Effects of Turning and Merging on Network Traffic Instability: A Simulation-Based Analysis of Human-Driven and Autonomous Vehicles

Ziyuan Gu, Meead Saberi*

*Research Centre for Integrated Transport Innovation (rCITI), School of Civil and Environmental Engineering, University of New South Wales (UNSW) Sydney, NSW 2052, Australia
*Corresponding author e-mail: meead.saberi@unsw.edu.au

Abstract

This paper analyzes network traffic instability resulting from turning and merging maneuvers of autonomous vehicles (AVs). The classical two-ring network is investigated through a microscopic simulation framework that models human-driven vehicles (HVs) and AVs by the human driver model (HDM) and the intelligent driver model (IDM), respectively. While results confirm the previous findings for HVs, we show that AVs performing turning and merging maneuvers have a much more significant impact on the network traffic instability, and that such impact becomes even more significant in the presence of a higher turning frequency. This highlights the importance of cooperative merging when AVs are widely deployed in urban networks.

Keywords: autonomous vehicles; instability; network fundamental diagram; turning; merging; two-ring network.

1 Introduction

It is no longer a matter of if, but of when autonomous vehicles (AVs) will be on the road and how they will change the operational performance of the road network. Although heated debate on various aspects of AVs has been around for some time, there are still quite a few open questions that require further investigation. This paper aims to provide insights into one of these less explored areas of AVs, that is, network traffic instability rendered by turning and merging maneuvers.

From a traffic engineering perspective, the impact of AVs is largely foreseeable. Due to tighter headways enabled by infinitesimal computer reaction times as compared with human drivers, road capacity is expected to increase substantially. This can be easily understood using traffic engineering basics – in particular, traffic flow fundamental diagrams (FDs) (Mahmassani 2016). In contrast, stability is a less intuitive car-following subject but is of equal importance to understand and analyze vehicular flow. The literature has identified two types of car-following stability (Wilson and Ward 2011): local or platoon stability and string stability. The former refers to the vehicle’s ability to recover from a perturbation rendered by its leader (e.g. a sudden brake), while the latter indicates if the perturbation grows or decays as it propagates upstream of the vehicle platoon. Since local stability is expected to hold in the presence of a well-established car-following model, studies to date tend to focus on string stability (Talebpour and Mahmassani 2016; Hu et al. 2017).

Nevertheless, limited effort has been made to date relating turning and merging maneuvers to network traffic instability, which is therefore taken as the primary focus of this paper. Previous studies have investigated instability arising from human-driven vehicles (HVs) only, using a classical two-ring system which is perfect for isolating the effects of turns (Daganzo et al. 2011; Gayah and Daganzo 2011) or a large-scale network model (Saberi, Mahmassani, and Zockaie 2014), Daganzo et al. (2011) and Gayah and Daganzo (2011) defined network traffic instability as “even for perfectly homogeneous networks with spatially uniform travel patterns, symmetric equilibrium patterns with equal flows and densities across all links are unstable if the average network density is sufficiently high; instead, the stable equilibrium patterns are
asymmetric.” This paper aims to extend this instability analysis to AVs using a more detailed microscopic car-following framework that distinguishes between HVs and AVs. We use SUMO (Lopez et al. 2018) as the simulation platform to build the two-ring network, and model HVs and AVs by the Human Driver Model (HDM) (Treiber et al. 2006) and the Intelligent Driver Model (IDM) (Treiber et al. 2000), respectively. Details of our modeling framework are presented in Section 2, and results in Section 3. Section 4 concludes the paper.

2 Modeling Framework

HV s and AVs have distinct operational characteristics that shall be modeled separately. While car-following parameters such as safe headway and jam spacing are arguably different between the two driving modes, human driving style also differs in several other aspects including reaction time, imperfect estimation, spatial and temporal anticipation (Treiber et al. 2006). Further, unlike AVs that are controlled by “intelligent” computers resulting in a deterministic driving style, human drivers are heterogeneous that exhibit a much higher level of stochasticity in their driving behavior.

Considering the above differences, we briefly revisit, respectively, the IDM (Treiber et al. 2000) for modeling AVs and the HDM (which is built upon the IDM) (Treiber et al. 2006) for modeling HVs in the following two subsections, followed by a description of the two-ring network. It should be noted that AVs modeled in this paper are assumed to be controlled by its on-board sensors only, and hence are not capable of communicating with the other vehicles or the infrastructure. As such, they differ from connected AVs (i.e. CAVs) which can further utilize information enabled by connectivity for better acceleration/deceleration control. The results presented in Section 3 are based on this critical assumption.

2.1 Intelligent Driver Model (IDM)

The governing equation of the IDM specifies the acceleration of the nth vehicle \( a_n(t) \) as a continuous function of its velocity \( v_n(t) \), the net distance gap \( s_n(t) \), and the velocity difference \( \Delta v_n(t) \) to its leader (\( t \) is omitted for simplicity):

\[
a_n = a \left[ 1 - \left( \frac{v_n}{v_0} \right)^4 - \frac{s^*(v_n, \Delta v_n)}{s_n} \right]^2
\]

where \( a \) is the maximum acceleration and \( v_0 \) is the desired velocity. Here, \( s^* \) is the so-called desired minimum gap calculated as follows:

\[
s^*(v_n, \Delta v_n) = s_0 + v_n T + \frac{v_n^2 \Delta v_n}{2 \sqrt{ab}}
\]

where \( s_0 \) is the minimum distance, \( T \) is the safe time headway, and \( b \) represents the comfortable deceleration.

The IDM is considered a suitable car-following model for AVs due to several reasons (Kesting et al. 2008; Treiber et al. 2006) including: (i) vehicles have instantaneous reaction (depending on the simulation step) and perfect estimation of the surrounding traffic conditions; (ii) the last term in Eq. (2) that only becomes active in non-stationary traffic enables a collision-free “intelligent” braking strategy; and (iii) the resulting vehicle dynamics corresponds to a natural and smooth driving behavior.

2.2 Human Driver Model (HDM)

The HDM was proposed as a metamodel introducing four human-specific features into a wide range of microscopic car-following models (Treiber et al. 2006): (i) finite reaction time; (ii) imperfect estimation capability; (iii) temporal anticipation; and (iv) spatial or multi-vehicle anticipation. In this paper, we apply the HDM extensions to the IDM for modeling HVs.

2.2.1 Finite Reaction Time

A reaction time \( T_{\text{react}} \) is incorporated by evaluating the right-hand side of Eq. (1) at \( t = T_{\text{react}} \). To reflect human drivers’ heterogeneity, we consider a hypothetical skewed normal distribution with a mean of 1.2 seconds (Green 2000), thereby associating each HV with a unique reaction time. It should be noted that this distribution is not calibrated or validated by any empirical data gathered by the authors. It is only an assumption made in this paper to represent human drivers’ heterogeneity.

2.2.2 Imperfect Estimation Capability

Human drivers are subject to estimation errors relating to the surrounding traffic conditions, two of which are the net distance and the velocity difference. Since the vehicle’s velocity can be read from the odometer, this error is negligible. There are two ways of incorporating estimation errors into the car-following model (Treiber et al. 2006): (i) temporally correlated multiplicative HDM noise; and (ii) white acceleration noise. Although the former approach introduces a few more parameters that have intuitive meanings, this paper adopts the latter approach due to its simplicity.

2.2.3 Temporal Anticipation
The critical assumption here is that human drivers are aware of their finite reaction times and hence anticipate the traffic conditions accordingly. To anticipate the future velocity and distance based on the reaction time, a constant-acceleration and constant-velocity heuristics are applied, respectively (Treiber et al. 2006). The combined effects of the finite reaction time, the imperfect estimation capability, and temporal anticipation results in a car-following metamodel of the following form (ε is a zero-mean Gaussian noise):

\[ a'_n = a'_n(s'_{n}, v'_{n}, \Delta v'_{n}) + \varepsilon \]  
\[ s'_{n}(t) = [s_n - T_{react}\Delta v_n]_{t-T_{react}} \]  
\[ v'_{n}(t) = [v_n - T_{react}a'_n]_{t-T_{react}} \]  
\[ \Delta v'_{n}(t) = [\Delta v_n]_{t-T_{react}} \]  

2.2.4 Spatial or Multi-Vehicle Anticipation

Assuming that human drivers take into account the movements of several vehicles ahead when driving, the car-following model can be decomposed into two parts (ignoring the noise term) consisting of a single-vehicle acceleration in free-flow conditions, \( a'_n \), and a braking deceleration that reflects interactions with the preceding vehicles, \( a_{n_{im}} \) (Treiber et al. 2006):

\[ a'_n = a'_{n_{free}} + \sum_{m=n-k}^{n-1} a^\text{int}_{n_{im}}(s'_{nm}, v'_{nm}, \Delta v'_{nm}) \]  

where \( k \) is the number of preceding vehicles included in the calculation. Here, \( a'_{n_{free}} = a \left( 1 - \left( \frac{v_n}{v_0} \right)^4 \right) \) and \( a^\text{int}_{n_{im}} = -a \left( \frac{v'_{nm}\Delta v'_{nm}}{s'_{nm}} \right)^2 \).

2.3 Two-Ring Network

As illustrated in Figure 1, the perfectly symmetric two-ring network is arguably the simplest system that isolates the effects of turning and merging maneuvers (Gayah and Daganzo 2011; Daganzo et al. 2011). While vehicles travel counter-clockwise on the left ring and clockwise on the right ring in an indefinite manner, each of them has the same fixed probability of turning and switching to the other ring. Unlike Gayah and Daganzo (2011) and Daganzo et al. (2011) where the two rings are tangentially connected (i.e., they only interact at the tangent point), we set a physical length to the link connecting one ring to the other as a more realistic representation of a real-world network. Note that equal priority is assumed whenever a conflict arises in the merging area between one vehicle traveling in its current ring and one switching from the other ring.

![Figure 1. Schematic illustration of the two-ring network](image-url)

3 Results and Discussion

3.1 Simulation Setup

Table 1 shows the model parameters for HVs and AVs, respectively. Compared with an HV, an AV is associated with a smaller safe time headway and jam spacing for being controlled by an “intelligent” computer. Note that the standard deviation of the acceleration noise of human drivers is 0.2 m/s², and that the number of anticipated vehicles \( k = 3 \). Each simulation run lasts for 30 minutes with a simulation step of 0.1 seconds (which is also the reaction time of AVs). Following a speed limit of 30 km/h, vehicles are symmetrically loaded onto the network at a rate of 180 veh/h.

| Parameter | HV | AV |
|-----------|----|----|
| Desired speed (km/h) | 120 | 120 |
| Safe time headway (s) | 1.5 | 0.5 |
| Maximum acceleration (m/s²) | 1.5 | 1.5 |
| Desired deceleration (m/s²) | 2 | 2 |
| Jam spacing (m) | 2 | 0.5 |

3.2 No Turning

We first restrict vehicles from switching between the two rings to obtain the simulated FDs in the absence of turning and merging maneuvers. Macroscopic traffic flow variables are calculated every 10 seconds based on extended Edie’s definitions (Saberi, Mahmassani, Hou, et al. 2014) using simulated vehicle trajectories. Our analysis hereafter will focus on two “extreme” scenarios only: one with 100% HVs and the other with 100% AVs, and hence no mixed traffic is considered. The reason or motivation is to show through these two highly contrasted scenarios that instability caused by turning and merging maneuvers still arises in an ideal fully autonomous but non-connected environment. In fact, the instability phenomenon becomes even more significant in the presence of full automation without connectivity, as we will show in Subsections 3.3 and 3.4.
Figure 2 shows the simulated FDs of the two rings, respectively, in comparison with the theoretical FD obtained using the speed limit as the free-flow speed, the reciprocal of the jam spacing as the jam density, and an estimated congestion wave speed (such that the maximum observed flow is enveloped).

As expected, replacing HVs with AVs results in a much larger critical density that pushes the peak of the FD toward the right. Accordingly, the maximum observed flow or capacity has nearly doubled due to vehicle automation (depending on the parameter values assumed), a finding consistent with Mahmassani (2016). Note how the simulated FDs of HVs deviate from the theoretical FD, especially during the congested regime immediately after the critical density, and that a slight capacity drop can be observed. In contrary, the simulated FDs of AVs align quite well with the theoretical FD except for a near plateau around the critical density rather than a peak. The above differences in FDs can be entirely explained by the distinct driving behaviors of HVs and AVs—human drivers are associated with a much higher level of heterogeneity and stochasticity, whereas AVs are equipped with a consistent and deterministic driving strategy.

3.3 Low Turning Probability

We now consider a low turning probability of 0.15 which is applied to all vehicles in the network. Given the simulation stochasticity, a total of six simulation runs are performed and the results are shown in Figure 3. Remarkably, regardless of vehicles being human-driven or autonomous, the FD of one ring gradually evolves toward the congested regime or gridlock, while the other remains at the free-flow or capacity regime. This observation verifies the argument of Daganzo et al. (2011) that, under congested traffic conditions, simultaneous congested...
regimes of the two rings are unstable equilibria, and that the two-ring system will always evolve toward the state where one ring is congested or gridlocked and the other free-flowing (i.e. stable equilibria).

A more important observation lies in the wide scatter exhibited by the simulated FDs of AVs. Under the human-driving scenario, the scatter only appears around the critical density on a rather small scale, whereas under the fully autonomous scenario, the scatter appears way before the critical density is reached and spreads to the congested regime on a much larger scale. As a result, the network fundamental diagram (NFD) or macroscopic fundamental diagram (MFD) exhibits a bifurcation prior to reaching the critical network density (i.e. the theoretical bifurcation point), as illustrated in Figure 3(d) in comparison with Figure 3(c). This observation can also be confirmed in Figure 4 – the turning points of the phase paths (i.e. the density-density relationships of the two rings) resulting from AVs arise much earlier before the theoretical bifurcation point.

Results suggest that, although being able to improve the network flow, AVs without connectivity have the potential to increase the network traffic instability caused by turning and merging maneuvers, even if such maneuvers are not frequent. In fact, with a high turning probability, the effects on instability become even more significant. This will be shown in the following subsection.

3.4 High Turning Probability

Here, we increase the turning probability to 0.5 and redo the analysis. Due to more frequent turning and merging maneuvers, the simulated FDs under the human-driven scenario as shown in Figure 5(a) exhibit, as expected, a greater scatter in comparison with Figure 3(a). It is interesting to note from Figure 5(b) that, under the fully autonomous scenario, the transition of one ring from the free-flow regime to the congested regime takes place very quickly without showing the same level of scatter as we previously observed in Figure 3(b).

Nevertheless, the NFDs shown in Figure 5(d) consistently undergo a bifurcation which, again, appears way before the critical network density is reached under the fully autonomous scenario. In fact, a closer comparison between Figure 6 and Figure 4 reveals that the tuning and merging maneuvers of AVs have a much greater impact.
on the network traffic instability, and that such impact from HVs are far less sensitive to the turning frequency.

**Figure 6. Phase paths with 0.5 turning probability**

(a) 100% HVs  
(b) 100% AVs

### 4 Conclusion

This paper extends the existing network instability analysis of HVs to AVs using a microscopic simulation framework that models HVs and AVs by the HDM and the IDM, respectively. While confirming the previous findings in the literature, the results demonstrate that the turning and merging maneuvers of AVs have a much more significant impact on the network traffic instability. This highlights the importance of controlling, optimizing, and cooperating the merging behavior of AVs possibly through connectivity. We are currently extending our instability analysis to verify the potentially positive effects of connectivity and hence the impact of learning versus non-learning AVs.

### References

Daganzo, Carlos F., Vikash V. Gayah, and Eric J. Gonzales. 2011. "Macroscopic relations of urban traffic variables: Bifurcations, multivaluedness and instability." *Transportation Research Part B: Methodological* 45 (1):278-288. doi: 10.1016/j.trb.2010.06.006.

Gayah, Vikash V., and Carlos F. Daganzo. 2011. "Effects of turning maneuvers and route choice on a simple network." *Transportation Research Record: Journal of the Transportation Research Board* 2249 (1):15-19. doi: 10.3141/2249-03.

Green, Marc. 2000. "How long does it take to stop?" *Transportation Human Factors* 2 (3):195-216. doi: 10.1207/S15327906THF0203_1.

Hu, San Gen, Hui Ying Wen, Lunhui Xu, and Hui Fu. 2017. "Stability of platoon of adaptive cruise control vehicles with time delay." *Transportation Letters*:1-10. doi: 10.1080/19427867.2017.1407488.

Kesting, Arne, Martin Treiber, Martin Schönhof, and Dirk Helbing. 2008. "Adaptive cruise control design for active congestion avoidance." *Transportation Research Part C: Emerging Technologies* 16 (6):668-683. doi: 10.1016/j.trc.2007.12.004.

Lopez, P. A., M. Behrisch, L. Bieker-Walz, J. Erdmann, Y. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. WieBner. 2018. Microscopic Traffic Simulation using SUMO. Paper presented at the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4-7 Nov. 2018.

Mahmassani, Hani S. 2016. "50th anniversary invited article—autonomous vehicles and connected vehicle systems: Flow and operations considerations." *Transportation Science* 50 (4):1140-1162. doi: 10.1287/trsc.2016.0712.

Saberi, Meead, Hani S. Mahmassani, Tian Hou, and Ali Zockaie. 2014. "Estimating Network Fundamental Diagram Using Three-Dimensional Vehicle Trajectories: Extending Edie’s Definitions of Traffic Flow Variables to Networks." *Transportation Research Record: Journal of the Transportation Research Board* (2422):12-20. doi: 10.3141/2422-02.

Saberi, Meead, Hani S. Mahmassani, and Ali Zockaie. 2014. "Network capacity, traffic instability, and adaptive driving: findings from simulated urban network experiments." *EURO Journal on Transportation and Logistics* 3 (3-4):289-308.

Talebpour, Alireza, and Hani S. Mahmassani. 2016. "Influence of connected and autonomous vehicles on traffic flow stability and throughput." *Transportation Research Part C: Emerging Technologies* 71:143-163. doi: 10.1016/j.trc.2016.07.007.

Treiber, Martin, Ansgar Hennecke, and Dirk Helbing. 2000. "Congested traffic states in empirical observations and microscopic simulations." *Physical Review E* 62 (2):1805. doi: 10.1103/PhysRevE.62.1805.

Treiber, Martin, Arne Kesting, and Dirk Helbing. 2006. "Delays, inaccuracies and anticipation in microscopic traffic models." *Physica A: Statistical Mechanics and its Applications* 360 (1):71-88. doi: 10.1016/j.physa.2005.05.001.

Wilson, R. Eddie, and Jonathan A. Ward. 2011. "Car-following models: fifty years of linear stability analysis—a mathematical perspective." *Transportation Planning and Technology* 34 (1):3-18. doi: 10.1080/03081060.2011.530826.