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Exploring the influence of automated driving styles on network efficiency

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Abstract

Automated vehicle technology can be beneficial for many aspects of transport, especially, improving traffic flow stability and efficiency. However, the influence of different automated driving styles on traffic efficiency is still not fully understood. Transport systems are very complex and non-linear, i.e. many participants with different characteristics interact with each other and the aggregated result of their interactions could cause a remarkable change in the entire network. Considering that automated vehicles with different driving styles interact with the environment in different ways, we try to understand the influence of different automated driving styles (e.g., cautious, normal, aggressive) on the important variables in traffic flow theory (e.g., speed) to reveal their impact on network efficiency. Characteristics of these driving styles are extracted by clustering the highD dataset and then, translated into different car-following models for simulation in the SUMO traffic simulator environment. Multiple scenarios of mixed traffic conditions (i.e. ranging different ratios of driving styles) are simulated on the network of Munich inner city.

Keywords: Automated vehicles; automated driving styles; network efficiency.

1. Introduction

Automation is an inevitable tendency in transportation since it can provide convenience to the daily commuting, enhance travel safety, and facilitate the development of transport network companies (TNCs). Consequently, for obtaining more benefits from automated vehicle technologies, studies are being conducted to investigate their superiority and potential impairments. To date, a number of studies have exploited the effects of automated vehicles on travel safety from both the technology side and the ethical side as it is the general public concern.

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It is known that traffic is a complex and non-linear system. Every participant interacts with other participants frequently in traffic. And vehicles with different driving styles affect the surrounding traffic differently, while the effect could be either positive or negative. So, it is imaginable that the interaction among vehicles will change on account of the introduction of automated vehicles, resulting in the change of traffic flow. Automated vehicles from different companies are controlled by distinct algorithms reflecting on different automated driving styles on the operations. For the automated vehicles from the same company, different driving styles can be observed by tuning parameters.

Considering the interactions among vehicles and their critical role in traffic flow, it is necessary to explore the influence of automated vehicles with different driving styles on traffic. This study tries to analyze the change of the important traffic flow variables after introducing different automated vehicles to reveal the change of network efficiency. Since it is impossible to deploy a large number of automated vehicles on the real network nowadays, SUMO simulator (Simulation of Urban MObility, Krajzewicz (2010)), will be used for conducting the experiments.

2. Related Literature

2.1. Driving styles

Driver's behavior is related to both internal factors and external factors. Driver's individual characteristics including demographic attributes, driving experience, involvement in traffic accidents, etc., are important components to constitute the driver's driving style (Ishibashi et al. (2007)). External factors (e.g., traffic conditions, surrounding environment) influence driving visibility and driver's perception (Ossen and Hoogendoorn (2011)). Since drivers have different personal attributes and are differently sensitive to the external conditions, it results in different driving styles. Ishibashi et al. (2007) developed a Driving Style Questionnaire (DSQ) to characterize drivers and measured the correlation between driving style and individual characteristics. The results showed that the principal components extracted from the data collected by the DSQ had significant correlations with the following distance. Considering the difference of driver's perception ability, Tang et al. (2012) proposed a new fundamental diagram theory which can better explain why the widely scattered speed-density and flow-density data arise in reality. It has been proven that different driving styles constructed by both internal and external factors indeed exist among extensive drivers.

Generally, drivers are classified into three styles, i.e., aggressive, neutral and conservative drivers (Tang et al. (2014), Li et al. (2018)). In Tang et al. (2014), the neutral driver was set as the reference substance, while the aggressive driver was defined as the driver whose speed and acceleration are greater than those of the neutral driver, and the conservative driver was defined as the driver with smaller speed and acceleration. Furthermore, some also incorporated anticipation ability in modeling driving behavior (Lenz et al. (1999), Zheng et al. (2012)). Differently, instead of describing specific driving styles, Ossen and Hoogendoorn (2011) attempted to categorize drivers by using trajectory data without setting a fixed number of driving styles beforehand. In other words, the number of driving styles could be different under different empirical scenarios.

Many methods have been proposed to distinguish driving styles. In Li et al. (2018), drivers were categorized simply based on their scores in a behavioral-psychological questionnaire for measuring aggressiveness. More complicatedly, Li et al. (2017) adopted random forest to classify the driving styles by using the maneuver transition features based on a conditional likelihood maximization method. To understand the influence of different driving styles on vehicle's speed, acceleration, fuel and exhaust emissions, Tang et al. (2014) modified the expected headway which is considered in a variant of the full velocity difference model (Jiang et al. (2001)) to represent driver's attributes. Different car-following models have different assumptions indicating critical stimuli considered by drivers. For instance, the intelligent driver model (IDM, Treiber et al. (2000)) assumed that a follower always aims at keeping a certain minimum desired distance headway to the leader. Inspired by this, Ossen and Hoogendoorn (2011) calibrated car-following models for each car-following maneuver trajectory. For some observations one performed best, while for another segment other models showed better results, which indicates differences between the driving styles of drivers. On the other hand, the evidence implying the heterogeneity within a driving style was given by the distribution spread of the calibrated model parameters.

The studies mentioned above give insights into modeling driving styles. However, to the best of our knowledge, the influence of different driving styles on traffic efficiency has not been investigated by the community.

2.2. Influence of automated vehicles

In the last few years, instead of enhancing mobility, sustainability, safety and reliability of traffic management systems by integrating wireless communication, processing power and sensing technologies into them, literature has attempted to improve them through vehicle-based innovation (Talebpour and Mahmassani (2016)). More efforts are spent on improving the reliability and control intelligence of automated vehicles.

According to the definition of five levels of automation provided by the Society of Automotive Engineers (SAE (2014)), automated vehicles (at least level-4) can control safety-critical functions in certain traffic conditions and surrounding environments (Sperling (2018)). Automated vehicle technology can be beneficial for traffic safety by preventing vehicle collisions with the preset program. On the other hand, it should not have negative impacts on traffic efficiency. Yang et al. (2016) investigated isolated intersection control methods for automated vehicles, demonstrating that automated vehicles can improve traffic operation at intersections considerably if the appropriate signal program is used. Talebpour and Mahmassani (2016) revealed that connected and automated vehicles have the potential to improve traffic string stability and throughput on highways under certain penetration rates. Moreover, the impacts of the usage of automated vehicles in shared services on traffic safety, travel behavior, transport economy, supply, land-use, environment, and policy has been concretely summarized in Narayanan et al. (2020). However, the influence of different automated driving styles on traffic efficiency is still not fully understood.

This research tries to find out the influence of different automated driving styles on network efficiency. The major contributions of this research are three-fold: 1) categorizing the vehicles into different categories by using the characteristics extracted from the car-following trajectory data; 2) calibrating car-following models for different vehicle categories to represent different driving styles; 3) it is one of the first works to investigate the influence of different automated driving styles on network efficiency.

3. Methodology

Different drivers have different driving styles depending on both internal factors (e.g., driving experience) and external factors (e.g., traffic conditions). Analogously, automated vehicles can fit the users' preferences by accepting different parameters in the control system. As the most essential component in describing urban driving behaviors, car-following maneuver is always used to distinguish different driving styles. Some applied different car-following models for different driving styles, while the others reached it by setting different parameters for the same model. The way to determine the parameters is critical for the latter method.

In this study, the trajectory data of car-following maneuver are categorized into three categories (i.e., cautious, normal, aggressive) based on time-to-collision (TTC), headway, and speed, respectively, by the K-means clustering algorithm (Steinhaus (1956)). Then Finite Difference Stochastic Approximation (FDSA) is adopted to calibrate the car-following model for each category. Finally, these car-following models are applied in the experiments to simulate the corresponding driving styles.

3.1. K-means clustering

K-means is considered as one of the most used algorithms in clustering problems due to its simplicity and effectiveness. K-means algorithm divides the data into K non-overlapping clusters in an iterative manner till there is no change to the clusters (or centroids). K is the only hyper-parameter which is pre-defined. Centroids are the centers of the clusters. K-means algorithm tries to make the data points located in the same cluster as similar as possible while ensuring the heterogeneity among clusters. The distance between points is used to measure the similarity. K-means solves the clustering problem by minimizing the sum of the squared distance between the data points and the corresponding centroids. For details of K-means algorithm, we refer the interested reader to Steinhaus (1956) and the references therein.

3.2. Calibrating car-following models

FDSA is a gradient-free stochastic approximation algorithm, which is always used for the calibration of non-linear problems where true gradient evaluation is impossible. In this study, it is used to calibrate car-following models for different trajectory categories. For details of FDSA, we refer the interested reader to Spall (2005) and the references therein.

The sum of absolute errors (SAE) is used as the objective function for evaluating the estimates. SAE is calculated by $S(v'_i, v_i) = \sum_{i=1}^{N} |v'_i - v_i|$, where v'_i is the estimated speed at step i; v_i is the observed speed at step i.

3.3. Data and methods

The highway drone data-set (highD) is a dataset consisting of 44,500 kilometers of naturalistic vehicle trajectories for 110,500 vehicles recorded across 147 driven hours on German highways (Krajewski et al. (2018)). In this study, K-means algorithm is applied to categorize the car-following maneuver trajectory data extracted from the highD dataset. Then, a specific car-following model is calibrated for each category.

We have 60 recordings from the highD dataset, and vehicles of each recording are classified via the method described in Section 3, resulting in $3 \times 3 \times 3 \times 60 = 1620$ kinds of vehicles. These vehicle types are categorized into cautious, normal, and aggressive, depending on the headway classes. Finally, parameters of the calibrated car-following models in the same category are averaged to capture the representative behavior of the vehicles involved.

Krauss model (Krau et al. (1997)), IDM and the default ACC model (Mintsis (2018)) in SUMO are chosen to simulate the trajectories. For more information about these models please refer to Krau et al. (1997), Treiber et al. (2000), and Mintsis (2018), respectively. The estimated result of a randomly selected vehicle is presented in Figure 1. The estimated curve from the Krauss model is distant from the observed, while that of IDM and ACC are closer. Since IDM is more stable compared to ACC, it is selected to operate the following experiments. Table 1 presents the calibrated parameters for different driving styles. It is worth noting that any car-following model can be applied in this framework.

Table 1: IDM parameters for three driving styles.

Parameter	Cautious drivers	Normal drivers	Aggressive drivers	Short interpretation
D_{min} (m)	2.66	2.92	1.25	Minimum gap when standing.
a_{max} (m/s^2)	2.00	2.00	2.00	The maximum desired acceleration following car.
$\|b_{max}\|$ (m/s^2)	7.30	8.01	8.60	The absolute of the maximum desire deceleration following car.
τ (s)	1.69	1.13	0.5	Safe time headway.
δ	4	4	4	Acceleration component.

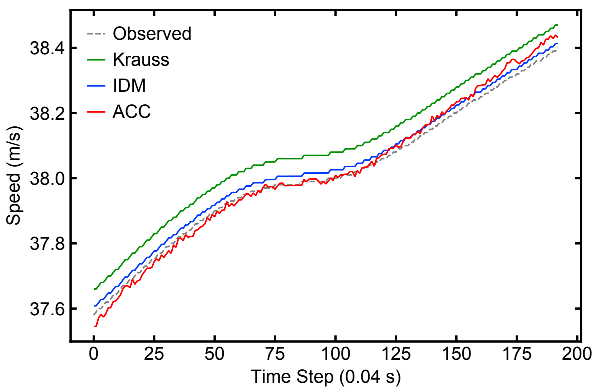

Fig. 1: Estimation results of car-following models

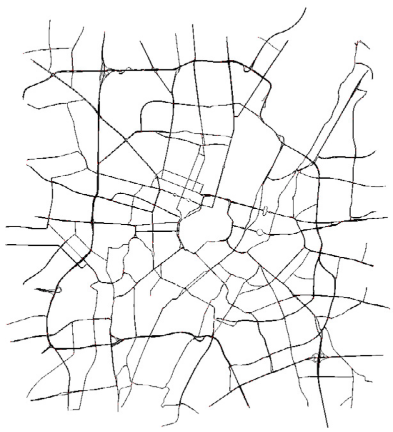

Fig. 2: Network of Munich city center

The network of the Munich city center is adopted in this study (Figure 2). The network consists of 2605 edge links with 564 detectors. The demand for the morning peak between 8 to 9 am with an OD matrix of 61×61 OD pairs is inputted. Simulations are executed in the microscopic resolution with trip-based (one-shot) stochastic user route choice assignment. To alleviate the influence of the stochasticity in the simulations, the results from 10 simulations are averaged to analyze the network efficiency for the specific experiment settings.

4. Experiments and Results

4.1. Results of the experiments with single automated driving style

To investigate the influence of different driving styles towards network efficiency, experiments with automated vehicles defined by one single driving style are simulated first. For simplicity, three driving styles are denoted as C (cautious), N (normal), and A (aggressive), respectively, in the figures.

Figure 3 concludes the distributions of the variables related to traffic efficiency. As can be seen from Figure 3(a), the distributions of flows under three different driving styles are in a similar shape. This phenomenon may be determined by the demand. Since the demand is the same for all scenarios, the number of trips does not change significantly such that the number of vehicles passing the same edge should be similar if the traffic is not extremely congested. However, the distributions of the space mean speed (Figure 3(c)) and occupancy (Figure 3(d)) show evident differences in different scenarios. Distribution of speeds in the scenario with cautious vehicles is more spread than that with normal driving vehicles, while that with normal driving vehicles is more spread than that with aggressive vehicles. It is worth noting that both spreads move to the left, which means the average speed in the normal driving style scenario is greater than that of the cautious style scenario but smaller than that of the aggressive driving style scenario. Figure 3(d) illustrates that lower aggressiveness produces less non-occupied edges.

Different from Figure 3(a), 3(c), 3(d) where data are extracted from the deployed detectors directly, travel time in Figure 3(b) is the time spent to finish the trips, which is the difference between the time when vehicles reaching their destinations and the time vehicles starting their trips from the origins. Obviously, the distributions for less aggressive driving styles are more spread than that of the more aggressive driving styles, and the spreads move to the right side. It is consistent with Figure 3(c). They imply more aggressive driving styles are faster.

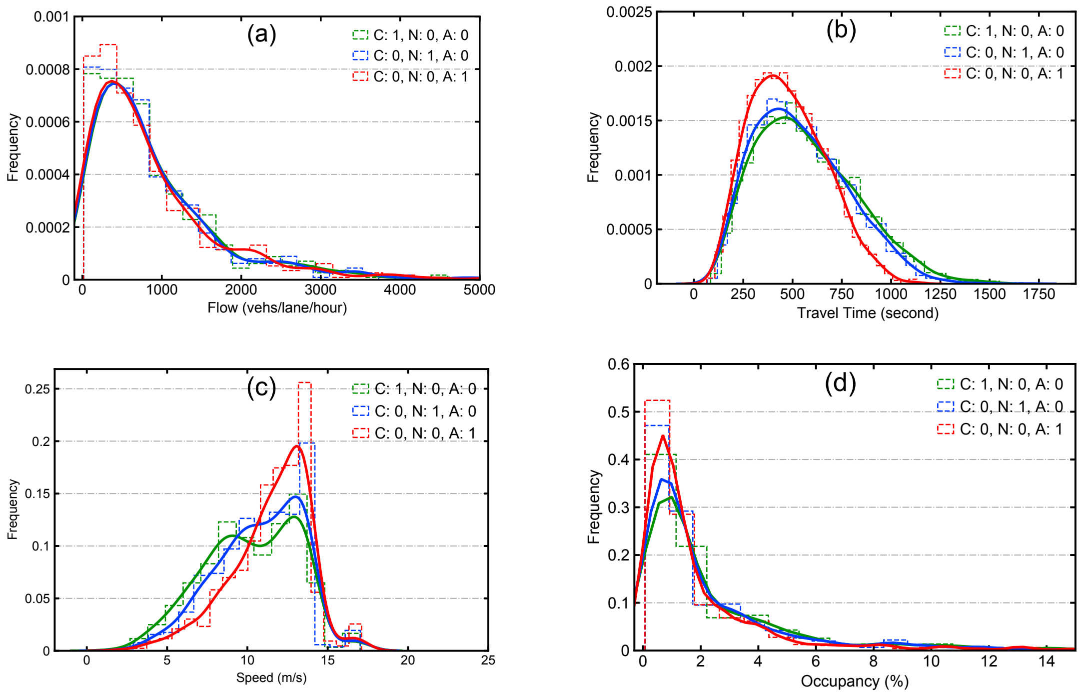

Fig. 3: Distributions of the important variables for traffic efficiency for the experiments with single driving styles

4.2. Results of the experiments with two driving styles

In this section, the variables described in Section 4.1 are averaged among the network such that a single value at the network level is obtained. Vehicles defined by two driving styles are generated for the experiments. The combination of cautious and normal driving style is denoted as $\mathcal{CN}$, while the set of cautious vehicles and aggressive vehicles is denoted as $\mathcal{CA}$, and the set of normal vehicles and aggressive vehicles is denoted as $\mathcal{NA}$.

Figure 4(a) says the increase of the ratio of cautious vehicles within $\mathcal{CN}$ does not affect the mean flow of the network dramatically. On the contrary, the increasing of the ratios of cautious vehicles in $\mathcal{CA}$ and normal vehicles in $\mathcal{NA}$ can improve the mean traffic flow of the network. It is worth noting that, $\mathcal{CN}$ can lead to a higher mean traffic flow than the others regardless of the ratio. However, the mean speed of $\mathcal{CN}$ is always smaller than that of $\mathcal{CA}$ and $\mathcal{NA}$ as shown in Figure 4(c). In 4(d), it is plausible to see $\mathcal{CN}$ leads to a higher occupancy rate than $\mathcal{CA}$ and $\mathcal{NA}$ in consistent with Figure 3(d). Figure 4(b) shows a similar shape to that of Figure 4(d). The lines for all combinations show a reverse U shape indicating the ratios of vehicles with different driving styles can indeed affect the network efficiency. And by adjusting the ratios, a preferential traffic state could be reached. Note that there is a cross between the lines of $\mathcal{CN}$ and $\mathcal{CA}$, which indicates that there are more than one ratio combination alternatives for changing the traffic state at the network level to a predefined state. Another point needed to notice is the mutation of mean speed, mean occupancy, and mean travel time at $r = 0.5$.

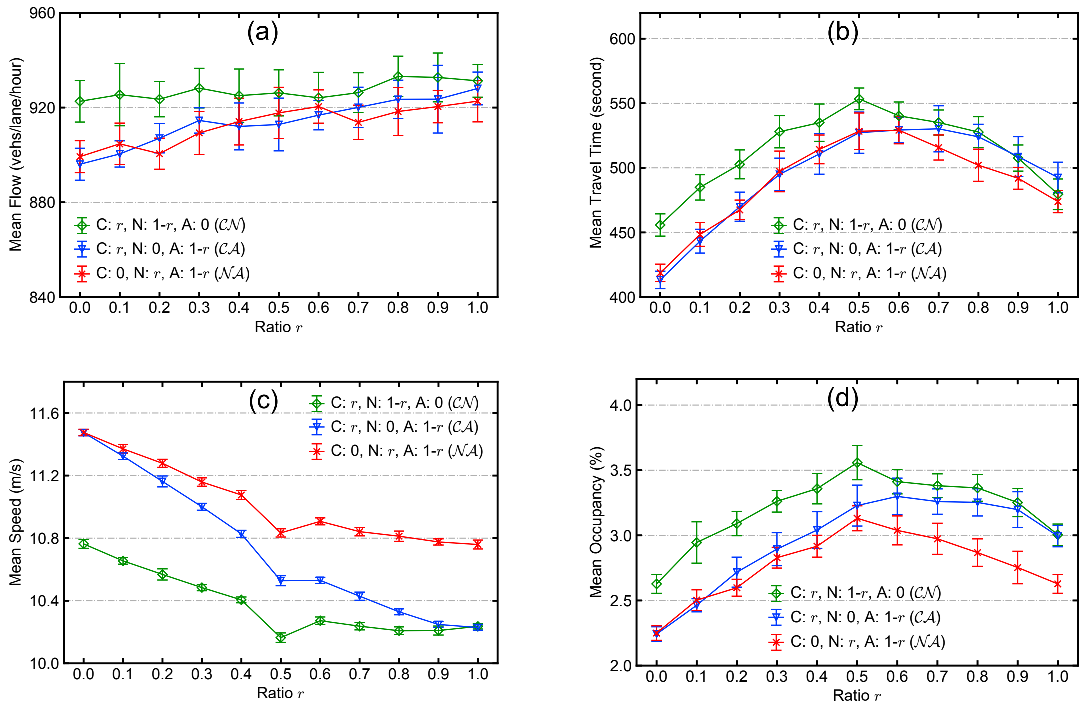

Fig. 4: Performance comparison of the scenarios of the combination of two driving styles

4.3. Results of the experiments with all driving styles

The driving style whose ratio is r is defined as the dominant driving style in this section. The combination whose dominant driving style is the cautious driving style denotes with $\mathcal{C}$, while the other two are denoted by $\mathcal{N}$ and $\mathcal{A}$, respectively.

Figure 5(a) gives no further information because all mean flows are almost the same. Figure 5(c) shows that increasing the ratio of cautious vehicles does not change the mean speed while keeping equal ratios for normal vehicles and aggressive vehicles. The same conclusion can be reached in $\mathcal{N}$. However, the mean speed is improved with the growing of r in $\mathcal{A}$. From 5(d) it can be drawn that both occupancy of $\mathcal{C}$ and $\mathcal{N}$ are keeping steady first and then decreasing, while that of $\mathcal{A}$ reduces from 3.9% to 2.9% steadily. Figure 5(b) has a similar trend as Figure 5(d), which is in accord with what is observed in Section 4.2.

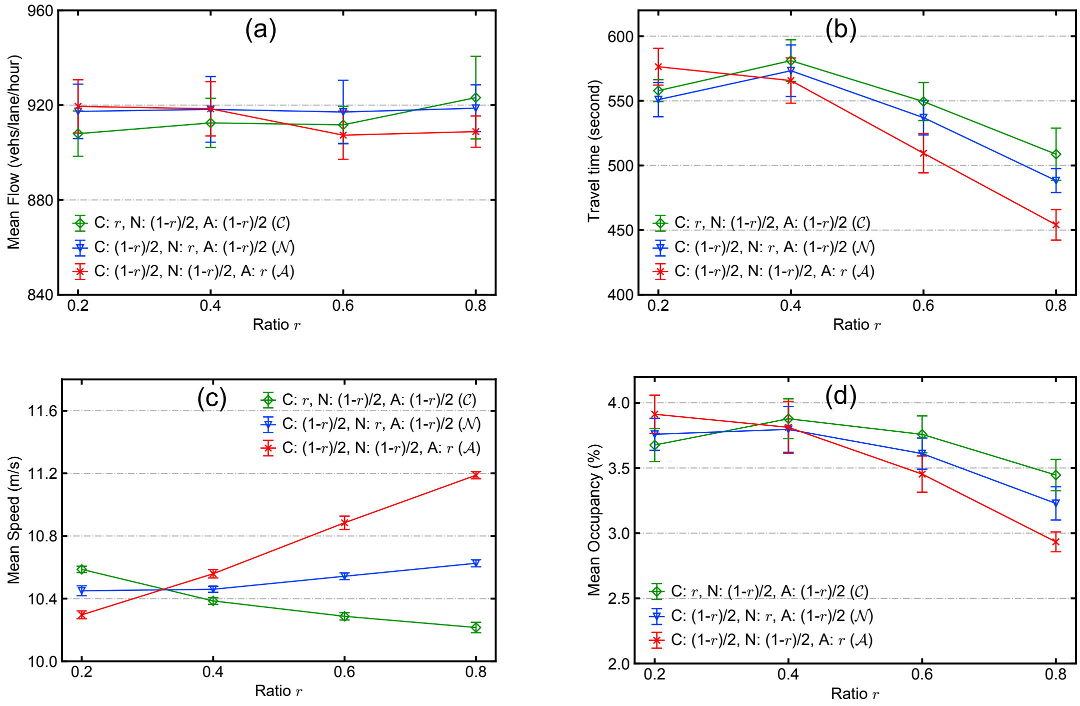

Fig. 5: Performance comparison of the scenarios of the combination of all driving styles

5. Discussions and Conclusions

In this study, we explore the influence of automated vehicles with different driving styles on the network efficiency. To this end, K-means algorithm is applied to categorize the car-following maneuver trajectories first, followed with the calibration of car-following models via FDSA. The calibrated car-following models are used to represent the automated vehicles with different driving styles.

Different deployment scenarios are designed and simulated on the network of Munich city center within the morning peak hour. When vehicles are assembled with the same driving style, it presents that aggressive vehicles lead to higher speeds and shorter travel times in general. However, out of our expectation, the flow distributions from three deployment scenarios are almost the same, which may be caused by the high demand. When the network (or part of the network) is extremely congested, the detected flow would not have a big change regardless of the assembled driving style in vehicles. In scenarios where vehicles are generated from two driving styles, $\mathcal{CN}$ outputs the highest flow and is influenced by the ratio least. It means $\mathcal{CN}$ can form the most stable network state and facilitate the 'delivery' efficiency of the network. Surprisingly, it is found that worst mean speed and travel time are obtained at $r = 0.5$ for all combinations. Furthermore, in the experiments with all three driving styles, $\mathcal{C}$ is least sensitive to the ratio, while $\mathcal{A}$ is the most sensitive.

Note that, due to lack of urban traffic data, we apply the car-following models calibrated via highway data to model urban traffic. This is a limitation of this study, which could be avoided in the future work when urban traffic data is available. Future work could focus on exploring these driving styles under different demand levels and different network characteristics (i.e. road types, network sizes) to draw more general conclusions. Another interested direction is to integrate data-driven traffic flow models (e.g., the car-following model in Papathanasopoulou and Antoniou

(2015), and the lane-changing model in Mahajan et al. (2020)) in modelling automated vehicles. And, also Macroscopic Fundamental Diagram (Geroliminis and Daganzo (2008), Daganzo and Geroliminis (2008)) could be used to further understand the underlying reasons behind the phenomenon observed in this study.

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