UCLA
Project Reports

Title

Modeling and Simulation Testbeds with a Mesoscopic Approach: A Sandbox for Analysis of New Mobility Impact in Large-scale Networks

Permalink

https://escholarship.org/uc/item/9z01k5c5

Authors

Liu, Jiachao
Zou, Qiling
Ma, Xiaoyu
et al.

Publication Date

2026-11-01

DOI

10.82903/B2KW2D

eScholarship.org Powered by the California Digital Library
University of California

CENTER OF EXCELLENCE
on New Mobility and Automated Vehicles

Modeling and Simulation Testbeds with a Mesoscopic Approach: A Sandbox for Analysis of New Mobility Impact in Large-scale Networks

November 2026

About the Center of Excellence on New Mobility and Automated Vehicles

The Center of Excellence on New Mobility and Automated Vehicles focuses on the impacts of new mobility technologies and highly automated vehicles on the evolving transportation system when deployed at scale. Launched in 2023, the center studies the anticipated long-term impacts of increased new mobility technologies and services on land use, real estate and urban design; transportation system optimization; access to mobility and job participation; and municipal budgets and cost-effective allocation of public resources. Established through a cooperative agreement between the Federal Highway Administration and UCLA, the Mobility COE is made up of five core partners and a community of practice from academia and nonprofit organizations. **www.mobilitycoe.org**

Acknowledgments

This material is based upon work supported by the Federal Highway Administration under Agreement No. 693JJ32350027. The two demonstrative examples of the mesoscopic simulation tool (MAC-POSTS) were generated through research projects (Qian et. al, 2023, Zhang and Qian, 2023) prior to this work. We use those two examples in this report to provide additional information regarding the simulation tool which leads to our work focusing on the impact of automated vehicles in regional networks.

The Mobility Center of Excellence at UCLA acknowledges the Gabrielino/Tongva peoples as the traditional land caretakers of Tovaangar (the Los Angeles basin and So. Channel Islands). As a land grant institution, we pay our respects to the Honuukvetam (Ancestors), ‘Ahiihirom (Elders) and ‘Eyoohiinkem (our relatives/relations) past, present and emerging.

Disclaimer

Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the Author(s) and do not necessarily reflect the view of the Federal Highway Administration.

Cite This Report

Suggested Citation: Liu, J., Zou, Q., Ma, X., & Qian, S. (2026). Modeling and Simulation Testbeds with a Mesoscopic Approach: A Sandbox for Analysis of New Mobility Impact in Large-scale Networks. *UCLA: Mobility Center of Excellence*. http://dx.doi.org/10.82903/B2KW2D

Modeling and Simulation Testbeds with a Mesoscopic Approach: A Sandbox for Analysis of New Mobility Impact in Large-scale Networks

Jiachao Liu, Ph.D. candidate, Carnegie Mellon University

Qiling Zou, Senior Project Scientist, Carnegie Mellon University

Xiaoyu Ma, Postdoctoral Research Associate, Carnegie Mellon University

Sean Qian, H. John Heinz III Professor of Civil and Environmental Engineering, Carnegie Mellon University

November, 2026

CENTER OF EXCELLENCE
on New Mobility and Automated Vehicles

Table of Contents

Executive Summary **9**

Objectives **11**

Methodologies **13**

Introduction of MAC-POSTS 13

Overview 13

Workflow 13

Demonstration 1 (Zhang and Qian, 2023): Southwestern Pennsylvania Commission (SPC) network 17

Demonstration 2 (Qian et al., 2023): Delaware Valley Regional Planning Commission (DVRPC) network 20

Modeling mixed traffic flow of automated and human driven vehicles in regional networks 25

Homogeneous distribution approach: uniform mixing across all vehicles and links 25

Heterogeneous distribution approach: class-specific and spatially differentiated mixing 27

Case study of Pittsburgh network **29**

Results from the homogenous approach 29

Results from the heterogeneous approach 32

Summary and Future Work **37**

References **38**

Appendix: a tutorial for modeling mixed traffic in MAC-POSTS **40**

Homogenous modeling approach 40

Heterogeneous modeling approach 40

List of Figures

Figure 1: Workflow in MAC-POSTS....14

Figure 2: Relationship among DODE, DTA, and DNL....16

Figure 3: SPC network (the area in dark gray contains the ten counties of the SPC region, and the point markers show all the origin/destination nodes). (Zhang and Qian, 2023)....17

Figure 4: Comparison of estimated and observed link traffic counts and zone demand for the SPC network. (Zhang and Qian, 2023)....18

Figure 5: Selected links to increase capacities. (Zhang and Qian, 2023)....19

Figure 6: Box plots of link travel times under different capacities for the selected links. (Zhang and Qian, 2023)....20

Figure 7: DVRPC network. (Qian et al., 2023)....21

Figure 8: Comparison of estimated and observed link traffic counts and zone demand for the DVRPC network (figures are car counts, truck counts, and total zone demand from left to right). (Qian et al., 2023)....21

Figure 9: Comparison of estimated and observed link travel times for the DVRPC network (figures are for car and truck travel times from left to right). (Qian et al., 2023)....22

Figure 10: Tolled bridge and its nearby bridges. (Qian et al., 2023)....22

Figure 11: One example of mixed FDs parametrized by penetration rate and headway....27

Figure 12: Bi-class FDs parametrized by penetration rate and headway setting of one representative link....28

Figure 13: Average delay for mixed flow under varying settings (diversion ratio = 0.4)....29

Figure 14: Total fuel consumption and pollute emission under varying settings (diversion ratio = 0.4)....30

Figure 15: Average delay for mixed flow under varying settings (diversion ratio = 1.0)....30

Figure 16: Total fuel consumption and pollute emission under varying settings (diversion ratio = 1.0)....31

Figure 17: Comparison of jam density settings for mixed flow FD (diversion ratio = 0.4)....32

Figure 18: Average delay for HDVs and AVs under varying settings (diversion ratio = 0.4)....33

Figure 19: Total fuel consumption and pollute emission under varying settings (diversion ratio = 0.4)....33

Figure 20: Average delay for HDVs and AVs under varying settings (diversion ratio = 1.0)....34

Figure 21: Total fuel consumption and pollutant emission under varying settings (diversion ratio = 1.0) 34

Figure 22: Comparison of jam density settings for bi-class FDs (diversion ratio = 0.4) 35

Figure 23: System metrics with 1.0 diversion ratio for AVs and 0.4 for HDVs 36

Figure 24: AV penetration map at 4 timestamps (penetration rate = 0.6, headway setting 1, diversion ratio = 0.4 for all vehicles) 36

List of Tables

Table 1: General metrics in the AM peak hours (Qian et al., 2023) 23

Table 2: Total toll revenues in the AM peak hours ($). (Qian et al., 2023) 23

Table 3: Percentage change of traffic flows of three bridges in the AM peak hours. (Qian et al., 2023) 24

Table 4: Scalars of FD in this study (based on Shi & Li, 2021) 25

Executive Summary

This report investigates the impacts of automated vehicle (AV) adoption on traffic performance, energy consumption, and emissions using the MAC-POSTS (Mobility data Analytics Center – Prediction, Optimization, and Simulation toolkit for Transportation Systems) package[1]. MAC-POSTS, developed at Carnegie Mellon University, is an open-source dynamic network modeling toolkit designed for large-scale transportation networks. It incorporates state-of-the-art algorithms for dynamic origin–destination (OD) demand estimation, dynamic traffic assignment (DTA), and dynamic network loading (DNL), offering high spatial–temporal granularity, multi-class vehicle representation, and flexibility for scenario analysis. MAC-POSTS has been successfully applied in multiple regional networks across the U.S. to evaluate the system impacts of tolling, road capacity expansion, vehicle automation, vehicle electrification, curb management, and other emerging mobility strategies.

Using the Pittsburgh, PA, regional network as a case study, we model scenarios of varying automated vehicle (AV) penetration and headway settings in an adaptive cruise control (ACC) system, i.e., basic automated longitudinal control. Two complementary approaches are applied: (1) homogeneous distribution approach, where AVs are uniformly distributed across the network and the traffic speed-flow-density relations of mixed traffic flow, also known as fundamental diagrams (FDs), evolve directly with penetration rates, and (2) heterogeneous distribution approach, where AVs and human-driven vehicles (HDVs) are modeled as separate classes, enabling visualization of spatio-temporal AV penetration. Simulation results show that system performances depend critically on headway settings and associated changes in FDs. **When AVs are modeled with aggressive but safe headways, the network achieves substantial system gains, particularly when vehicles are fully adaptive in routing. By contrast, conservative headway settings suppress or reverse these benefits, as reduced jam densities and road capacity of mixed traffic flow harm overall system performance even at high AV penetration rates.** Adaptive routing magnifies positive outcomes under aggressive headways but cannot offset the performance losses associated with conservative AV settings. Moreover, the heterogeneous approach provides insights on spatio-temporal distribution of AVs across the network, offering opportunity to design targeted AV regulation and infrastructure coordination plans. A quick tutorial of the modeling approaches is attached in the Appendix.

These experiments reveal that **AV adoption alone does not guarantee improvements for the network; instead, system performance depends on AV routing behavior, car-following technology, and infrastructure conditions.** AV deployment strategies must ensure aggressive but safe headway policies in ACC systems to unlock significant system gain in efficiency and sustainability. Moreover, equipping AVs with advanced routing systems can benefit the system, and an optimal penetration range may exist to maximize system-wide gains, which requires careful experiments.

Future work will focus on developing more refined behavior paradigms for AVs and exploring opportunities to optimize mixed traffic systems through Transportation Systems Management and Operations (TSMO) strategies and technologies. In addition, safety metrics can be

[1] Available [online]: https://github.com/maccmu/macposts

incorporated into the model to better balance efficiency and safety. As more real-world data on AV operation become available, they can be integrated into the proposed model to enhance calibration of AV-related demand and traffic characteristics.

MAC-POSTS is released as an open-source toolkit, which makes this study's workflow fully reproducible and easy to extend by researchers, agencies, and industry partners. Because the codebase, data interfaces, and scenario configuration files can be accessed and modified transparently, MAC-POSTS functions as a practical *sandbox* for testing "what-if" mobility policies (e.g., AV headway regulations, routing logic, pricing/tolling, electrification, curb and lane management) on large-scale networks without requiring proprietary simulation platforms. This open architecture also supports rapid community-driven improvements—such as adding new vehicle classes, integrating emerging real-world AV trajectory and operational datasets for calibration, and contributing new performance metrics (including safety surrogates) as modules—so that the sandbox can evolve alongside the state of practice while preserving traceability of assumptions and results.

Objectives

The increasing deployment of automated driving systems (ADS) in commercial vehicles is expected to fundamentally alter traffic flow dynamics. Among these features, the adaptive cruise control (ACC) system has become particularly widespread in recent vehicle models. ACC relies on on-vehicle sensors such as millimeter-wave radar, coupled with real-time control units, to automatically regulate vehicle speed and maintain safe headways relative to leading vehicles (Wang et al., 2019). Unlike human-driven vehicles (HDV), which are subject to uncertain, delayed, and often inconsistent driving behaviors, automated vehicles (AV) with ACC respond quickly and precisely according to computer-controlled algorithms. This contrast in driving behavior implies that the presence of AVs modifies critical traffic flow-speed-density relationships such as the flow capacity, critical density, and jam density represented in fundamental diagrams (FDs).

Traditionally, the fundamental diagram (FD) describes the macroscopic relationship among traffic flow, speed, and density, and is commonly used to characterize the operational performance and capacity of a roadway. Under conventional traffic conditions dominated by HDVs, the shape of the FD reflects the aggregate effects of human driving behavior, including reaction time, desired speed, car-following preferences, and variations in acceleration and deceleration. The introduction of AVs, however, alters these behavioral characteristics by enabling more consistent car-following, shorter reaction times, and more precise control of vehicle spacing and speed. As a result, increasing AV penetration can change the shape and key parameters of the FD, potentially shifting the maximum flow rate, critical density, and congested-flow regime. Depending on the control strategy and AV penetration rate, these changes may increase roadway capacity and traffic stability, while also fundamentally modifying the transition between free-flow and congested traffic states.

As AV penetration increases, these changes in FDs of each road segment are expected to jointly influence overall system stability and congestion patterns in the network (Auld et al., 2018; Soteropoulos et al., 2019). Recent empirical experimentation has demonstrated that various penetration rates of AVs can influence the shape of mixed flow FDs (Shi & Li, 2021), but the resulting network-wide impact is not fully understood.

To fill this gap, this study leverages a mesoscopic simulation, MAC-POSTS, to study the system impacts of introducing AVs in regional networks. Two complementary approaches are developed to model the mixed traffic flow of AVs and HDVs: one assumes AVs are homogeneously distributed across time and space in the network. The other approach considers heterogeneous spatio-temporal AV penetration and splits demand by HDVs and AVs to model separate behaviors and interaction of bi-class flow dynamics. The penetration rates and headway settings of AVs are varied and represented by modifying the parameters of the link-level FDs. The Pittsburgh, PA, regional network is used as a case study to examine the impacts of AV penetration in a city-scale network. Scenario simulations with these setting changes reflect different outcomes in terms of system efficiency and energy use.

This general framework enables agencies and researchers to use MAC-POSTS as a reusable simulation sandbox for evaluating a wide range of ADS deployment scenarios. By varying parameters in traffic dynamics and routing models, users can examine how these factors affect

traffic flow, congestion, energy consumption, and emissions across large-scale networks. The resulting scenario comparisons can support AV deployment planning, policy evaluation, and infrastructure investment decisions.

This report briefly introduces MAC-POSTS (Mobility data Analytics Center – Prediction, Optimization, and Simulation toolkit for Transportation Systems) package, alongside its basic network representation and modeling logics. Two demonstrations of network impact of transportation policies through MAC-POSTS are presented. Then specifics of Fundamental Diagrams (FDs) are altered to incorporate AV penetration rates. Finally, a case study examining AV penetration in the Pittsburgh regional network is conducted, with key insights and practical guidance from the analysis being replicated in other cities also presented.

Methodologies

Introduction of MAC-POSTS

This section introduces the workflow and core models of MAC-POSTS and illustrates its application through two demonstrations on large-scale regional networks. The two demonstrations illustrate the capability of MAC-POSTS that examine the impact of link-level change in infrastructure or flow characteristics on the regional network.

Overview

MAC-POSTS (Mobility data Analytics Center - Prediction, Optimization, and Simulation toolkit for Transportation Systems) is a toolkit for dynamic network modeling developed by Mobility data Analytics Center at Carnegie Mellon University. It is designed to deal with dynamic network modeling tasks for large-scale transportation networks and help transportation planners and researchers estimate dynamic origin-destination (OD) demand, assess traffic congestion, fuel consumption, and emissions, evaluate the effectiveness of a variety of traffic management measures, and devise cost-effective traffic management plans.

As an open-source dynamic traffic analysis toolkit, MAC-POSTS is robust, user-friendly, and relatively easy to calibrate using real-world multi-source data. It incorporates multiple state-of-the-art dynamic models and demand estimation algorithms. Its core traffic simulation module is coded in C++ for performance purposes while it also provides convenient Python application programming interfaces (APIs) that promote ease of use. The GitHub repository can be found at https://github.com/maccmu/macposts.

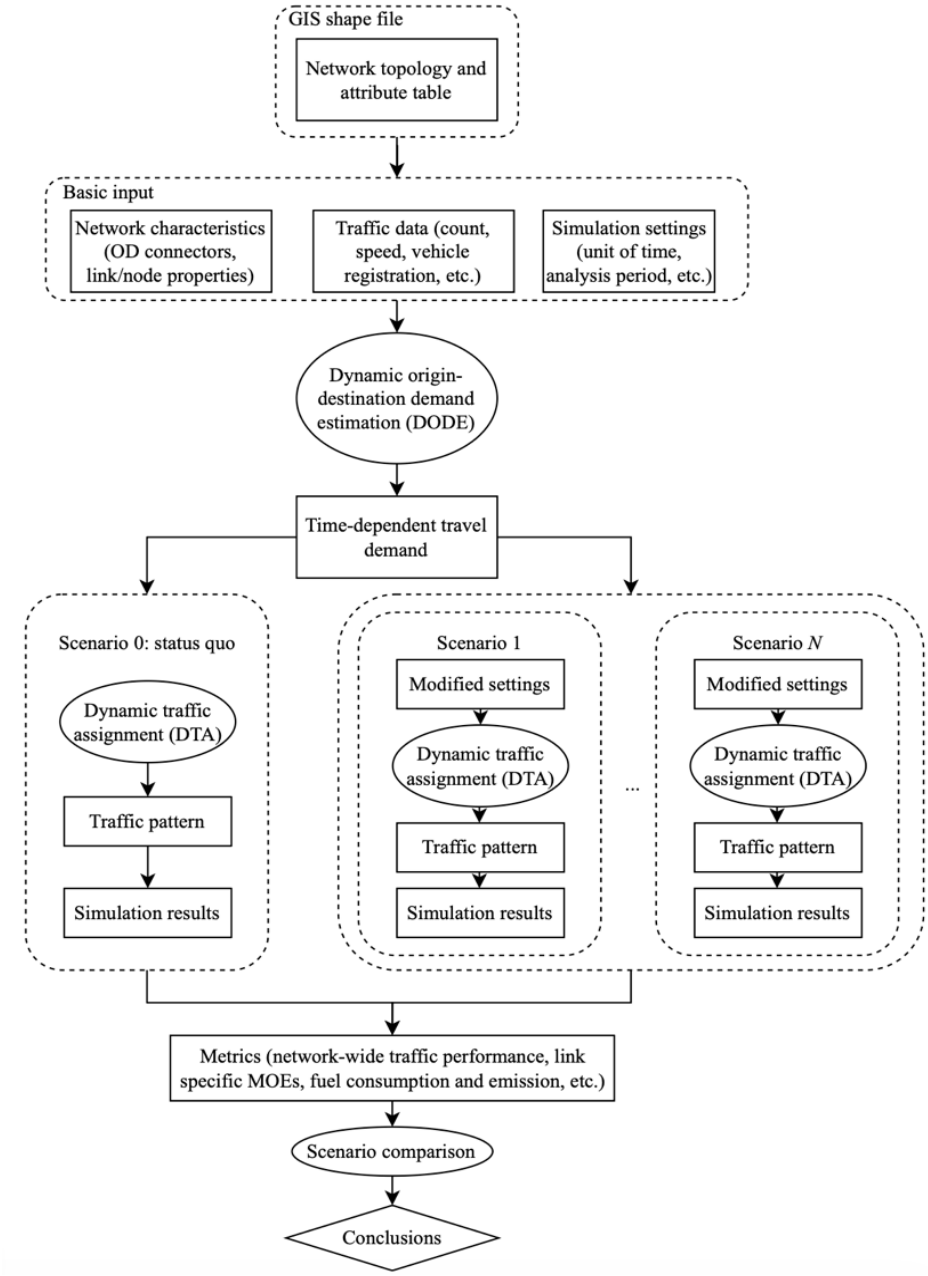
Particularly, MAC-POSTS has the following highlighted features:

- High spatial and temporal granularity
- Large-scale simulation
- High fidelity
- Multi-source data
- Multi-class vehicles
- Hybrid route choice model
- Various traffic and emission metrics
- Flexibility and extensibility

Workflow

Figure 1 illustrates the workflow of using MAC-POSTS to perform a complete dynamic network modeling task.

Figure 1: Workflow in MAC-POSTS



Data collection

The task starts with collecting both network and traffic data. The raw network data usually comes as GIS shapefiles. Users need to extract the following necessary information from GIS shapefiles as text files to be read by MAC-POSTS:

- Link attribute (number of lanes, free-flow speed, length, traffic capacity, and jam density)
- Topology (a list of links and their associated two endpoint nodes)
- Origins, destinations, and OD connectors

The traffic data is used to calibrate the dynamic network model. MAC-POSTS takes various types of data such as historical demand, traffic count, travel time/speed, vehicle registration information, parking records and remote sensing data (e.g., high-resolution satellite imagery).

Dynamic origin-destination demand estimation (DODE)

Once the network and traffic data are ready, users can carry out DODE to calibrate the model, which is to estimate time-varying OD demand so that the model can produce results (e.g., traffic flow) matching the real-world observations. Particularly, if multi-class vehicle data (e.g. personal cars, trucks, ride-sourcing vehicles, connected vehicles, etc.) is available, MAC-POSTS can provide the multi-class dynamic origin-destination demand (MCDOD), which represents the number of vehicles in each general vehicle class departing from an origin and heading to a destination in a particular time interval. The definition of "classes" is very general: by vehicle sizes, specifications, and nature of trips. The MCDOD reveals the fine-grained traffic demand information for different vehicle classes, and the overall spatio-temporal mobility patterns can be inferred from the OD demand and its resultant path/link flows. Policymakers can understand the departure/arrival patterns of multi-class vehicles through the MCDOD. The MCDOD also helps the policymakers understand the impact of each vehicle class on the roads, and hence each class of vehicles can be managed separately. In addition, most Advanced Traveler Information Systems/Advanced Traffic Management Systems (ATIS/ATMS) would require accurate MCDOD as the model input.

MAC-POSTS adopts a state-of-the-art computational-graph-based DODE algorithm which is suitable for large-scale networks with large-scale traffic data. This algorithm is a reformulation of the standard iterative heuristic methods for solving bi-level optimizations, while it provides a novel perspective to view the DODE problem as a machine learning task. Based on the constructed computational graph, the gradient of the loss with respect to the demand is derived. Users can choose from multiple off-the-shelf optimizers in PyTorch (e.g., Adam, NAdam, and SGD) to solve the DODE problem (Paszke et al., 2019). More details about the DODE algorithm can be found in Ma et al. (2020).

Dynamic traffic assignment (DTA)

Given the dynamic OD demand, DTA is to assign this demand to routes based on the route choice model. The output of DTA is time-dependent path flows. Depending on the route choice model, MAC-POSTS has three types of DTA models:

- Dynamic user equilibrium (DUE): DUE aims to find a time-dependent flow pattern in a network such that no user can improve his/her experienced travel time by unilaterally switching routes for a given departure time, namely, the temporal extension of the Wardropian UE condition (Peeta & Mahmassani, 1995). MAC-POSTS uses a path-based formulation of DUE and adopts two solution methods: the traditional method of successive averages (MSA) and the closed-form gradient projection (GP) method (Pi et al., 2019).

- Dynamic system optimal (DSO): DSO aims to determine a time-dependent flow pattern in a network such that the total network cost is minimized. It is well known that under a path-based formulation, the DSO can be transformed into a standard DUE by replacing the path marginal cost (PMC) with the path cost, and then the solution methods for DUE can be applied. The PMC is notoriously difficult to obtain. In MAC-POSTS, the approximation of

PMC proposed by (Qian et al., 2011) is adopted, in which approximate PMCs are obtained by tracing flow perturbations across regular links, merges, and diverges in a network.

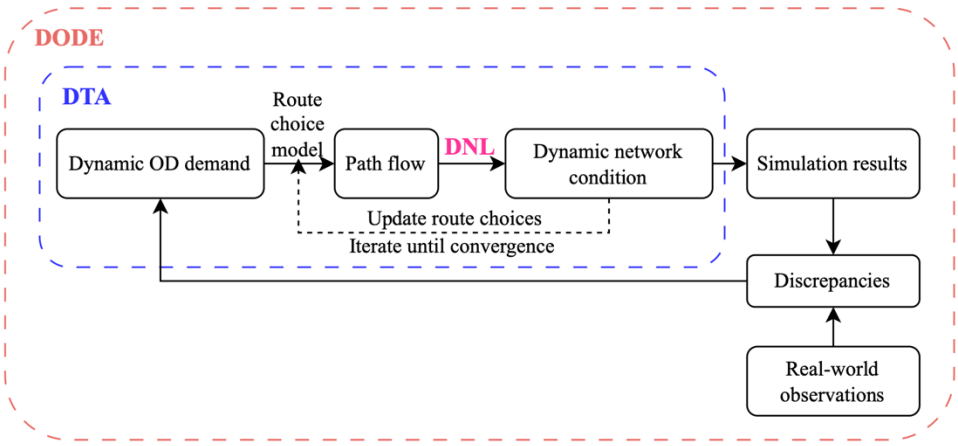
- Hybrid routing: A portion of the travelers, habitual travelers, will take the prescribed route according to their day-to-day experience or anticipated travel time, regardless of real-time traffic conditions on the network, while other travelers, referred to as adaptive travelers, will respond to dynamic traffic conditions and choose their routes as they go. Users have the flexibility to choose the portions of habitual travelers and adaptive travelers (diversion ratio) in the network to produce realistic traffic conditions and network performance. Unlike the DUE and DSO, which require many iterations to converge, the hybrid model is iteration-free and more computationally efficient (Qian & Zhang, 2013).

Dynamic network loading (DNL)

The DNL propagates time-dependent path flows through route links and determines the dynamic traffic pattern as a result of dynamic demand and supply interaction. MAC-POSTS adopts a mesoscopic model that models the vehicles individually while tracking their movements by macroscopic models and thus balances the level of modeling details and the computational cost. The link model and the node model are the most important components of the DNL. The link model characterizes the evolution of vehicle flows on road segments while the node model delineates the merging and diverging behavior of traffic flows on road junctions. In MAC-POSTS, users can choose from different link and node models to establish a DNL based on their needs.

The DODE, DTA, and DNL are intertwined with each other, and their relationship is depicted in Figure 2.

Figure 2: Relationship among DODE, DTA, and DNL



Scenario analysis and comparison

Once the dynamic model is calibrated with DODE, this model reflects the status quo of the network. Based on this, users can change settings, create different possible scenarios, re-run the DTA/DNL model, and carry out comparative analyses. This is particularly useful to answer "what-if" questions. For example, possible scenarios may include but are not limited to: setting tolls on some links, setting up a work zone, increasing/decreasing demand for some OD pairs, and implementing different traffic management strategies. Those changes to OD demand, demand characteristics, and infrastructure can be easily executed by altering the inputs to the calibrated

network model in MAC-POSTS. By comparing the corresponding metrics of interest (e.g., congestion) from different scenarios, users can gain a better understanding of the impacts of introducing such changes quantitatively at both disaggregate or aggregate levels and may then draw some conclusions or make decisions.

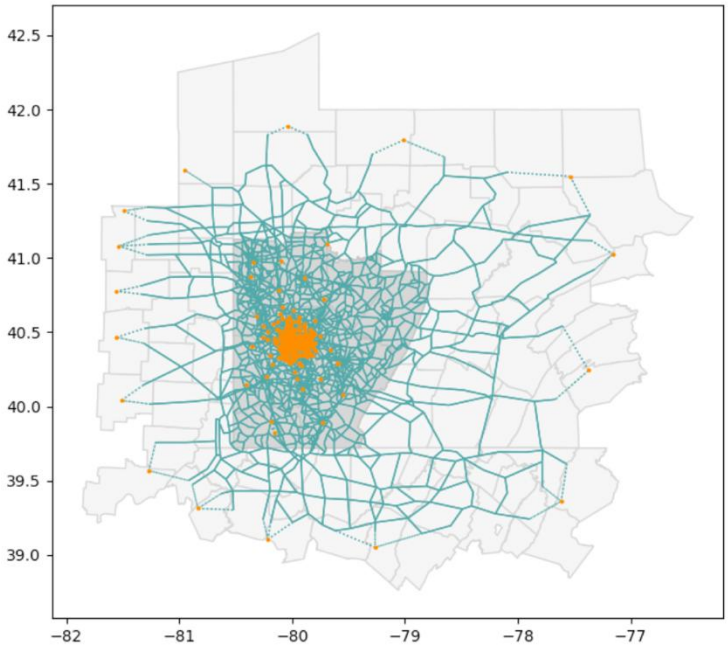
More details can be referred to the user manual in the GitHub repository.

Demonstration 1 (Zhang and Qian, 2023): Southwestern Pennsylvania Commission (SPC) network

Network description

The SPC network is shown in Figure 3. This network covers ten counties of the southwestern Pennsylvania region, with Pittsburgh city located in the center. The network includes a population of around 2.57 million and an area of 7,112 square miles. The number of links is 16,110, and the number of nodes is 6,297. There are 283 origins and 283 destinations, which totals up to 80,089 O-D pairs. The analysis period is from 6am to 11am on a typical workday.

Figure 3: SPC network (the area in dark gray contains the ten counties of the SPC region, and the point markers show all the origin/destination nodes). (Zhang and Qian, 2023)



Traffic data

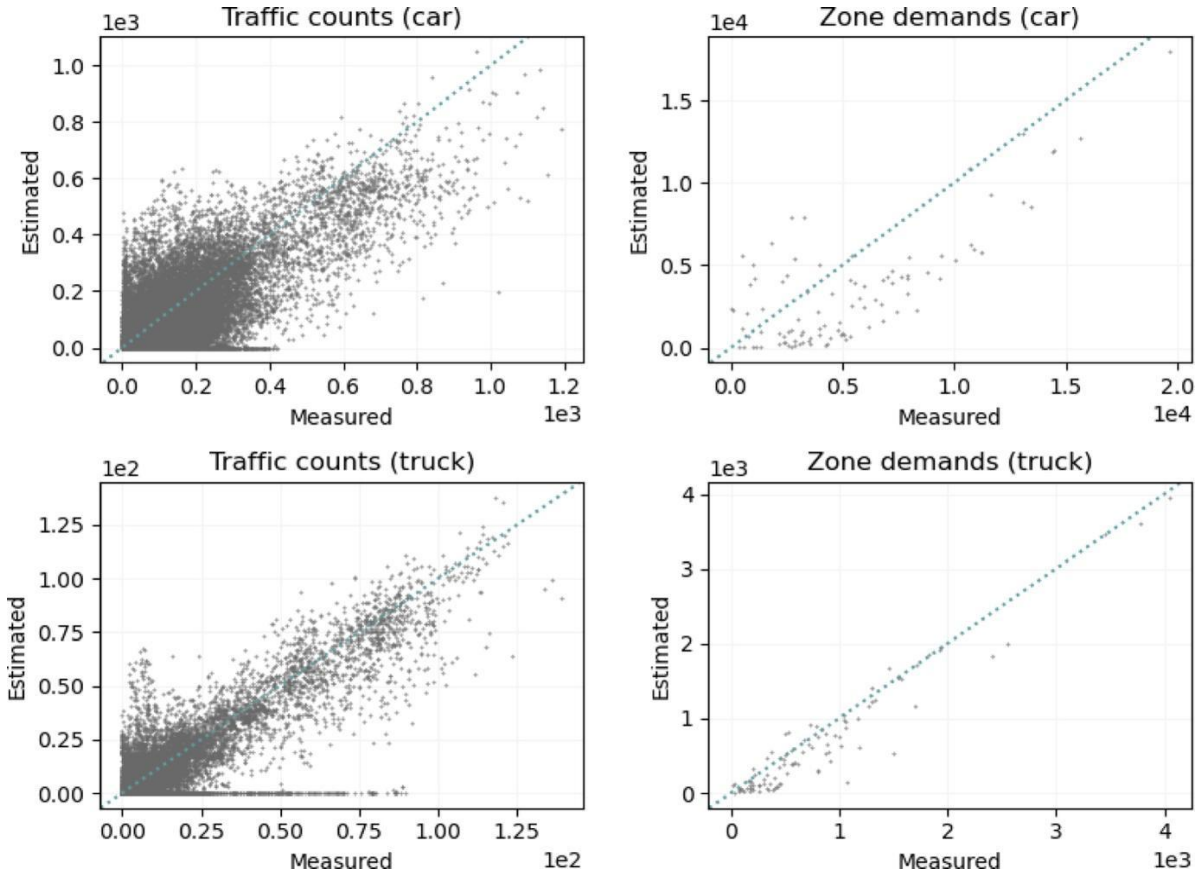
To calibrate the model, traffic data used includes traffic flow data, traffic speed data, and vehicle registration data, optionally with some additional data sets like the historical travel demands, etc. The traffic flow data is from the Pennsylvania Department of Transportation (PennDOT) and Southwestern Pennsylvania Commission through a data request. The data are collected hourly on selected locations on certain state-owned roadways. To ease the computation, we interpolate the hourly observations into traffic counts per 15 minutes. The car traffic volume counts and truck traffic volume counts are collected separately, where car traffic volume counts are measured for all passenger cars and passenger trucks, and truck traffic volume counts include all kinds of

trucks (e.g., light commercial trucks, short-haul trucks, and long-haul trucks) at the measured location. There are 608 locations in total that have valid car and truck volume counts. The traffic speed data comes from the Federal Highway Administration through National Performance Management Research Data Set (NPMRDS). In the data set, traffic speed values were collected every five minutes on some highway segments. Similarly, we aggregate the data into 15-minute intervals. In total, there are 945 locations with valid car and truck travel time observations. For vehicle registration data, we use the 2017 vehicle registration records from PennDOT through a data request, with the necessary pre-processing steps.

Dynamic Origin-destination (O-D) demand estimation results

The Dynamic O-D demand estimation (DODE) results are depicted in Figure 4. We use the coefficient of determination R-squared to measure the goodness of fit of our model. The R-squared scores for estimates of traffic counts are 0.32 and 0.70 for cars and trucks, respectively, and for zone travel demands those scores are 0.34 for cars and 0.89 for trucks.

Figure 4: Comparison of estimated and observed link traffic counts and zone demand for the SPC network. (Zhang and Qian, 2023)



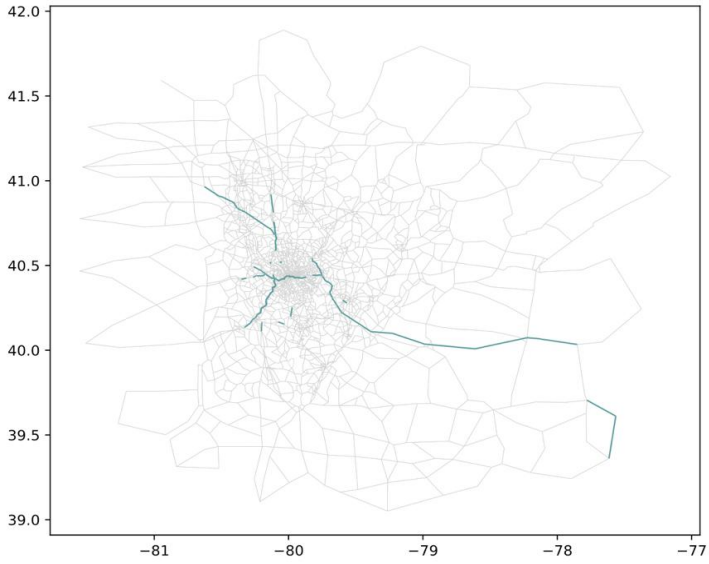
The estimates for cars are worse than those for trucks in this example. Inspection of the learning curves shows that the worse performance for cars is likely due to the discrepancy between the link-level traffic counts and zone-level vehicle registration records. Unlike trucks, cars tend to be used in a wide variety of ways. Therefore, simply aggregated values of registered passenger cars and passenger trucks may not be good proxies for travel demands of cars. It might be helpful to

process and use the vehicle registration data in a fine-grained way, but that also brings the concern of revealing private information about drivers. How to better utilize vehicle registration data for cars remains an important direction of future work.

Scenario: impacts of increasing roadway capacities on congestion

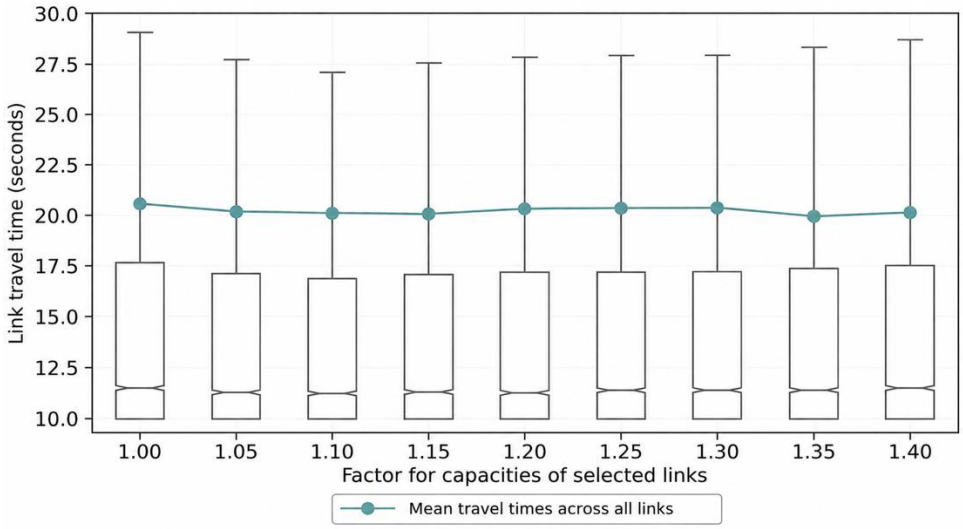
We select some major highways (shown in Figure 5) with high demand and congestion level in the downtown Pittsburgh area where the traffic conditions are highly complicated and roadways are often congested.

Figure 5: Selected links to increase capacities. (Zhang and Qian, 2023)



In the DTA model, we set 65% of vehicles to follow the adaptive routing strategy: they will change their routes periodically to the currently fastest route to their destinations. Therefore, there exist two contradictory effects on the link travel times. Increasing the capacities of a link reduces the link travel time when the traffic volume stays the same, but those adaptive travelers will soon be aware of that and reroute towards those links, making them potentially more congested, which can be seen from Figure 6. Thus, increasing roadway capacities does not necessarily reduce average link travel times. Even worse, because the downtown area generally has a high volume of traffic, all the roadway segments nearby could also be in the congested state. Therefore, it would be difficult for those adaptive travelers to reroute to other roadways, making the traffic conditions more complicated and unpredictable. More details of this study can be referred to Zhang & Qian (2023).

Figure 6: Box plots of link travel times under different capacities for the selected links. (Zhang and Qian, 2023)



Demonstration 2 (Qian et al., 2023): Delaware Valley Regional Planning Commission (DVRPC) network

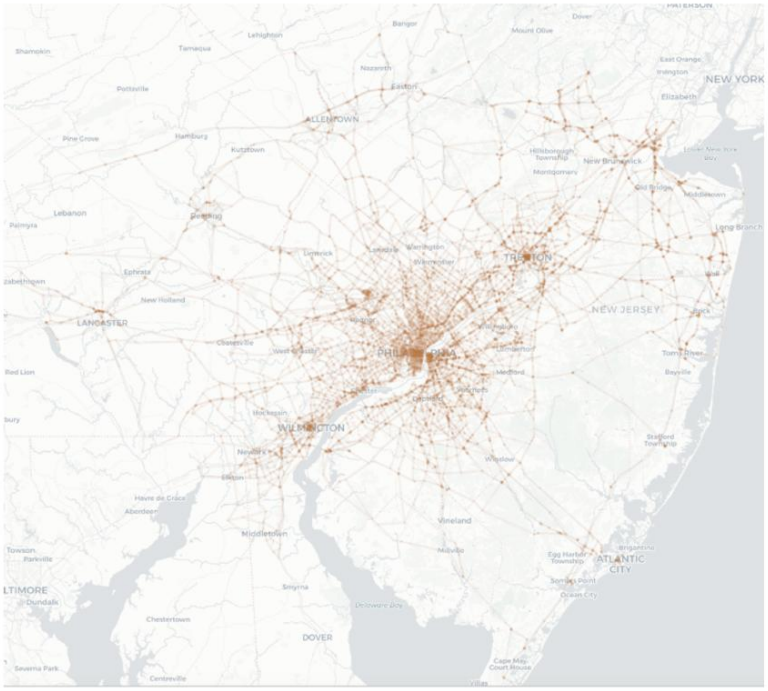
Network description

The DVRPC network covers nine counties in the Greater Philadelphia Region with Philadelphia city in the central area, as shown in Figure 7. Note that the original network data is trimmed so that there are no isolated nodes and links. The isolated nodes and links represent the parkways in the real world, and the absence of such nodes and links does not affect the network analysis. In addition, some neighboring links with small lengths and the same speed limit are further consolidated, which can substantially reduce the network size.

Traffic data

We also use traffic count, travel speed, and vehicle registration data to calibrate the model. The traffic count data is provided by the DVRPC through a data request. The original count data contains 15-minute traffic volume counts for different vehicle types at selected locations in this region each day in 2019. The count data is carefully examined and cleaned and matched to the links in the transportation network. Two vehicle types, i.e., cars and trucks, are counted separately in the data, which represent smaller private or ride-hailing vehicles and larger freight trucks, respectively. In total, there are 1,920 locations with valid car and truck volumes. Traffic speed data is obtained from INRIX for the year 2019 through Federal Highway Administration through National Performance Management Research Data Set (NPMRDS). Speeds of different vehicle types are measured separately, and hence both passenger car speeds and freight truck speeds are available. All the speed data is measured every 5 minutes of each day, and we average the data for different days in 2019 and aggregate the data to 15-minute intervals. There are a total of 3,420 locations with valid car and truck speed measurements. Vehicle registration data is also from PennDOT.

Figure 7: DVRPC network. (Qian et al., 2023)



Dynamic Origin-destination (O-D) demand estimation results

Figure 8 presents the comparison between simulated traffic volumes and observed traffic volumes, in which the y-axis is the simulated counts and the x-axis is the observed counts. The R-squared is 0.37, 0.42, and 0.97, for the car flow, truck flow, and origin vehicle demand, respectively. Figure 9 depicts the comparison between simulated travel speeds and observed travel speeds, in which the y-axis is the simulated travel speed and the x-axis is the observed travel speed. The R-squared values are 0.87 and 0.89 for the car and truck travel times, respectively.

Figure 8: Comparison of estimated and observed link traffic counts and zone demand for the DVRPC network (figures are car counts, truck counts, and total zone demand from left to right). (Qian et al., 2023)

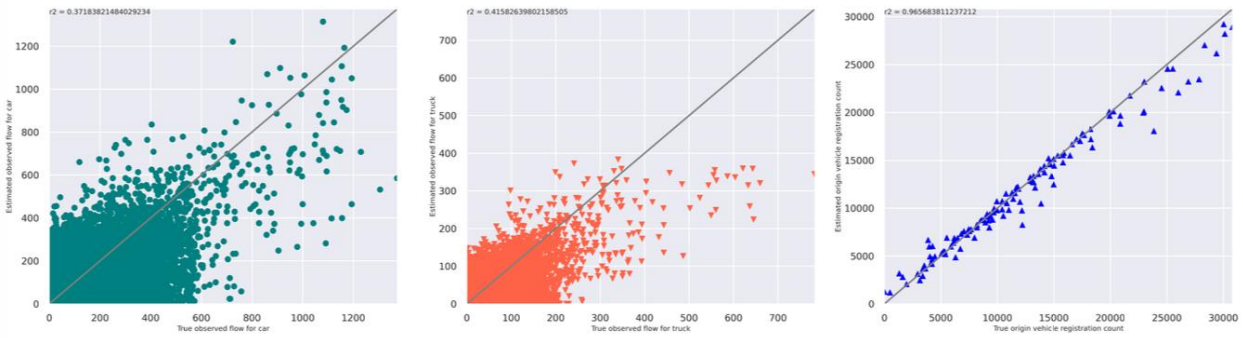
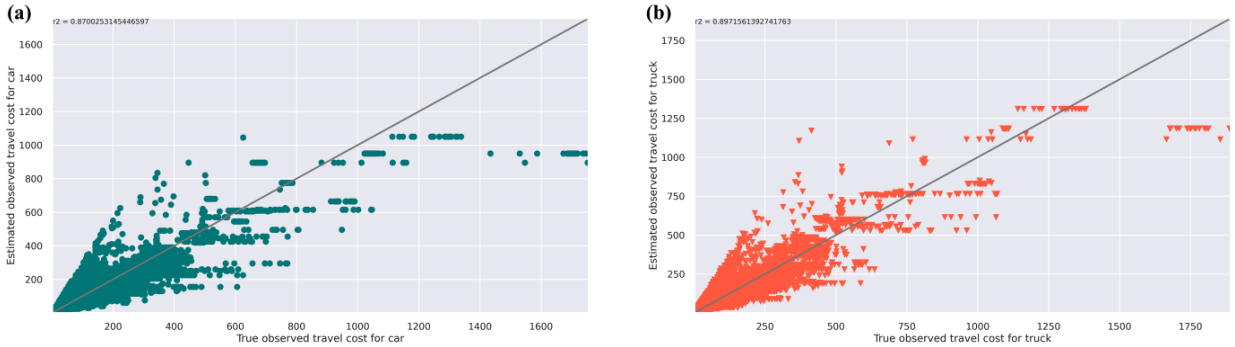


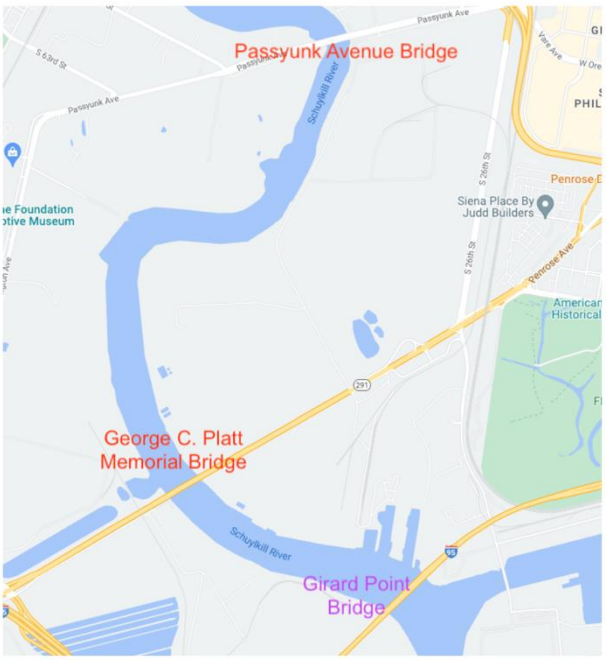
Figure 9: Comparison of estimated and observed link travel times for the DVRPC network (figures are for car and truck travel times from left to right). (Qian et al., 2023)



Scenario: impacts of tolling a bridge

We consider setting a toll on Girard Point Bridge on the I-95 interstate in Philadelphia County, as shown in Figure 10. Three scenarios are set up to investigate the impact of tolling on regional traffic. The baseline scenario represents the current no-toll situation. Scenarios 1 and 2 assume a toll of $1.00 and $2.00, respectively, for both directions for each vehicle using this bridge. In our simulation, 65% of travelers will adapt to this tolling and may change their routes while the remaining 35% travelers will still stick to the pre-determined routes.

Figure 10: Tolled bridge and its nearby bridges. (Qian et al., 2023)



The metric changes from the baseline scenario to different tolling scenarios are shown in Table 1. The average (total) travel time indicates the average (total) time spent within the DVRPC region. With the introduction of tolling in this case, travel time, fuel consumption, and emissions are increased. This is no surprise, given that the total O-D demand remains the same and a fraction of travelers choose to take alternative routes that are longer in both distance and travel time. This case study of tolling differs from congestion pricing tolls where the goal is to reduce the total O-D demand by shifting to alternative travel modes in addition to alternative travel routes. Since this

is a large regional network, the relative changes in these metrics at the system level caused by only one bridge tolling may not be very significant, but in the absolute values, it still indicates some substantial impacts on fuel consumption and emissions. It is expected that these metrics change for a more local area near the bridge can be more significant, leading to reduction in VHT and VMT locally. In comparing Scenario 1 with Scenario 2, it was counterintuitively observed that tolling price increases result in an increase in travel time, fuel consumption, and emissions because travelers are more likely to take detours when facing a higher toll.

Table 1: General metrics in the AM peak hours (Qian et al., 2023)

case	class	Total vehicle #	Total travel time (h)	Average travel time (h)	Vehicle Mile traveled	Fuel (gallon)	CO (ton)	HC (ton)	NOX (ton)
Baseline	car	1,604,373	2,052,337.1	1.3	52,975,339.9	1,908,235.5	63.8	44.6	59.5
	truck	399,947	571,819.9	1.4	17,331,507.4	941,201.6	82.3	30.2	117.6
Scenario 1 ($1 Toll)	car	1,604,387	2,113,781.6	1.3	53,163,655.5	1,919,841.5	64.1	44.9	59.8
	truck	400,143	585,932.5	1.5	17,419,338.4	947,672.6	82.8	30.4	118.4
Scenario 2 ($2 Toll)	car	1,604,330	2,157,446.0	1.3	53,890,143.4	1,947,461.6	64.9	45.8	60.6
	truck	400,043	599,026.1	1.5	17,636,433.9	960,328.7	83.5	31.0	120.1

The total toll revenues in different scenarios can be estimated by multiplying the toll with the number of passing vehicles and are presented in Table 2. We can also examine the primary vehicle detour routes due to the tolling on Girard Point Bridge to help public agencies understand how travelers' behavior changes.

Table 2: Total toll revenues in the AM peak hours ($). (Qian et al., 2023)

	Scenario 1		Scenario 2	
direction	cars	trucks	cars	trucks
westbound	12,774.5	4,005.5	23,231.0	6,910.0
eastbound	10,381.0	3,333.5	12,465.0	4,095.0
total	30,494.5		46,701.0	

As shown in Figure 10, there are two primary detour routes travelers can take to avoid the toll on Girard Point Bridge: George C. Platt Memorial Bridge and Passyunk Avenue Bridge. The percentage changes in traffic flows of three scenarios are presented in Table 3. It can be found that the introduction of a toll on Girard Point Bridge indeed induces travelers to take detours and thus reduce its own traffic flows. More specifically, a toll of $1.00 in Scenario 1 can decrease the traffic flow in the baseline by almost 50%, and a toll of $2.00 in Scenario 2 can decrease the traffic

flow in the baseline by 60%. In comparison, the traffic flows on both George C. Platt Memorial Bridge and Passyunk Avenue Bridge increased significantly. Due to its closer distance to Girard Point Bridge, George C. Platt Memorial Bridge experiences more traffic growth than Passyunk Avenue Bridge. It can also be found that a higher toll leads to more traffic reduction on Girard Point Bridge and more traffic increase on the other two bridges. More details of this study can be found in Qian et al. (2023).

Table 3: Percentage change of traffic flows of three bridges in the AM peak hours. (Qian et al., 2023)

		Baseline		Scenario 1 ($1 Toll)		Scenario 2 ($2 Toll)	
class		cars	trucks	cars	trucks	cars	trucks
Girard Point Bridge	westbound	0.0%	0.0%	-49.1%	-46.2%	-53.7%	-53.6%
	eastbound	0.0%	0.0%	-33.3%	-23.1%	-60.0%	-52.7%
George C. Platt Memorial Bridge	westbound	0.0%	0.0%	76.4%	77.0%	79.7%	79.0%
	eastbound	0.0%	0.0%	24.3%	12.1%	58.6%	48.7%
Passyunk Avenue Bridge	westbound	0.0%	0.0%	7.1%	33.7%	20.1%	35.9%
	eastbound	0.0%	0.0%	14.8%	20.9%	27.7%	32.1%

Modeling mixed traffic flow of automated and human driven vehicles in regional networks

The model in this study builds upon the parameter settings and empirical findings reported in Shi & Li (2021). In that study, real-world experiments were conducted to derive FDs for a mixed traffic environment. The experimental fleet consisted of two commercially available AVs and one conventional vehicle equipped with an adaptive cruise control system. Four distinct headway settings ranging from short to long, were tested and denoted as Headway settings 1 to 4 indicated in Table 4. Detailed descriptions of the experiments can be found in Shi & Li (2021). In this study, we adopt a subset of the fitted parameters for triangular FDs provided in Shi & Li (2021). Because parameters reported in their results were found to be inconsistent in magnitude with our base model, we apply a uniform scaling factor to adjust the values to match the Pittsburgh network. This adjustment ensures that the FD parameters remain consistent with local traffic characteristics of the Pittsburgh network. The scalars used in this study are summarized in Table 4.

Table 4: Scalars of FD in this study (based on Shi & Li, 2021)

Scenario	Headway setting	Road capacity scalar	jam density scalar
AV	1	2900/2000	80.77/94.4
	2	2250/2000	74.96/94.4
	3	1850/2000	86.11/94.4
	4	1500/2000	90.77/94.4
Human-driven	-	1.0	1.0

We develop two approaches to model mixed traffic flow in our DNL model:

- The first homogenous approach assumes a uniform mixing of AVs and HDVs across the network. The mixed FDs parametrized by AVs penetration rate is used to govern mixed traffic dynamics.
- The second approach explicitly differentiates between HDVs and AVs, separately governed by a set of FD parameters (in pure AV and HDV environments) and the heterogenous traffic flow dynamics is determined by bi-class dynamics across time and space in the network (Qian et al. 2017).

We describe the modeling approach in the following sections and attached a tutorial in the Appendix.

Homogeneous distribution approach: uniform mixing across all vehicles and links

In the homogeneous distribution approach, we assume that automated vehicles (AVs) are uniformly distributed across the network in both spatial and temporal dimensions. Under this assumption, the fundamental diagrams (FDs) of all roadway segments adopt a triangular form,

parameterized by a specified penetration rate and headway setting in ACC of AVs. For a specific penetration rate, p, and headway setting, Equations (1) and (2) are used to update the mixed FD parameters for each link using FD parameters of pure AV and HDV flow environments. The FDs of HDVs are from the car class in the baseline model, and the AV FDs are obtained by multiplying the scalars in Table 2.1. The penetration rate is applied consistently across vehicle classes (0%-100%, 20% increments), such that both cars and trucks have an identical fraction of AVs.

$$q_{mix}^{cap}(p) = \frac{v_f}{\frac{(v_f + w_{AV})p}{q_{AV}^{cap}\left(1 + \frac{w_{AV}}{v_f}\right)} + \frac{(v_f + w_{HDV})(1-p)}{q_{HDV}^{cap}\left(1 + \frac{w_{HDV}}{v_f}\right)}}$$

$$k_{mix}^{jam}(p) = \frac{1}{\frac{w_{AV} \cdot p}{q_{AV}^{cap}\left(1 + \frac{w_{AV}}{v_f}\right)} + \frac{w_{HDV}(1-p)}{q_{HDV}^{cap}\left(1 + \frac{w_{HDV}}{v_f}\right)}}$$

Where $q_{mix}^{cap}(p)$ is the Capacity of the mixed AV–HDV traffic stream at AV penetration rate p, in veh/hour. $k_{mix}^{jam}(p)$ is the Jam density of the mixed AV–HDV traffic stream at AV penetration rate p, in veh/km. v_f is the Free-flow speed of both AVs and HDVs. w is the backward wave speed in km/hour.

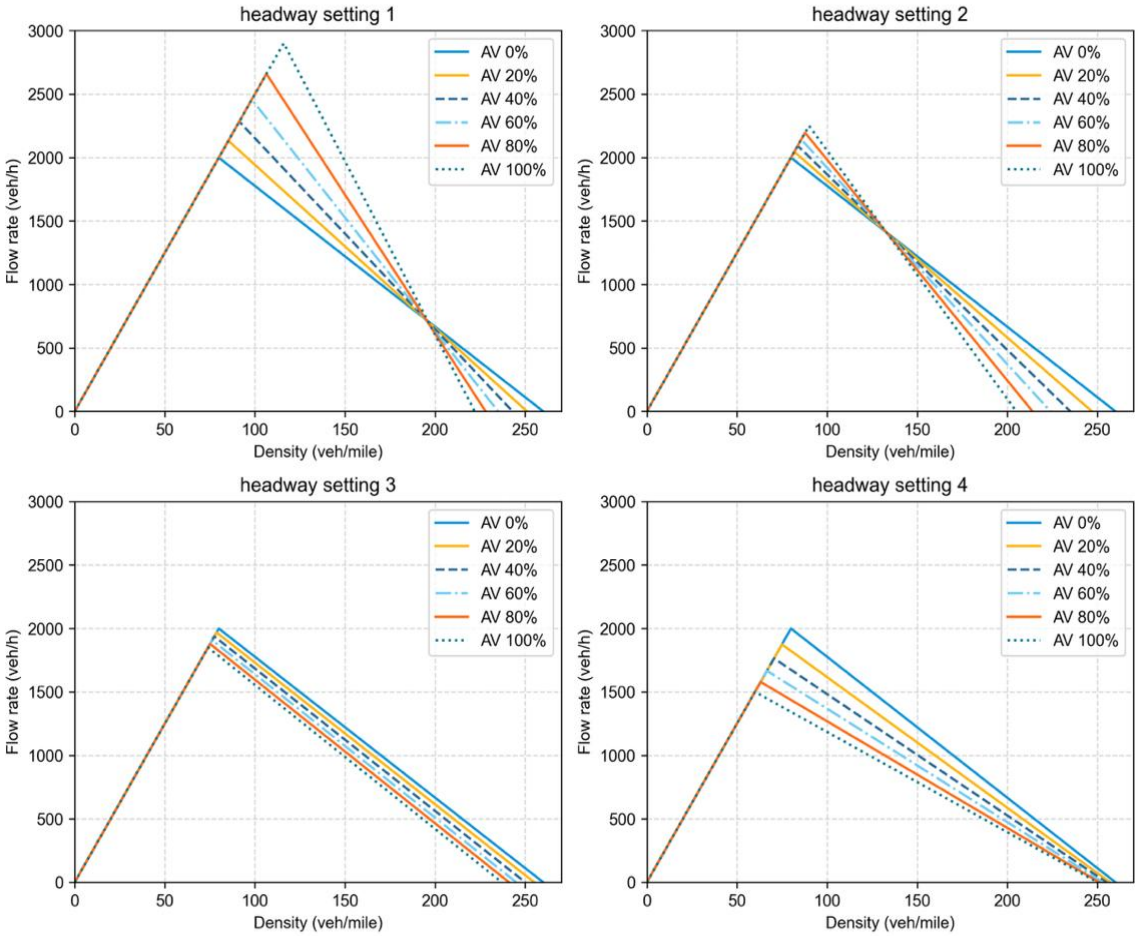
The resulting mixed FDs under different headway settings of one representative link are illustrated in Figures 11. It shows that flow capacity and jam density evolve differently as the AV increases from 0% to 100% and the magnitude also depends on headway settings. These patterns resemble those reported in Shi & Li (2021), confirming the consistency of the proposed model in capturing mixed traffic flow dynamics. In this study, the fraction of adaptive routing vehicles is set to the same for all vehicles, implying that AVs and human-driven vehicles (HDVs) exhibit the same behavioral model. The demand is treated as mixed traffic without explicit disaggregation by HDV and AV classes, meaning that the demand matrix keeps the same as the baseline with varying FD parameters only to reflect the variation of penetration rates and headway settings.

Figure 11 illustrates the effects of AV penetration and ACC headway settings on the fundamental diagram of the mixed traffic stream. The results indicate that the impact of AV penetration on traffic capacity is highly dependent on the headway adopted by AVs. Under headway setting 1, increasing the AV penetration rate substantially increases the maximum flow rate, with capacity increasing from approximately 2,100 veh/h for the all-HDV condition to nearly 2,900 veh/h for the all-AV condition. A similar but considerably weaker capacity improvement is observed under headway setting 2. In contrast, headway settings 3 and 4 exhibit the opposite trend, with increasing AV penetration leading to reductions in capacity, due to conservative headway settings. The effect is particularly pronounced under headway setting 4, where capacity decreases from approximately 2,000 veh/h at 0% AV penetration to about 1,500 veh/h at 100% AV penetration.

These results demonstrate that the presence of AVs alone does not necessarily improve roadway capacity. Instead, the operational impacts of AVs are strongly influenced by their car-following and headway control strategies. Shorter headways can allow AVs to maintain closer vehicle

spacing and thereby increase traffic throughput, whereas more conservative headway settings may offset or even reverse the potential capacity benefits of automation. In addition to capacity, the critical and jam densities also vary with AV penetration, indicating that AV deployment can modify multiple characteristics of the fundamental diagram rather than simply shifting its capacity. Overall, the results highlight the importance of explicitly considering AV control parameters, particularly ACC headway settings, when evaluating the traffic-flow impacts of increasing AV penetration.

Figure 11: One example of mixed FDs parametrized by penetration rate and headway

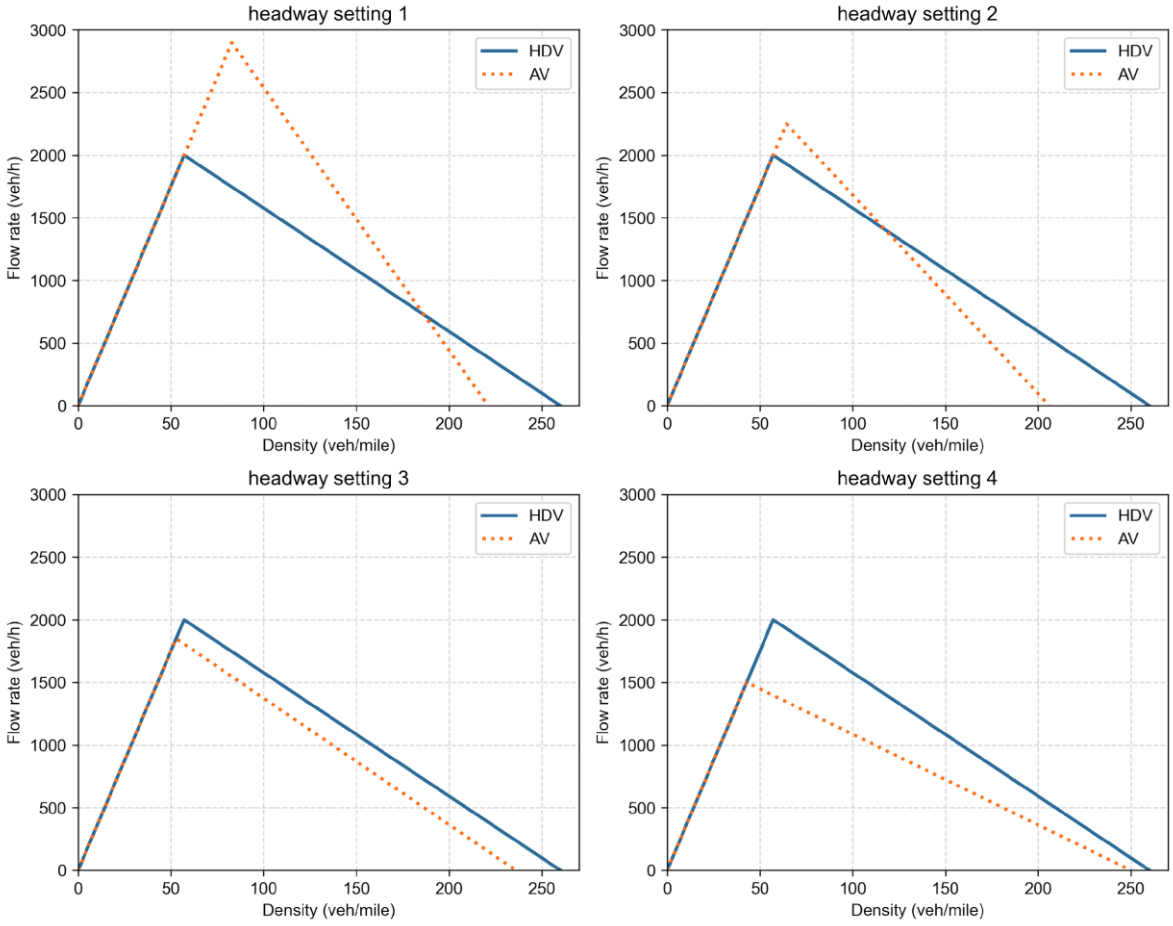


Heterogeneous distribution approach: class-specific and spatially differentiated mixing

The heterogeneous scenario explicitly differentiates between two vehicle classes: HDVs and AVs, each governed by a distinct set of FD parameters in a pure AV or HDV traffic environment. The OD demand matrix is partitioned into two classes according to the specified penetration rate. The link dynamic of heterogeneous mixed traffic is determined by the flow interaction across the two classes (Qian et al. 2017). Figure 12 shows the separate FDs that govern the link flow dynamic of each class. In this study, we use the same route choice proportion as the baseline model for AVs and HDVs.

This approach reflects the reality that AVs may not be evenly distributed across the network. Instead, their route choices and behavioral adaptations can generate spatio-temporal heterogeneity in links and paths throughout the network, rather than assuming a predetermined uniform penetration among all links and paths in the homogeneous distribution approach. It captures the potential divergence in network performance and congestion patterns that arises when AVs and HDVs operate with distinct behavioral characteristics.

Figure 12: Bi-class FDs parametrized by penetration rate and headway setting of one representative link



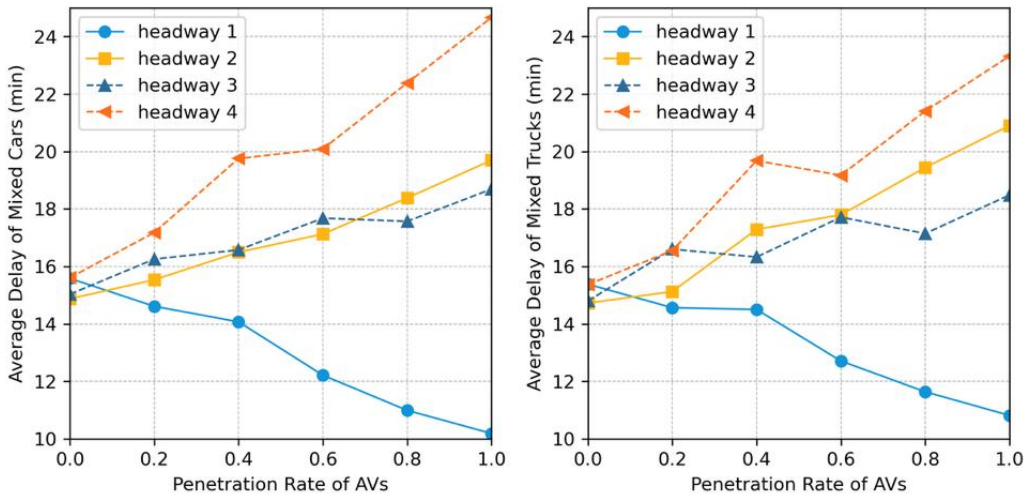
Case study of Pittsburgh network

We use the Pittsburgh network as a case study to evaluate the impacts of AV penetration. The network covers the City of Pittsburgh and the broader Allegheny County, consisting of 8,074 links, 3,707 nodes, 490 origins/destinations, and 62,750 O–D pairs. The baseline model is calibrated using historical bi-class traffic count and speed data, representing traffic conditions during the PM peak period (3:00–6:00 pm) on a typical weekday. Because the real-world AV operation data is not yet available, we design synthetic scenarios to capture potential impacts under different penetration rates, using two approaches introduced in previous sections.

Results from the homogenous approach

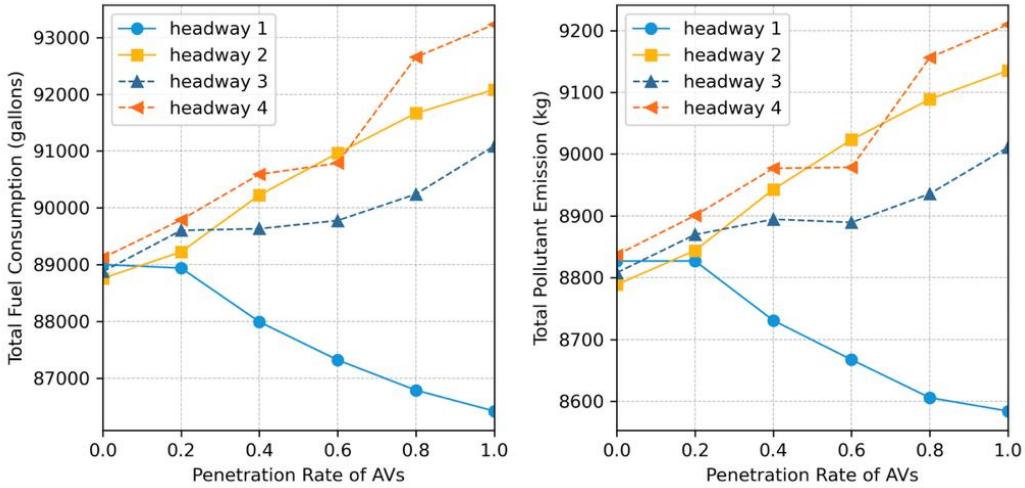
The homogeneous approach assumes a uniform mixing of AVs and HDVs throughout the network. The diversion ratio represents the proportion of vehicles that actively seek better routes while en route, relative to those traveling on prescribed fixed routes. Figure 13 presents the system-level efficiency performance, represented by the average vehicle delay, under homogeneous mixing of AVs and HDVs across varying headway settings and penetration rates. Figure 14 further shows the total fuel usage and pollutant emissions. For headway setting 1, both mixed cars and mixed trucks benefit substantially as AV fraction increases. Average delays for both cars and trucks decline consistently, and reductions in fuel consumption, and pollutant emissions are observed. By contrast, headway settings 2, 3, and 4 all show limited or negative impacts as penetration increases. In these cases, delays remain flat or grow with penetration increase, and fuel consumption and emissions consistently increase, with the steepest degradation observed under headway setting 4.

Figure 13: Average delay for mixed flow under varying settings (diversion ratio = 0.4)



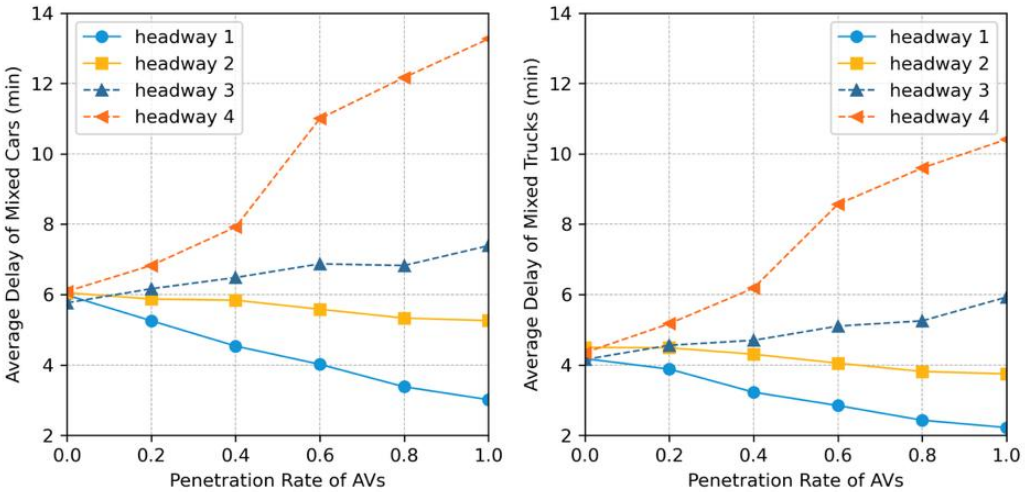
These results highlight that conservative headway settings in ACC not only suppress potential benefits but can also exacerbate congestion and environmental burdens. Importantly, headway setting 2 consistently yields worse performance than setting 3 across penetration levels, indicating that the sharper reduction in jam density (under setting 2) offsets the capacity increase, ultimately worsening network performance. These results also emphasize that jam density in FDs of mixed traffic is as critical as capacity, suggesting that AV car-following policies must be carefully designed to balance capacity and jam density and avoid unintended congestion.

Figure 14: Total fuel consumption and pollute emission under varying settings (diversion ratio = 0.4)



We next set the diversion ratio to 1.0 and rerun the simulations (Figure 15, 16). In this case, all vehicles are allowed to adapt their routes dynamically in response to real-time traffic.

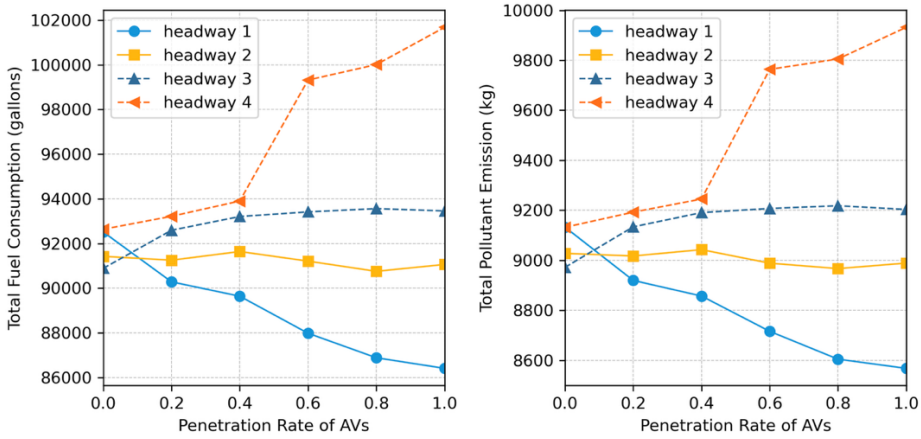
Figure 15: Average delay for mixed flow under varying settings (diversion ratio = 1.0)



For headway setting 1, the system achieves consistent and substantial gains in delay reduction, fuel savings, and emission decreases, with larger improvements than in the case of 0.4 diversion ratio. This indicates routing flexibility amplifies the capacity advantage of AVs that enables

system-wide benefits. For headway setting 2 and 3, delays remain relatively flat or rise slightly, while fuel use and emissions show no clear downward trends. These outcomes suggest that adaptive routing can partially mitigate the negative impacts of reduced capacity and jam density when conservative AVs are introduced, but only to a limited extent. In headway setting 4, where AVs impose the largest capacity reduction, overall system performance remains the worst (but the values in all metrics are smaller than 0.4 case), demonstrating that routing adaptation cannot fully overcome disadvantages in the traffic flow characteristics of conservative AV.

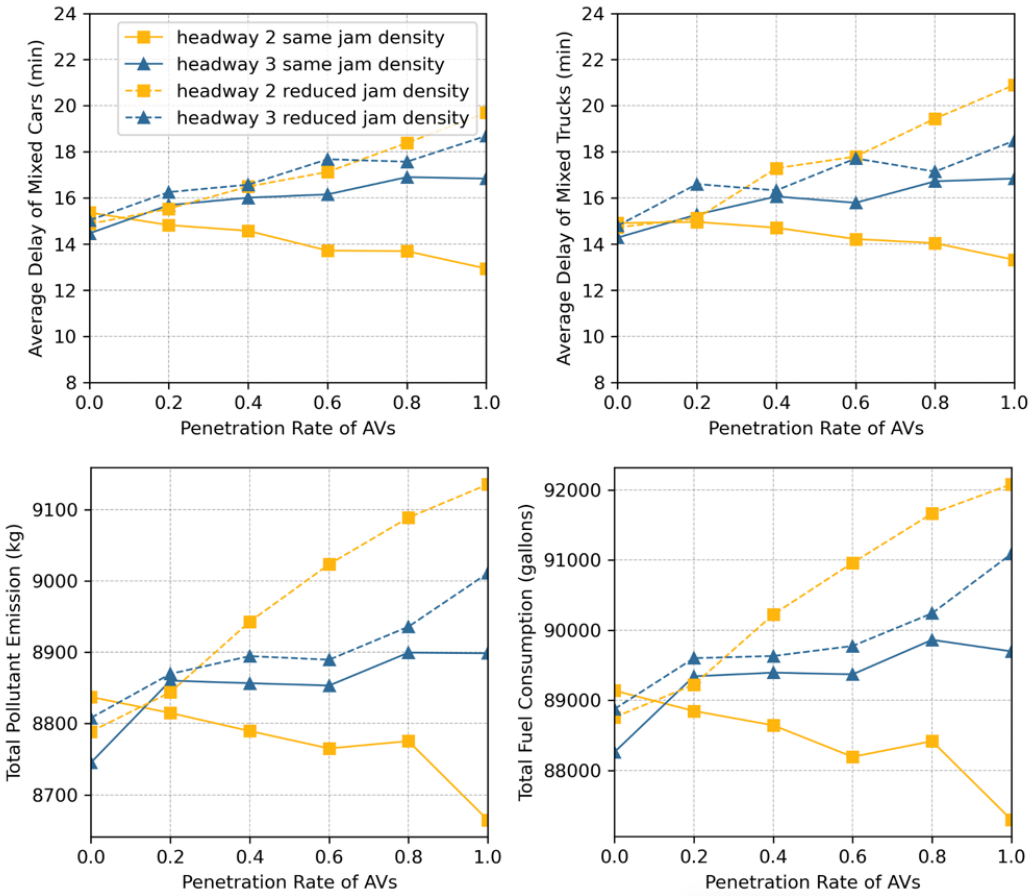
Figure 16: Total fuel consumption and pollute emission under varying settings (diversion ratio = 1.0)



To further examine if the system deterioration is related to density reduction, especially in headway setting 2 and 3, we keep jam density unchanged in mixed FD and rerun the simulations. Figure 17 compares the average delay with respect to jam density settings. We can observe that when we use the unchanged jam density for mixed traffic and simply increase capacity (i.e., headway setting 2 same density), all metrics tend to decrease when more AVs penetrate the network, which reveals opposite trends compared with cases with reduced jam density.

But for headway setting 3, which has reduced capacity, keeping jam density unchanged does not change the overall upward pattern with increased AV penetration but yields better performance at all penetration rates. These findings indicate that the jam density deterioration of mixed traffic may have negative impact but also depends on the capacity improvement. There are also some theoretical or simulation studies assuming the jam density will not be reduced (or even increased) for mixed traffic (Zhou & Zhu, 2020, Yao et al. 2019), but more real-world data and empirical evidence are required to validate these assumptions.

Figure 17: Comparison of jam density settings for mixed flow FD (diversion ratio = 0.4)



Results from the heterogeneous approach

Figure 18 shows the system efficiency under varying settings, represented by average vehicle delays for AVs and HDVs separately. Figure 19 reports total fuel use and emissions. Under headway setting 1, delays for both AVs and HDVs decline steadily as penetration increases, and AV delays are consistently smaller than HDVs. The fuel consumption and emission also yield significant reductions together. This demonstrates that the higher capacity of AVs effectively leads to AV specific system gains even though AVs may occupy slightly more space due to safety concerns in congested regimes. By contrast, headway setting 2 exhibits relatively flat delay fluctuation for both classes, and emissions and fuel consumption follow a similar upward trend, suggesting that the moderate capacity increase of AVs is insufficient to offset congestion effects in mixed flow, and the large reduction in jam density can even hurt system energy efficiency performance. Headway setting 2 leads to the second worst fuel usage and emissions performance.

Figure 18: Average delay for HDVs and AVs under varying settings (diversion ratio = 0.4)

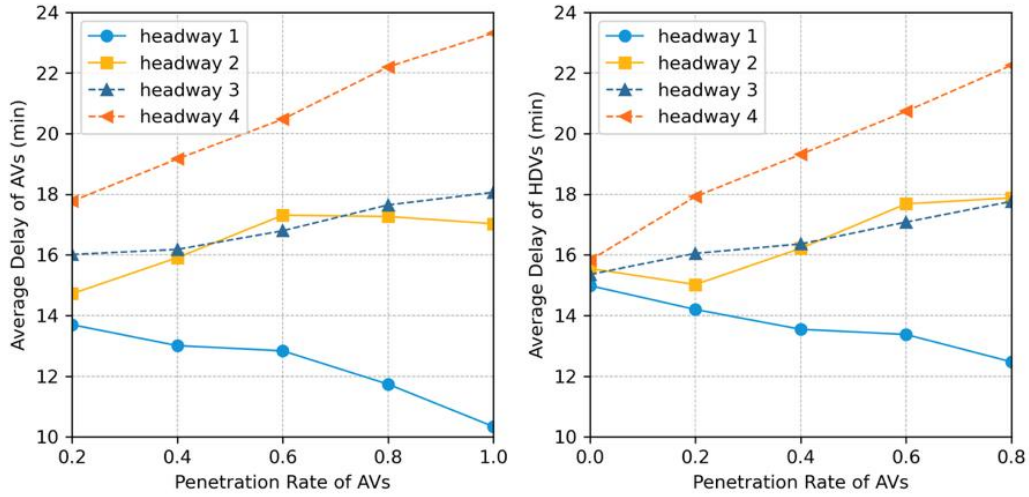
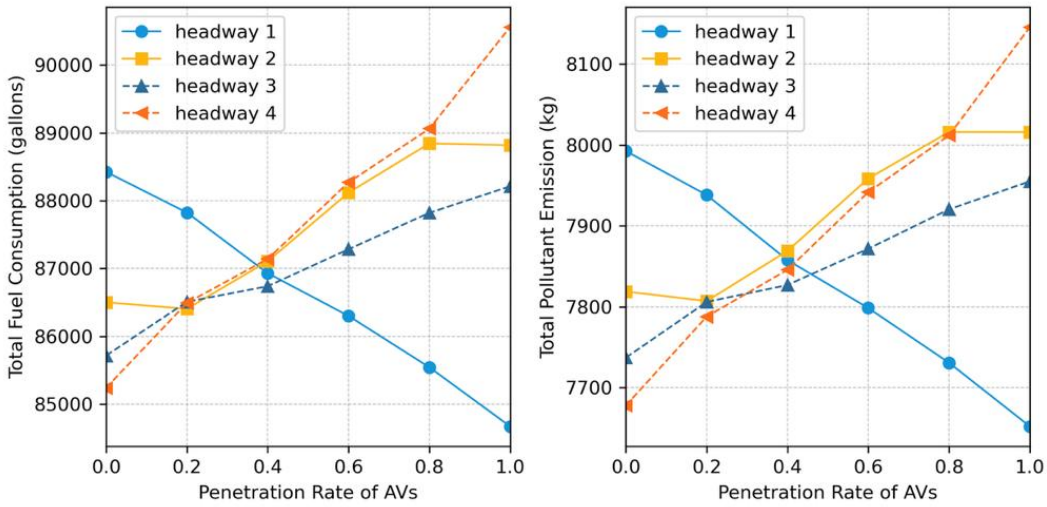


Figure 19: Total fuel consumption and pollute emission under varying settings (diversion ratio = 0.4)



Headway setting 3 yields moderate performance: delays remain higher, and fuel use and emissions gradually rise with penetration increase, reflecting the conservative FD characteristics of AVs. Headway setting 4 produces the worst outcomes, with delays for both AVs and HDVs increasing monotonically with penetration and fuel/emissions escalating sharply. Overall, these results underscore that AV adoption can either enhance or degrade network performance depending on headway settings; aggressive headway reductions (setting 1) result in increased capacity and efficiency, whereas conservative headway assumptions (settings 2–4) may exacerbate congestion as AV penetration grows. Meanwhile, the density reduction caused by conservative ACC may yield worse performance than reduction of capacity due to more space for large vehicles, indicating careful automation design is needed for large vehicles which occupy larger space. These findings are consistent with the homogeneous approach.

Like the homogenous case, we further change the diversion ratio to be 1.0. The results are shown in Figure 20 and 21. When all vehicles are allowed to adapt their routes in real time, the system generally achieves lower average delays and improved environmental outcomes compared to the case where only 40% of vehicles adapt. Delays for both AVs and HDVs are consistently reduced, particularly under headway settings 2, where routing flexibility helps better utilize available capacity and avoid congestion, resulting in an opposite trend.

Figure 20: Average delay for HDVs and AVs under varying settings (diversion ratio = 1.0)

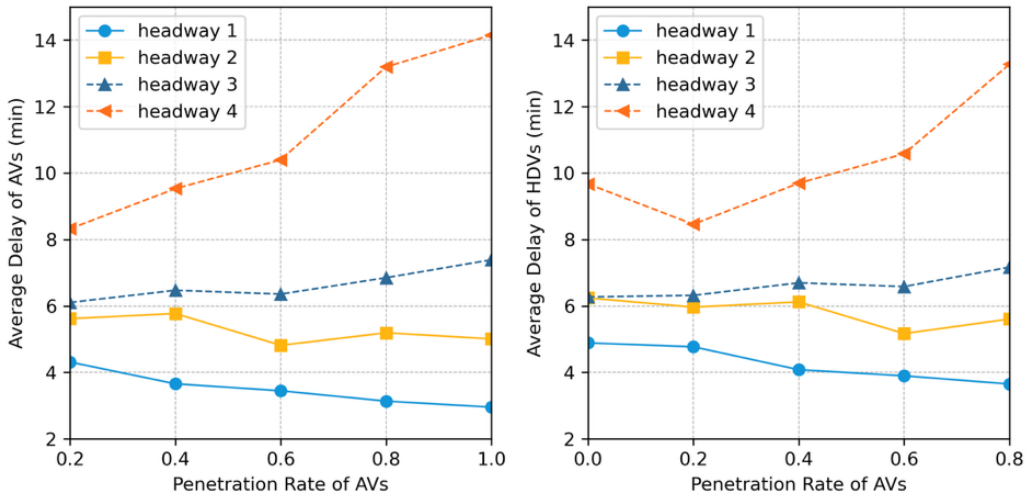
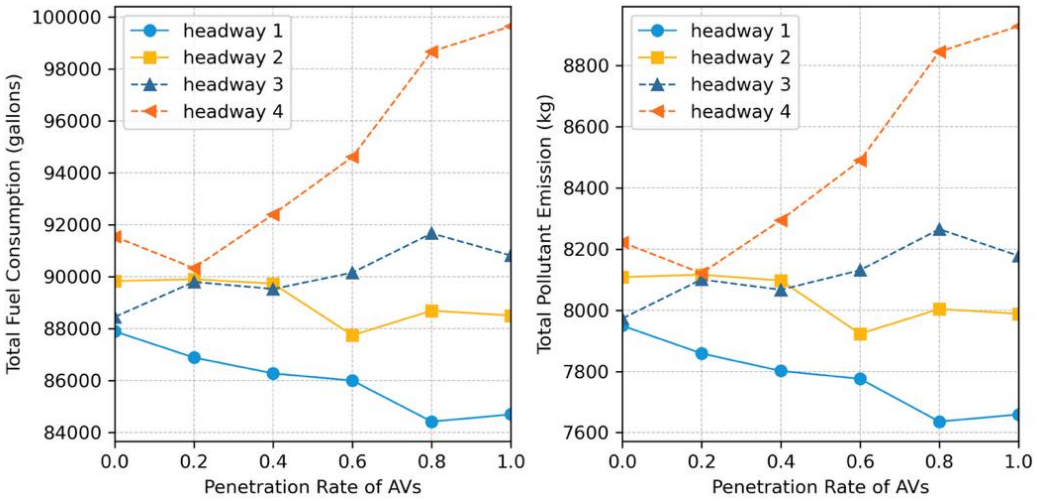


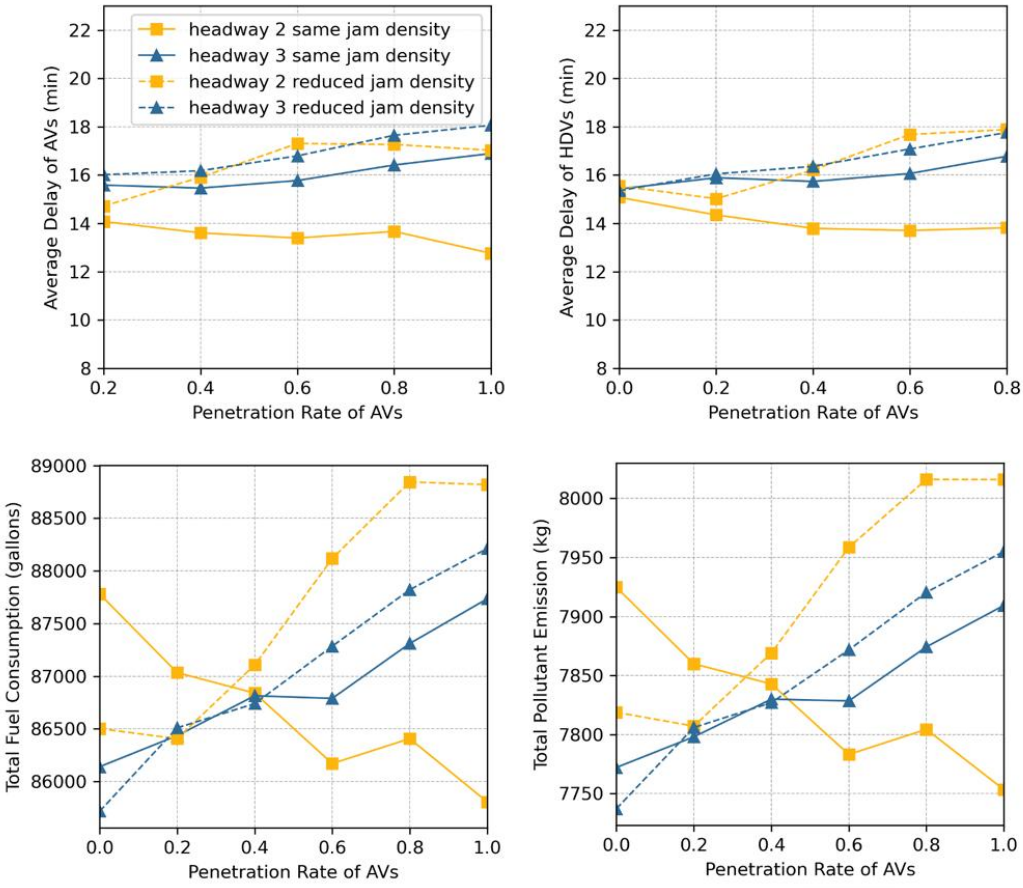
Figure 21: Total fuel consumption and pollutant emission under varying settings (diversion ratio = 1.0)



Emission and fuel consumption trends also improve under settings 1 and 2, showing declines with higher AV penetration, in contrast to the flatter or even increasing trends observed in the scenario of 0.4 diversion ratio. However, for conservative headway settings (3 and 4), the benefits of full adaptivity are limited, leading to the same upward trends. These results are also consistent with the homogenous modeling case.

We also examine scenarios where AVs and HDVs share the same jam density in the fundamental diagrams, with results presented in Figure 22. The overall patterns are consistent with those observed in the homogeneous case that keeping jam densities equal improves performance under conservative headway assumptions. In headway setting 2, the comparison between same density and reduced density cases shows diverging trends. In headway setting 3, adopting the same jam density improves efficiency, fuel consumption, and pollutant emissions relative to the reduced-density case. **These results reinforce the need to deploy ACC systems which prioritize shorter headways without unnecessarily reducing jam density, which can lead to better system outcomes.**

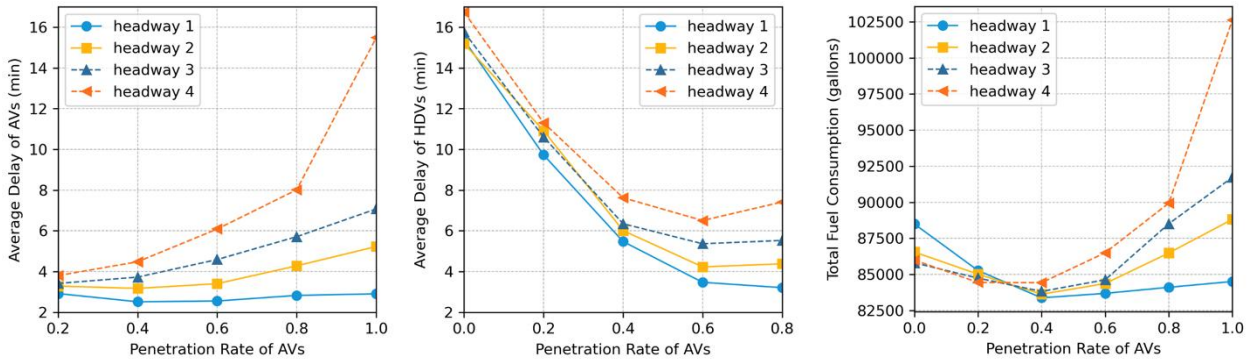
Figure 22: Comparison of jam density settings for bi-class FDs (diversion ratio = 0.4)



As the heterogeneous approach allows different behavior (routing) models for AVs and HDVs, we further examine scenarios where all introduced AVs can fully adapt their routes (diversion ratio = 1.0) while the remaining HDVs keep 0.4 diversion ratio by default. This setting examines the potential of AVs with advanced real-time routing policy to enhance overall system performance. Results are shown in Figure 23. As more AVs with full adaptation in routing replace HDVs, the average delay of HDVs drops sharply across all headway settings, reaching its lowest value around 0.6 penetration rate. Meanwhile, the average delay of AVs remains stable, with only slight increases before 0.8 penetration even under conservative headways. System-level sustainability metrics also reflect similar trends with the minimum values achieved near 0.4 penetration rate. These findings suggest that equipping AVs with advanced routing systems can benefit system efficiency, and **an optimal penetration range may exist to maximize system-wide gains, beyond**

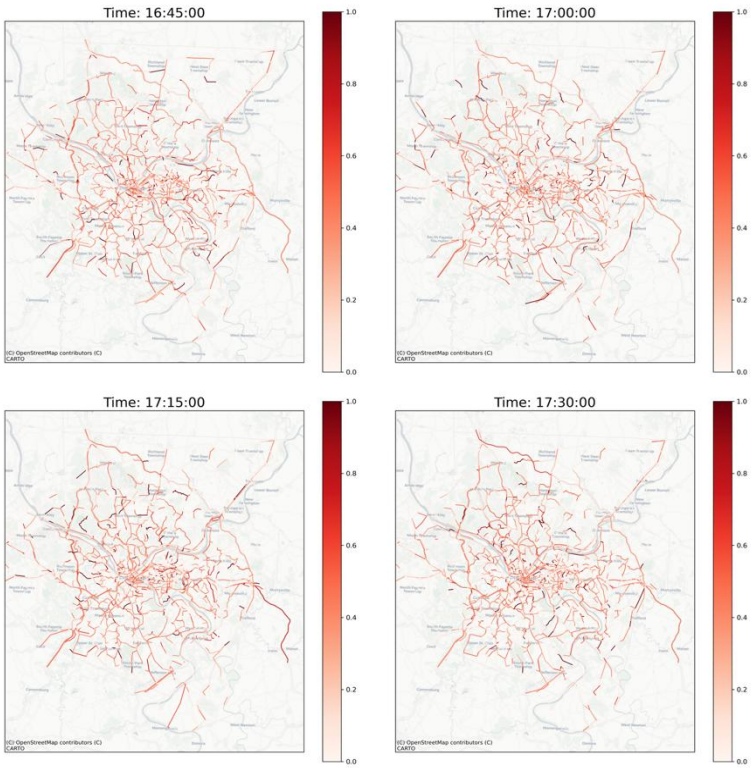
which additional AV penetration may in fact lead to system inefficiency, depending on AV headway configurations.

Figure 23: System metrics with 1.0 diversion ratio for AVs and 0.4 for HDVs



Another advantage of using a heterogeneous modeling approach is its ability to capture the spatio-temporal distribution of AV penetration. As illustrated in Figure 24, spatial AV penetration is shown at four different times, revealing that AV traffic distribution varies across time and space. This visualization can be helpful to support AV-related decision makings such as the design of regulatory strategies and the coordination of infrastructure investments to better accommodate varying AV demand.

Figure 24: AV penetration map at 4 timestamps (penetration rate = 0.6, headway setting 1, diversion ratio = 0.4 for all vehicles)



Summary and Future Work

The objective of this study is to develop a reusable simulation sandbox for evaluating how automated vehicles may affect traffic operations, energy use, and pollutant emissions in large transportation networks. The framework is intended to help agencies and researchers compare different automated vehicle deployment scenarios and identify their potential system-wide impacts.

Using MAC-POSTS, we design two complementary approaches for modeling traffic flow with mixed automated vehicles (AVs) and human-driven vehicles (HDVs): the homogeneous approach and the heterogeneous approach. In the homogeneous approach, AVs are assumed to be uniformly distributed across the network in both spatial and temporal dimensions. Fundamental diagrams (FDs) for each link are parameterized by the AV penetration rate and headway setting across two vehicle classes. This approach simplifies mixed traffic systems, enabling direct evaluation of aggregate performance. The heterogeneous approach explicitly models AVs and HDVs as separate vehicle classes, allowing differences in their FD parameters to capture heterogeneous route choices and link dynamics. This representation also enables the visualization of spatio-temporal AV penetration patterns, highlighting how AV adoption evolves unevenly across space and time and providing additional insights for AV-related decision-making.

Using the Pittsburgh regional network, this study evaluates the system impact of different AV penetration rates, headway settings, and routing behaviors. The results show that **AV adoption does not automatically improve network performance. Shorter but safe headways can increase roadway capacity and reduce delay, fuel consumption, and emissions, while more conservative settings may worsen congestion.** Jam density is also important because capacity gains can be offset when vehicles require more roadway space. Adaptive routing policy for AVs generally improves performance, but it cannot fully overcome inefficient car-following behavior. The results also suggest that **benefits may peak at an intermediate AV penetration level and may vary across location and times of day.**

Overall, these findings emphasize that **ADS deployment should be evaluated based on how the technology operates, not only on how many vehicles are automated.** Agencies should consider headway design, routing model, vehicle type, roadway capacity, vehicle storage, and interactions with human-driven vehicles. The framework can also help identify locations and time periods where targeted traffic management or infrastructure investment for AVs can be most valuable.

Future work can focus on several directions:

- Developing more refined behavior paradigms for AVs and exploring opportunities to optimize mixed traffic systems by actively controlling AV behaviors.
- Incorporating safety metrics into the model to better balance efficiency, sustainability and safety.
- Integrating more real-world data on AV operation as they become available into the proposed model to enhance calibration of AV-related demand and traffic characteristics.

References

Auld, J., Sokolov, V., Stephens, T.S., 2017. Analysis of the effects of connected-automated vehicle technologies on travel demand. Transp. Res. Rec. 2625, 1–8.

Ma, W., Pi, X., & Qian, S. (2020). Estimating multi-class dynamic origin-destination demand through a forward-backward algorithm on computational graphs. Transportation Research Part C: Emerging Technologies, 119, 102747.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., ... & Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. Advances in neural information processing systems, 32.

Peeta, S., & Mahmassani, H. S. (1995). System optimal and user equilibrium time-dependent traffic assignment in congested networks. Annals of Operations Research, 60(1), 81-113.

Pi, X., Ma, W., & Qian, Z. S. (2019). A general formulation for multi-modal dynamic traffic assignment considering multi-class vehicles, public transit and parking. Transportation Research Part C: Emerging Technologies, 104, 369-389.

Qian, Z., & Zhang, H. M. (2011). Computing individual path marginal cost in networks with queue spillbacks. Transportation Research Record, 2263(1), 9-18.

Qian, Z., & Zhang, H. M. (2013). A hybrid route choice model for dynamic traffic assignment. Networks and Spatial Economics, 13(2), 183-203.

Qian, S., Zou, Q., & Zhang, P. (2023). Modeling the Impact of Tolling in Large-Scale Regional Networks: A Case Study for DVRPC. A technical report to Mobility21 University Transportation Center. Accessed on Sep 28, 2025 at https://rosap.ntl.bts.gov/view/dot/71818

Qian, Z. S., Li, J., Li, X., Zhang, M., & Wang, H. (2017). Modeling heterogeneous traffic flow: A pragmatic approach. Transportation Research Part B: Methodological, 99, 183-204.

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

Soteropoulos, A., Berger, M., Ciari, F., 2019. Impacts of automated vehicles on travel behavior and land use: an international review of modelling studies. Transp. Rev. 39, 29–49.

Wang, Z., Shi, X., Li, X., 2019. Review of Lane-Changing Maneuvers of Connected and Automated Vehicles: models, Algorithms and Traffic Impact Analyses. J. Indian Inst. Sci.

Yao, Z., Hu, R., Wang, Y., Jiang, Y., Ran, B., & Chen, Y. (2019). Stability analysis and the fundamental diagram for mixed connected automated and human-driven vehicles. Physica A: Statistical Mechanics and Its Applications, 533, 121931.

Zhang, P., & Qian, S. (2023). Estimating environmental impacts of large-scale transportation networks with vehicle registration data. Transportation Research Part D: Transport and Environment, 123, 103901.

Zhou, J., & Zhu, F. (2020). Modeling the fundamental diagram of mixed human-driven and connected automated vehicles. Transportation research part C: emerging technologies, 115, 102614.

Appendix: a tutorial for modeling mixed traffic in MAC-POSTS

Homogenous modeling approach

Step 0: Before revising the input files for modeling mixed traffic, make sure the baseline input files are consistent and can run DNL using them.

Step 1: Choose a penetration rate and headway setting. The link attributes (capacity, jam density) in raw link input file are for pure HDV traffic. Multiply them by the scalars according to the penetration rate and headway setting (Table 2.1) and obtain the capacity and jam density for pure AV traffic. Do the same calculation for cars and trucks.

Step 2: Using Equation (1) and (2) to calculate the capacity and jam density for mixed traffic using the pure FD parameters from Step 2. Do the same calculation for cars and trucks. Then update the attributes in link input file accordingly.

Step 3: The diversion ratio (*adaptive_ratio_car/truck* in config file) can be changed to reflect the behavior diversion. Keep all other files unchanged and run the DNL.

Heterogeneous modeling approach

Step 0: Before revising the input files for modeling mixed traffic, make sure the baseline input files are consistent and can run DNL using them.

Step 1: Choose a penetration rate and headway setting. The link attributes (capacity, jam density) in raw link input file are for pure HDV traffic. Multiply them by the scalars according to the penetration rate and headway setting (Table 2.1) and obtain the capacity and jam density for pure AV traffic. Do the calculation for cars only (as we model cars in this approach)

Step 2: Use capacities and jam densities of pure HDV and pure AV to update link attributes. And update *convert_factor* to be 1.0 in link input and node input files.

Step 3: Aggregate car and truck demand for each assignment interval and then split them into AVs and HDVs according to the penetration rate. Update demand file accordingly.

Step 4: Use the same route choice proportion from baseline model for two classes.

Step 5: The diversion ratio (*adaptive_ratio_car/truck* in config file) can be changed to reflect the behavior diversion. Keep all other files unchanged and run the DNL.

420 Westwood Plaza, 7702 Boelter Hall
Los Angeles, CA 90095-1600

mobilitycoe@ucla.edu
mobilitycoe.org

CENTER OF EXCELLENCE
on New Mobility and Automated Vehicles