MFD relationships between network average speed and density have been presented for each performed scenario. The scenarios in Fig. 5 are the same as those in Fig. 3. For the same vehicle density, scenarios with higher CAVs penetration have relatively higher average speeds. This is in line with the simulation results of Barcelona's central business district in Tympakianaki et al. (2022).

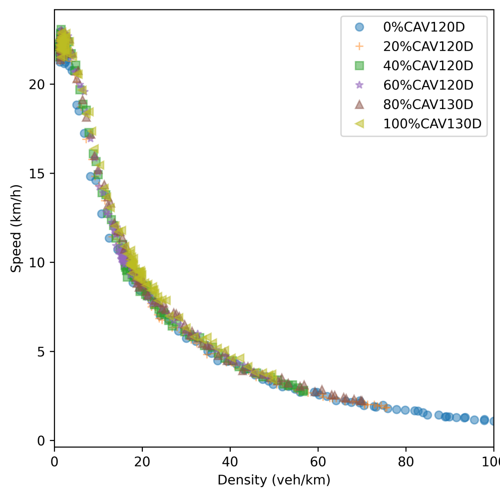

Figure 5: Speed density relationship.

4.3 Simulation State

SUMO provides a statistical output that reveals overall information about the simulation. Table 3 shows a part of the statistic results, the critical density, and the maximum flow of different scenarios. As shown in Table 3, the variable Vehicles means how many vehicles are loaded and finished their trips. The speed (in kilometers per hour) is the average trip speed. Duration (in second) is the average trip duration. Waiting time (in seconds) is the average time each vehicle spends standing because of congestion or red traffic light. Time loss (in seconds), including waiting time, is the average time lost due to driving slower than the desired speed. Route length (in meters) is the average route length. Critical density and maximum flow were obtained from the fitted MFD curves. Comparing the average speed of different scenarios with the same travel demand, we can find that the average speed increase with a higher percentage of CAVs. From the time loss and waiting time, one can conclude that it is the waiting time that contributes much more to the delay than the slower velocity. The maximum flow is increasing with a higher CAV penetration rate. The maximum flow of the network increased by 13.55% with a 100% of CAV penetration rate. The improvements in critical density and the maximum flow have a similar trend.

Table 3: Simulation state.

Scenario	Vehicles	Speed	Duration	Waiting time	Time loss	Route length	Critical density	Maximum Flow
0%CAV120D	501597	10.48	15986.35	13834.23	15331.16	5782.56	32.25	176.01
20%CAV120D	501597	14.04	5515.88	4401.23	5070.34	4478.76	34.02 (+5.49%)	179.39 (+1.92%)
40%CAV120D	501597	16.34	2718.95	2054.61	2397.55	3317.37	36.58 (+13.43%)	187.15 (+6.33%)
60%CAV120D	501597	17.50	1901.73	1382.55	1621.13	2927.44	37.75 (+17.05%)	187.90 (+6.76%)
80%CAV120D	501597	20.81	599.33	306.51	397.68	2138.77	-	-
100%CAV120D	501597	21.85	482.1	224.89	293.78	2015.42	-	-
80%CAV130D	543396	15.37	4108.37	3326.23	3707.46	4086.4	37.56 (+16.47%)	191.62 (+8.87%)
100%CAV130D	543396	16.92	2141.14	1630.65	1838.31	3153.62	38.74 (+20.12%)	199..86 (+13.55%)

4.4 Congestion Duration and Roadway Over-Saturation Degree

From Table 4, one can evaluate that in the case of 100% or even 110% of the original demand, all HDVs scenarios have already had considerable congestion. However, congestion does not occur yet in other simulated scenarios. This shows that the introduction of CAVs alleviates traffic congestion. When one looks at the 120% of the original demand, the higher the CAV penetration rate, the smaller the congestion duration and over-saturated degree. Moreover, when the CAV penetration rate is higher than 80%, one will not observe over-congestion. The demand is increased proportionally to observe the congestion in 80% and 100% CAV scenarios. When the demand is increased to 130% of the original demand, congestion appears in these two scenarios. When the demand is increased to 130%, the 80% CAV penetration scenario have slightly heavier congestion than all HDV scenario with the original demand. Moreover, the full CAV scenario has lighter congestion than all HDV with the original demand scenario.

Table 4: Δ and $S\%$ for different scenarios.

Scenario	100% Demand		110% Demand		120% Demand		130% Demand	
	s%	Δ	s%	Δ	s%	Δ	s%	Δ
0%CAV	128.67	940	269	2290	306.32	3220	-	-
20%CAV	-63.22	0	-9.6	0	162.05	1700	-	-
40%CAV	-71.67	0	-52.72	0	73.92	880	-	-
60%CAV	-73.13	0	-63.69	0	44.21	600	-	-
80%CAV	-74.66	0	-66.39	0	-42.52	0	118.24	1300
100%CAV	-78.43	0	-71.13	0	-58.03	0	52.67	680

When comparing the increase in maximum flows and demands, one may see that even if the maximum flow is increased only by 13.55%, the proportionally increased demand that the road network can carry can increase by more than 30%. This is because that trip demand varies during the simulation.

Through Fig. 6, one can intuitively observe traffic improvement with different CAV penetration rates. Fig. 6 shows the accumulated vehicle density changes during each simulation. The critical density shown in the figure is the critical density of the full HDV scenario. The demand of the illustrated scenarios is 120% of the original demand. The simulation without

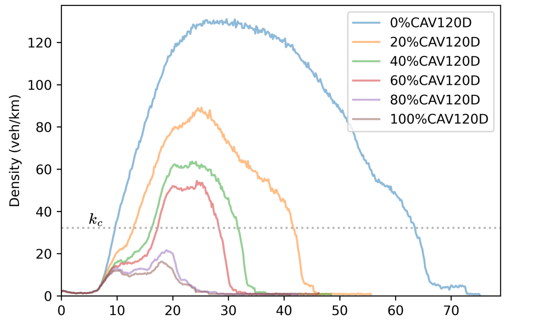

Figure 6: Vehicle density changes during the simulation.

CAVs lasts more than 70 hours to finish. The running time of other scenarios is obviously shorter. Therefore, a low CAVs penetration rate, such as 20%, may contribute much to reducing simulation time.

5 CONCLUSIONS

This paper investigated the impacts of different CAV penetration rates on the urban road network. The CAVs have been assumed to have shorter time headway, less speed deviation, and better lane-changing cooperation. Dublin city center was selected as the urban network for this research. The MFDs were used to illustrate the impacts on the road network's maximum flow and average speed with different CAVs penetration. This work verified that a road network could have less scattered MFDs, even if the traffic flow is distributed heterogeneously in a simulation way. Congestion duration and roadway over-saturation degree were introduced to show the ability of different CAVs penetration to deal with the over-congested situation. As detailed in section 4, 20 simulations with different CAV penetration rates and demands had been run.

Simulation results show that the application of CAVs benefits the maximum achieved flow of the urban road network. This conclusion is consistent with previous researches that had demonstrated the benefits of CAVs on urban traffic (Tympakianaki et al., 2022; Mavromatis et al., 2020). As shown in the results section, the maximum flow of 100% CAVs penetration rate increased by approximately 13.55% compared with the all HDVs scenario. Moreover, the improvements in critical density for different scenarios have a similar trend with the maximum flow improvements. In terms of congestion level, even a low CAV penetration rate may greatly improve the traffic condition. Table 4 shows that 20% of CAVs penetration rate eliminates the congestion in the original demand and 110% demand scenarios. In the 120% demand scenario, 20% CAVs greatly reduce traffic congestion level. Last but not least, when the CAV penetration rate rises from 0% to 100%, the increase in the proportional demand the network can carry under the same congestion degree is much more significant than the increase in the maximum flow. In this work, the increase in the proportional demand is more than two times the increase in maximum flow. This is due to the introduction of CAVs reducing the congestion level and making the congestion dissipate faster. At the same time, a daily demand rather than a constant demand enlarges the advantage.

However, there is a limitation in this study. The traffic flow is heterogeneously distributed, which means the transportation system still has untapped potential. The capacity of the traffic system will be more fully utilized if a control algorithm is used to control the distribution of traffic as homogeneously as possible, which we leave as future work.

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REFERENCES

Ambühl, L., Loder, A., Bliemer, M. C., Menendez, M., and Axhausen, K. W. (2020). A functional form with a physical meaning for the macroscopic fundamental diagram. *Transportation Research Part B: Methodological*, 137:119–132.

Chen, D., Ahn, S., Chitturi, M., and Noyce, D. A. (2017). Towards vehicle automation: Roadway capacity formulation for traffic mixed with regular and automated vehicles. *Transportation research part B: methodological*, 100:196–221.

Daganzo, C. F. (2007). Urban gridlock: Macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological*, 41(1):49–62.

Geroliminis, N. and Daganzo, C. F. (2008). Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological*, 42(9):759–770.

Geroliminis, N. and Sun, J. (2011). Properties of a well-defined macroscopic fundamental diagram for urban traffic. *Transportation Research Part B: Methodological*, 45(3):605–617.

Ghiasi, A., Hussain, O., Qian, Z. S., and Li, X. (2017). A mixed traffic capacity analysis and lane management model for connected automated vehicles: A markov chain method. *Transportation Research Part B: Methodological*, 106:266–292.

Godfrey, J. (1969). The mechanism of a road network. *Traffic Engineering & Control*, 8(8).

Goodall, N. J., Smith, B. L., and Park, B. (2013). Traffic signal control with connected vehicles. *Transportation Research Record*, 2381(1):65–72.

Guériau, M. and Dusparic, I. (2020). Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–8. IEEE.

Herman, R. and Prigogine, I. (1979). A two-fluid approach to town traffic. *Science*, 204(4389):148–151.

Hu, G., Lu, W., Whalin, R. W., Wang, F., and Kwembe, T. A. (2021). Analytical approximation for macroscopic fundamental diagram of urban corridor with mixed human and connected and autonomous traffic. *IET Intelligent Transport Systems*, 15(2):261–272.

Liu, H., Kan, X., Shladover, S. E., Lu, X.-Y., and Ferlis, R. E. (2018). Impact of cooperative adaptive cruise control on multilane freeway merge capacity. *Journal of Intelligent Transportation Systems*, 22(3):263–275.

Loder, A., Ambühl, L., Menendez, M., and Axhausen, K. W. (2019). Understanding traffic capacity of urban networks. *Scientific reports*, 9(1):1–10.

Lopez, P. A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.-P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., and Wießner, E. (2018). Microscopic traffic simulation using SUMO. In *2018 21st international conference on intelligent transportation systems (ITSC)*, pages 2575–2582. IEEE.

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

Lücken, L., Mintsis, E., Kallirroi, N. P., Alms, R., Flötteröd, Y.-P., and Koutras, D. (2019). From automated to manual - modeling control transitions with SUMO. In Weber, M., Bieker-Walz, L., Hilbrich, R., and Behrisch, M., editors, *SUMO User Conference 2019*, volume 62 of *EPiC Series in Computing*, pages 124–144. EasyChair.

Mahmud, S. S., Ferreira, L., Hoque, M. S., and Tavassoli, A. (2017). Application of proximal surrogate indicators for safety evaluation: A review of recent developments and research needs. *IATSS research*, 41(4):153–163.

Maske, H., Chu, T., and Kalabić, U. (2019). Large-scale traffic control using autonomous vehicles and decentralized deep reinforcement learning. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 3816–3821. IEEE.

Mavromatis, I., Tassi, A., Piechocki, R. J., and Sooriyabandara, M. (2020). On urban traffic flow benefits of connected and automated vehicles. In *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, pages 1–7. IEEE.

Mersky, A. C. and Samaras, C. (2016). Fuel economy testing of autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 65:31–48.

Milanés, V. and Shladover, S. E. (2014). Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. *Transportation Research Part C: Emerging Technologies*, 48:285–300.

Papadoulis, A., Quddus, M., and Imprialou, M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. *Accident Analysis & Prevention*, 124:12–22.

Raju, N. and Farah, H. (2021). Evolution of traffic microsimulation and its use for modeling connected and automated vehicles. *Journal of Advanced Transportation*, 2021:1–29.

Shi, X. and Li, X. (2021). Constructing a fundamental diagram for traffic flow with automated vehicles: Methodology and demonstration. *Transportation Research Part B: Methodological*, 150:279–292.

Treiber, M., Hennecke, A., and Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical review E*, 62(2):1805.

Treiber, M. and Kesting, A. (2013). Traffic flow dynamics. *Traffic Flow Dynamics: Data, Models and Simulation, Springer-Verlag Berlin Heidelberg*, pages 983–1000.

Tympakianaki, A., Nogues, L., Casas, J., Brackstone, M., Oikonomou, M. G., Vlahogianni, E. I., Djukic, T., and Yannis, G. (2022). Autonomous vehicles in urban networks: A simulation-based assessment. *Transportation Research Record*, 2676(10):540–552.

Van Arem, B., Van Driel, C. J., and Visser, R. (2006). The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Transactions on intelligent transportation systems*, 7(4):429–436.

Wang, M., Daamen, W., Hoogendoorn, S. P., and van Arem, B. (2015). Cooperative car-following control: Distributed algorithm and impact on moving jam features. *IEEE Transactions on Intelligent Transportation Systems*, 17(5):1459–1471.

Xie, H., Tanin, E., Karunasekera, S., Qi, J., Zhang, R., Kulik, L., and Ramamohanarao, K. (2019). Quantifying the impact of autonomous vehicles using microscopic simulations. In *Proceedings of the 12th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, pages 1–10.

Xie, Y., Zhang, H., Gartner, N. H., and Arsava, T. (2017). Collaborative merging strategy for freeway ramp operations in a connected and autonomous vehicles environment. *Journal of Intelligent Transportation Systems*, 21(2):136–147.

Ye, L. and Yamamoto, T. (2018). Modeling connected and autonomous vehicles in heterogeneous traffic flow. *Physica A: Statistical Mechanics and its Applications*, 490:269–277.