Incorporating a Mixed Fleet of Autonomous, Connected, and Human-driven Vehicles into a Mesoscopic Simulation Tool Considering Network Capacity Variations with Heterogeneous Drivers

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1. Introduction

Connected and autonomous vehicles are expected to improve mobility and safety in transportation networks. However, these vehicles are not fully deployed in practice at large-scale. Thus, the level and significance of these improvements are still unknown to researchers. Traffic simulations are the only available tools to reproduce traffic flow with a mixed fleet of autonomous (AV), connected (CV), and human-driven (RV) vehicles without connectivity. The impacts of connectivity and automation of vehicles on congestion have been widely studied at the segment level (1–4). However, only a few studies have investigated these impacts on traffic flow at the network level. Most of these studies consider a uniform distribution of connected or autonomous vehicles over the network, which is not a realistic assumption (5). An example of this non-uniform distribution of traffic flow is the presence of adaptive (en-route) users (6,7). Connected and autonomous vehicles (CAV) and a portion of RVs are expected to have this technology. This study aims to realistically observe the impacts of connectivity and automation of vehicles on traffic flow at the network level by incorporating adaptive fundamental diagrams in the mesoscopic simulation tool of DYNASMART-P (8). This study also incorporates different microscopic modeling frameworks for various vehicle types (i.e., RV, CV, AV) and captures the collective effects of the interactions between them on traffic flow dynamics. The NGSIM data is used to establish different sets of parameters for the microscopic models of heterogeneous drivers for RVs and CVs (9). The main contribution of this study is to incorporate a simulation model that captures the impacts of CAVs by considering the following unique features:

- A mixed traffic of RVs, CVs, and AVs for large-scale applications
- Heterogeneous drivers for RVs and CVs in terms of acceleration behavior (calibrated by real trajectories)
- Spatially/temporally-varying distributions of RVs, CVs, and AVs over the network
- Capacity variations at intersections in the presence of different shares of CAVs, which is mainly neglected in the literature at the network level (10,11)
- Adjusting traffic flow models in arterials due to the presence of CAVs
- CAVs as en-route users

2. Simulation Framework

The stochastic acceleration model of Hamdar et al. (12), the Intelligent Driver Model (13), and the model of Talebpour and Mahmassani (1) are utilized to model the acceleration behavior of RVs, CVs, and AVs, respectively. In order to obtain the equilibrium relation between velocity and spacing, all vehicles should acquire the same and constant speed over each time interval (14). Therefore, the spacing of each vehicle type (i.e., RV, CV, AV) with its leading vehicle is estimated as below.

$$s_{RV}(v) = s_0 + \sqrt{2}\alpha v\tau\sqrt{\ln\left(\frac{\tau}{v}\right) + \ln\left(\frac{w_c}{\sqrt{2\pi}\alpha}\right)} \tag{1}$$

$$s_{CV}(v) = \frac{(s_0+T_n v)}{\sqrt{1-\left(\frac{v}{v_0}\right)^{\delta_n}}} \tag{2}$$

$$s_{AV}(v) = v\tau \tag{3}$$

where τ, w_c, α, and s_0 are parameters to be estimated. The congested part of the macroscopic fundamental diagram can be obtained by following relation.

$$k = \frac{1}{\sum_i \sum_j p_{ij}\left(l_{veh} + s_{ij}(v)\right)} \tag{4}$$

where k is the density, l_{veh} is the length of vehicle, and s_{ij} is the spatial gap of the vehicle type i with driver class j with its leading vehicle. As AVs are driverless, j is considered 1 for them. p_{ij} denotes the proportion of vehicles with type i and driver class j on the segment. The acceleration model of different vehicle types are calibrated against Next Generation Simulation (NGSIM) data (9). With an assumption that all vehicles on a segment are from the same vehicle type and are driven by one specific driver class (10 RV driver types and 6 CV driver types), the calibrated fundamental diagrams are demonstrated in Figure 1.

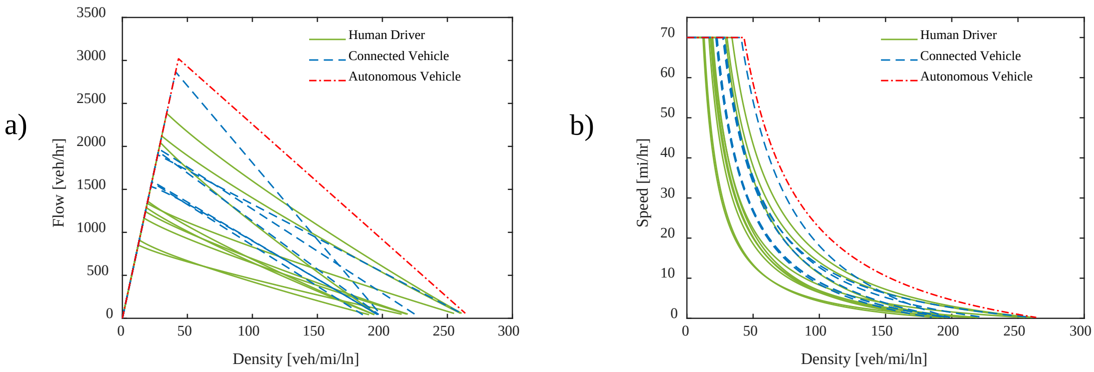

Figure 1. a) Flow-density and b) speed-density calibrated relationships at the equilibrium

To perceive traffic flow dynamics in a connected and automated environment from the micro-scale to the meso-scale in the DYNASMART-P simulation tool, the spacing-density relationship presented in Equations 4 is used. For each link in the network, the counts of different vehicle types with specific drivers are estimated at each time interval. Using the proportion of this count for each driver and vehicle type to the total number of drivers on the link, a nonlinear equation is solved using golden section method (15), to find a link speed that results into an average spacing between different vehicles. For each vehicle type and driver class, a desired spacing can be estimated based on the link speed and Equations 1-3. In addition, to consider the presence of a shared road network with heterogeneous drivers on arterials, an adjustment factor is derived for each vehicle type to relate traffic models of CAVs to RVs with the assumption that CAVs have the same impact on the traffic flow in freeways and arterials. Furthermore, the current study modifies the mesoscopic simulation tool to account for variable maximum flow rates at intersections depending on the share of passing vehicles and their driver classes.

3. Numerical Experiments

The presented simulation frameworks are applied to AM peak period of the Chicago downtown network with 1,578 nodes and 4,805 links. Figure 2 illustrates the NFD graphs (Figure 2a-2d) and hysteresis loop area (Figure 2e) for different proportions of RVs, CVs, and AVs in the network. According to this figure, connectivity and automation of vehicles facilitate the network recovery from congestion. In addition, the network faces a reduction in the maximum density and the area of hysteresis loop by an increase in MPR of CVs or AVs, or both. Therefore, a higher stability in the recovery phase is observed for the scenarios with higher CAV proportions. The significant reduction in hysteresis loop area by having more CAVs denotes that the gridlock dissipation and system recovery are accomplished faster for higher MPRs of CAVs. According to Figure 2b, with a mixed traffic consists of all three vehicle types, the scenario with equal penetration rates of CVs and AVs (25%) falls between the two scenarios of 50% CV and 50% AV. This result highlights the superiority of CVs to the RVs and AVs to the CVs in mitigating the traffic congestions in the network with a mixed traffic stream. Furthermore, it shows the applicability of the proposed methodology to consider a traffic mix including all three types of vehicles.

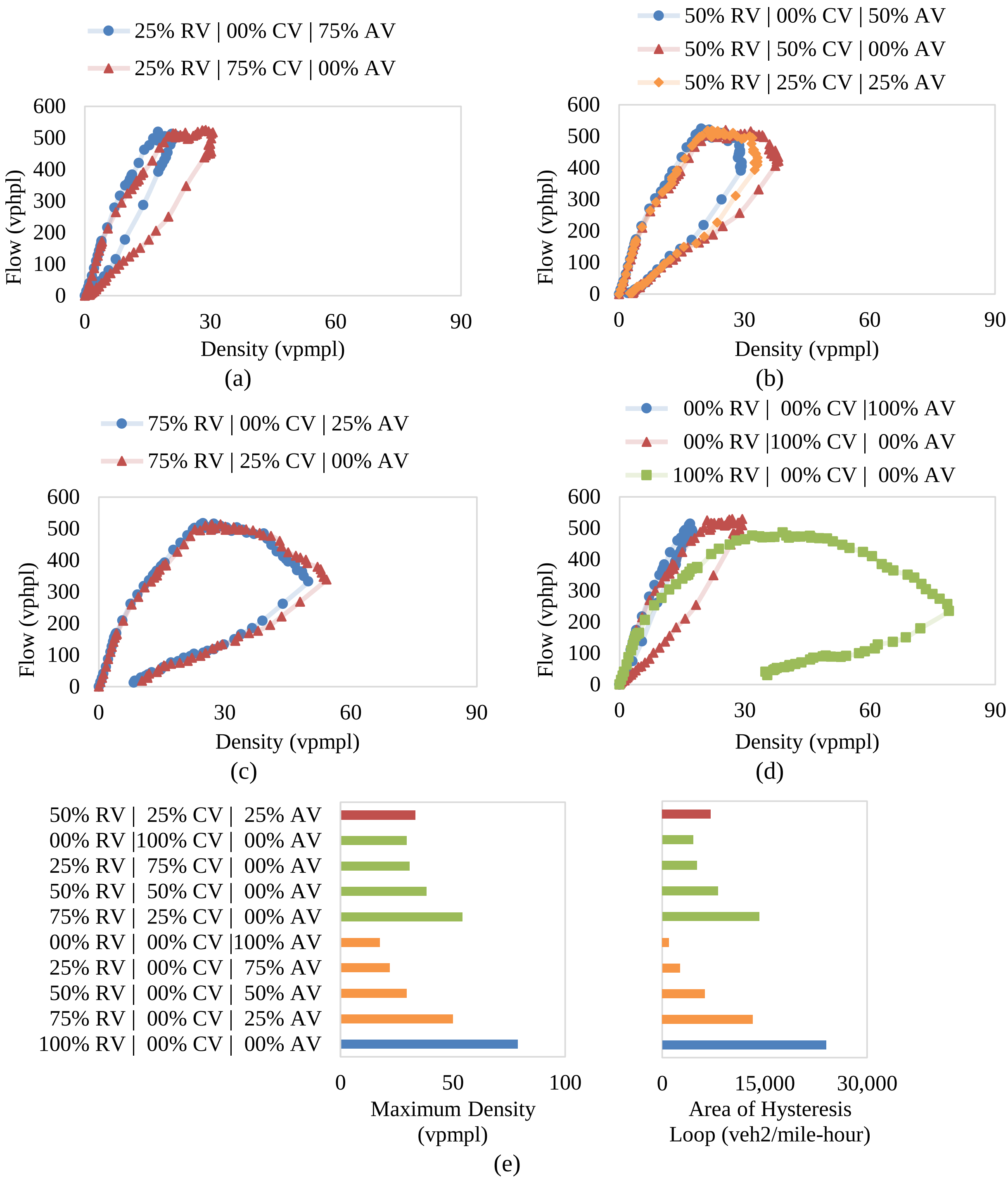

Figure 2 (a-d) NFD and (e) maximum density and area of hysteresis loop for different MPRs of RVs, CVs, and AVs

4. Conclusion

This study updates the DTA simulation tool of DYNASMART-P by incorporating adaptive fundamental diagrams considering spatial- and temporal-varying distributions of different vehicle types with heterogeneous drivers. This study considers the movement capacity variations at intersections due to a mixed vehicle fleet. Adjustment factors are also presented to modify the fundamental diagram in arterials when CAVs occupy a portion of arterial links. The numerical experiments of the large-scale application show that with a constant proportion of RVs in the network, higher MPRs of CAVs lead to a lower maximum density and smaller hysteresis loop area, meaning a faster network recovery from congestion. In addition, higher proportions of CAVs relative to RVs result in a lower maximum density, slightly higher maximum flow, and a more stable network. A mixed traffic condition with all three vehicle types shows a different impact from the scenarios with only two vehicle types. The injection of AVs in the network is also more effective on traffic flow conditions than CVs. Therefore, it is necessary to consider different shares of CAVs to investigate a realistic impact of these vehicles with heterogeneous drivers on traffic flow at the network level.

5. References

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