

Simulation-Based Evaluation of Autonomous Vehicle Penetration on Urban Traffic Efficiency and CO₂ Emissions via Integrated PTV VISSIM and Bosch ESTM

Authors: Melika Ansarinejad, Ying Huang, Pan Lu

Presenter: Melika Ansarinejad

Advisor: Dr. Ying Huang

Department of Civil, Construction and Environmental Engineering

North Dakota State University; Fargo- ND, USA

Email: melika.ansarinejad@ndsu.edu



Presenter's Experience

Research/ Work experience

- Graduate Research Assistant, Upper Great Plains Transportation Institute- Fargo, ND (Aug. 2024- Aug. 2025)
- Graduate Research Assistant, North Dakota State University- Fargo, ND (Jan. 2022- Dec. 2023)
- Transportation Engineering Intern, Upper Great Plains Transportation Institute- Fargo, ND (May-Aug. 2023)

Publications

- User Experience of Navigating Work Zones with Autonomous Vehicles: Insights from YouTube on Challenges and Strengths, Journal of Smart Cities, 2025
- Autonomous Vehicles in Rural Areas: A Review of Challenges, Opportunities, and Solutions, Journal of Applied Sciences, 2025
- Assessing the Efficacy of Pre-trained Large Language Models in Analyzing Autonomous Vehicle Field Test Disengagements; Journal of Accident Analysis & Prevention; 2025
- Analyzing the Safety and Operational Dynamics of a Freeway Under Adverse Weather Conditions in Mixed Traffic Flow: A Microsimulation Model Approach Examining Different Market Penetration Rates of Autonomous Vehicles; Road Safety and Simulation Conference (RSS); Lexington- KY; 2024
- Safety and operational impacts of different Autonomous Vehicle operations on freeway work zones; Journal of Advances in Transportation Studies; 2024
- Huang, Y; Ansarinejad, M; Lu, P; Assessing Mobility under Inclement Weather Using VISSIM Microsimulation- A Case Study in US; Proceedings of the 9th International Conference on Civil Structural and Transportation Engineering (ICCSTE'24); Toronto, Canada; 2024
- Ansarinejad, M.; Huang, Y., and Qiu, A.; Impact of Fog on Vehicular Emissions and Fuel Consumption in a Mixed Traffic Flow of Autonomous Vehicles (AV) and Traditional Vehicles (TVs)- ASCE International. Conference on Transportation and Development; Austin- Texas; June 2023

Introduction

Autonomous Vehicles (AVs) Overview

AVs, also known as self-driving cars, are transforming transportation through advanced technologies that enable them to operate with minimal or no human intervention.

Anticipated Future Trends

Privately owned Level 4 AVs will make up approximately 24.8% of vehicles on roadways in the U.S. by 2045[1].

AV Manufacturer with Driverless Testing Permit (CA DMV, 2024)

- 1. Apollo Autonomous Driving USA LLC,
- 2. AutoX Technologies,Inc.
- 3. Nuro Inc.
- 4. R3 Nuro Robot
- 5. Waymo LLC.
- 6. WeRide Corp
- 7. DBA WeRide AI
- 8. Zoox Inc.

SOCIETY OF AUTOMOTIVE ENGINEERS (SAE) AUTOMATION LEVELS













Figure 1: Levels of Autonomy; Source: Society of Automotive Engineers



Figure 2: Amazons' Zoox Robotaxi, Las Vegas, Nevada- Sept. 2025 Source: Bloomberg

Literature Review

Author(s)	Study Focus	Key Findings	Methodology/Tools
Alessandrini et al.(2012)[2]	Impact of driving style on fuel consumption (Eco Index)	Eco-driving reduces CO ₂ emissions by up to 30% at 10 km/h (gasoline) and 22% at 40 km/h (diesel); no significant reduction at speeds >80-90 km/h.	Real-world data, COPERT program
Olia et al.(2016)[3]	Impact of penetration rate of connected autonomous vehicle (CAV) on emission	Increasing CAV penetration reduces emissions, with the maximum benefit at 50% CAV penetration.	PARAMICS microsimulation, CMEM emission model
Stogios et al.(2019)[4]	Impact of AV (aggressive and Cautious) mixed traffic flows on Emissions	Headway time significantly impacts emissions under different AV penetration rates in mixed traffic.	VISSIM microscopic traffic simulation, MOVES emission model
Conlon & Lin(2019)[5]	Impact of congested urban road networks on CO ₂ emissions of AVs	Emissions increase at lower AV penetration rates but reduce significantly and plateau between 40%-90% AV penetration.	SUMO microsimulation, Newton- based greenhouse gas model (NGM)
Szumska & Jurecki(2020)[6]	Impact of driving behavior on fuel consumption and emissions	Aggressive driving in urban areas increases pollutant emissions by ~40% compared to calm driving.	Onboard emission analyzers, real- world tests
Miotti et al. (2021)[7]	Impact of Eco-driving on emissions	Eco-driving, whether human-driven or with low-level automation, significantly reduces GHG emissions.	Trip Energy simulation
Suarez et al.(2022)[8]	Impact of acceleration behavior on CO2 emissions	Aggressive acceleration increases CO ₂ emissions by up to 5% compared to mild acceleration.	WLTP tests, CO2MPAS simulations

Vehicular Emissions Measurement Methods

1) Lab Tests (Figure 3)

- Conducted in a **controlled** environment, Based on **predetermined** driving patterns
- Tool for developing average or instantaneous speed models

2) Field/ Real-world Measurement (Figure 4)

- Dynamometer-based models: steady-state nature, not represent the variability of actual driving conditions
- Portable gas analyzers, commonly Portable Emissions Measurement System(PEMS): real-time as the vehicle is driven



Figure 3. Lab Test Method for Emission Measurement Source: EPA



Figure 4. Field Test Method for Emission Measurement Source: UNECE

Vehicular Emissions Measurement Methods and Challenges

3) Emission Models

• <u>Macroscopic</u> (regional level): Make use of aggregated inputs, include elements like average speed and vehicle kilometers traveled (VMT)

Commonly used for calculating regional emission inventories

- <u>Mesoscopic</u> (corridor level): Cost-effective method for creating detailed simulations, Considers individual vehicles without addressing their interaction
- <u>Microscopic</u> (individual vehicle level)

Microsimulation Emission Estimation Challenges/ Gaps

- Developing most simulation models requires complex integration of traffic and external emission models.
- The process often involves extensive and error-prone data handling.
- Current approaches offer only limited ability to evaluate CO₂ emissions across different autonomous vehicle (AV) penetration scenarios.

> Traffic Simulation Tool: PTV VISSIM

- Solid graphical user interface
- Versatile Road System Modeling
- Discrete Time Step Simulation
- Behavior-Based Traffic Modeling (psychophysical car-following)
- High degree of accuracy
- Integration with Emission Models at various scales
- Customizable Lane change and Car-Following Settings



Figure 5. Vissim-Bosch Integration

Source: PTV Group

> Software/Emission Simulation Model: Bosch ESTM

- Integration and Data Transmission with VISSIM
- Precision Emission Measurement (second-by-second emission statistics)
- Including CO2 emission besides CO, NOx, HC, PM, and fuel consumption immediately after traffic simulation completion.
- Comprehensive Vehicle Classification: vehicle classes using 6 key elements: Emission vehicle category, class, stage, Fuel type, Size class, and Use class.
- Real-Time Impact Assessment: Monitor changes in vehicle emissions and air quality in VISSIM environment
- Flexible Data Aggregation: Aggregated data for Link Evaluation per segment or based on vehicle classes in Vehicle Network Performance Evaluation.



Figure 6. Emission Visualization in Vissim Software Source: PTV Group, Bosch ESTM [9]

1) Establish VISSIM Network Layout

Base Map (Site of the Project)

- ➤ Geographic Orientation: Saratoga Springs, Utah, USA
- ➤ Intersection: Intersection of Redwood Road and Pioneer Crossing
- ➤ Roads Involved: Redwood Road (North-South) and Pioneer Crossing (East-West)
- > Road Configuration: principal five-lane arterials



Figure 7. Project Site, Saratoga Springs, UT, USA



Figure 8. Part of the Saratoga Springs Master Plan Including the Project Site

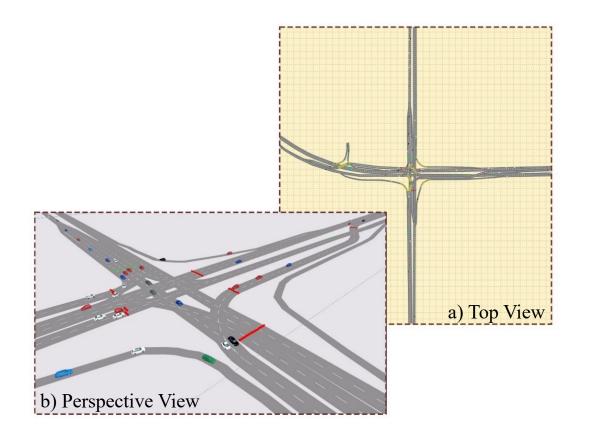


Figure 9. PTV VISSIM model for mobility and emission analysis

2) Calibration of VISSIM Model

- Traffic Demand Input: 1.5 hour of weekday evening peak-hour conditions (4.00-5.30 pm)
- Vehicle Composition Input: baseline scenario (0% AV) + 10 scenarios of mixed traffic flow of AV and Human-driven Vehicles (From 0% to 100%, in 10% increments)
- **Speed Distribution Input:** AV: deviation of only 2 km/h from the speed limit[10], Human Driven Vehicles: based on naturalistic driving data[11]
- -Traffic signals: Using a ring-and-barrier structure; in accordance with the Utah DOT's traffic signal timing guidelines[12]
- Driving Behavior Input (Table 2)

-Number of Simulation Runs and Resolution: 10 Runs with resolution of 10 time-step Table 2

Parameter Category	W99 Car following Parameters	Definition	Autonomous (Normal)[13]	Human- Driven[14
	CC0 (m)	Standstill Distance	1.5	4.45
Thresholds for Safety Distance (Δx)	CC1(s)	Headway Time	0.9	0.87
	CC2 (m)	Following Variation	0	5.28
	CC3 (s)	Threshold for Entering Following	-8	-7.92
	CC4 (m/s)	Negative Following Threshold	-0.1	-1.52
Thresholds for Speed (Δv)	CC5 (m/s)	Positive Following Threshold	0.1	1.52
- , , , ,	CC6 (-)	Speed Dependency of Oscillation	0	0.71
	$CC7 (m/s^2)$	Oscillation Acceleration	0.1	0.31
Acceleration Rates	$CC8 (m/s^2)$	Standstill Acceleration	3.5	1.03
	$CC9 (m/s^2)$	Acceleration at Speed of 80 km/h	1.5	0.33

3) Application of ESTM Service of Bosch

Define Emission Class Distribution:

Predefined MOVES-based 2022 profile for light-duty gas and diesel passenger vehicles, representing U.S. fleet composition from 1992–2020.

4) Simulation Process

- Within 5400s of the simulation time, a warm-up period of 900s was applied at the beginning and the end of each simulation run, in accordance with the PTV VISSIM Manual, to ensure that the results capture stabilized traffic conditions[15].
- During simulation, VISSIM generates a trajectory for each vehicle, which is then transferred to ESTM for emission calculation.
- The driving behavior element that most impacts emissions in Bosch ESTM is the dynamic profile of vehicle movement; particularly accelerations, decelerations, and stop-and-go patterns.

Ira

Traffic Flow Results

1) Stops

Phase 1 (0% to 10% AV penetration):

• Slight increase in the number of stops.

Phase 2 (10% to 90% AV penetration):

- Consistent and significant reduction in stops.
- Most notable reduction occurs between 40% and 80%, where traffic efficiency is significantly enhanced.

Phase 3 (90% to 100% AV penetration):

• Slight uptick in stops after reaching the lowest point at 90%.

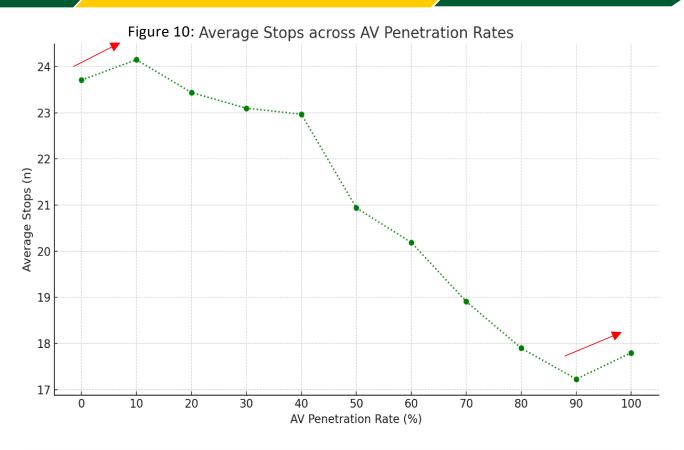
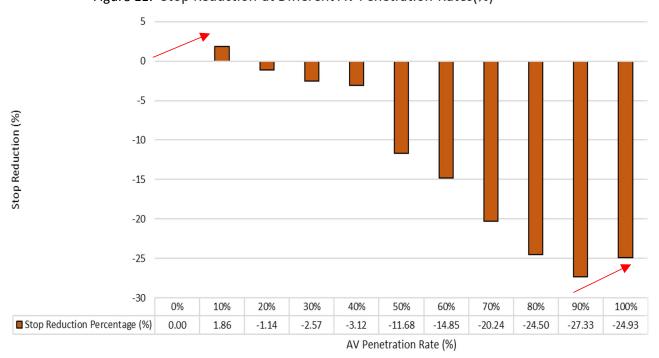


Figure 11: Stop Reduction at Different AV Penetration Rates(%)



Traffic Flow Results

2) Delay

Phase 1 (0% to 50% AV penetration):

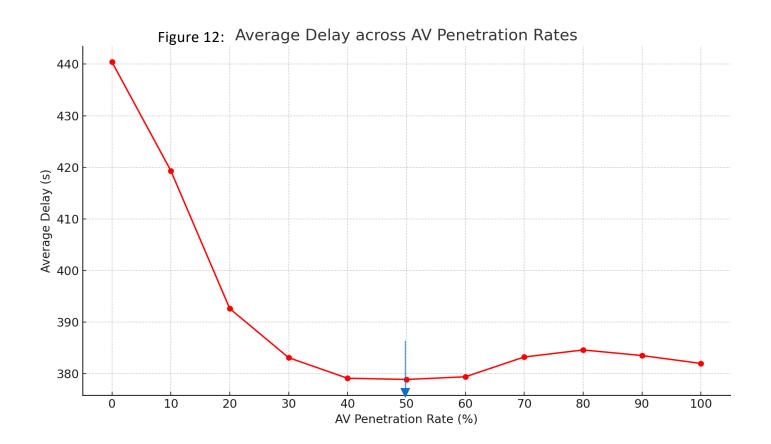
- Sharp decline- Delay steadily decreases
- From 440 seconds at 0% reaching to a minimum of below 380 seconds at 50% AV penetration rate.

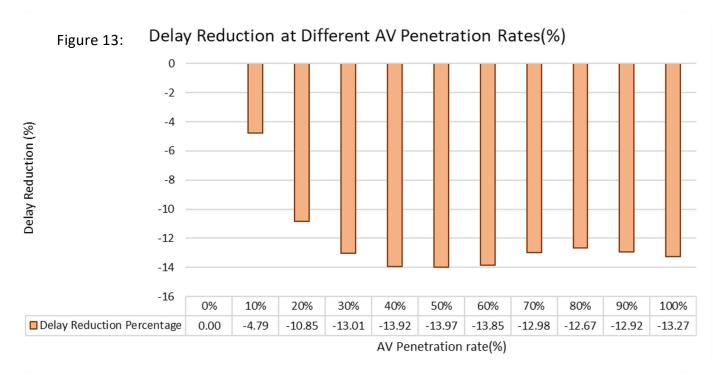
Phase 2 (60% to 100% AV penetration):

- Fluctuating trend
- Delay slightly increases and fluctuates, with a small peak at around 80% AV penetration, where the delay rises slightly above 384 seconds.

<u>Overall trend:</u> Higher AV penetration rates consistently reduce delays, with the greatest impact occurring at lower to moderate levels, then fluctuates slightly, stabilizing near 382 seconds at full penetration

• Further delay reductions may require more advanced AV capabilities and supportive infrastructure adaptations to fully realize the benefits.





Traffic Flow Results

3) Average Speed

> Phase 1 (0% to 50% AV Penetration)

- Steady rise in average speed
- Reaches 71.81 km/h at 50% penetration
- Enhanced traffic efficiency with the introduction of AVs

Phase 2 (50% to 100% AV Penetration)

- Average speed continues to increase at a slower rate
- Highest recorded speed of 73.92 km/h at 100% penetration
- Fewer disruptions and improved coordination with full AV integration

Validation Note

The recorded approach speed (38 mph/61 km/h) shown in Figure 14-a, closely matched the average speed of the simulation model(Figure 14-b), (38.7 mph/62.38 km/h), yielding 97.78% accuracy.

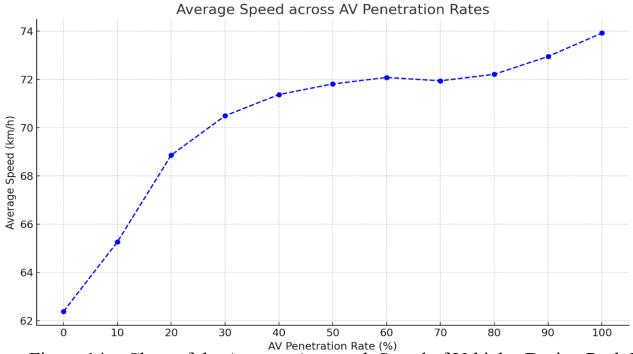
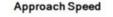


Figure 14-a: Chart of the Average Approach Speed of Vehicles During Peak Hour; Example of Westbound Through (WBT)- Utah ATSPM[25]



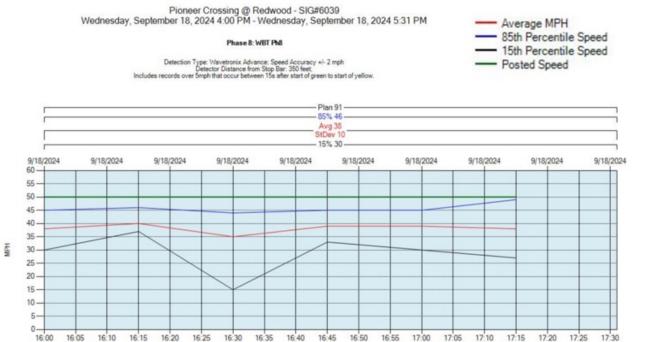


Figure 14-b

4) Air Quality Measurement

- > Phase 1 (0% to 20% AV Penetration)
- CO₂ Emissions drop by about 8%
- > Phase 2 (20% to 50% AV Penetration)
- CO₂ Emissions decline by around 12.5%
- > Phase 3 (50% to 100% AV Penetration)
- Most pronounced reduction in CO₂ emission, about 34%

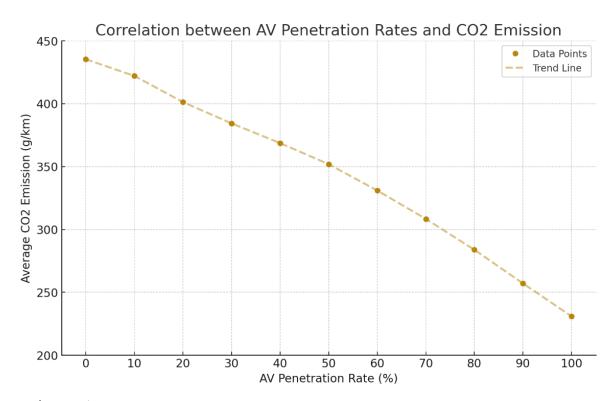


Figure 15

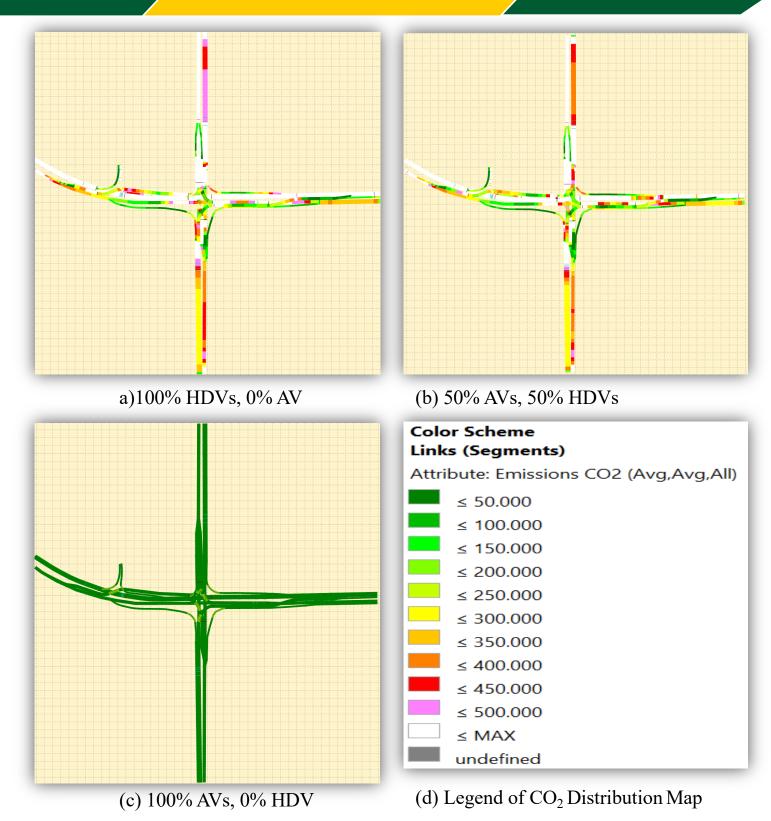


Figure 16. CO₂ emission comparison for three AV Penetration Rates

Parallel Analysis of Driving Behavior, Traffic Flow and emission Outcomes

Table3

Parameters	AVs	Human-Driven Vehicles
Level of Caution (CC0 and CC1, CC2)		
Level of Perception-Reaction (CC3)		
Level of Sensitivity to the Dec/Acc (CC4, CC5)		
Level of Acceleration Oscillation (CC7)		
Level of Standstill acceleration (CC8)		
Speed Distribution Range		
Vissim Mobility Measures	Mixed Traffic Flow	Traditional Network
Average Speed (km/h)		
Average Stops (-)		
Average Delay(s)		
Bosch Emission Measures		
CO ₂ Emission		
Fuel Consumption		

> Conclusion

Successful Integration of VISSIM and Bosch ESTM:

- Streamlined approach to emission calculations with no need for intermediary software.
- Consistent with previous literature on emissions estimation using alternative simulation models.

Performance of AVs:

- Substantial environmental benefits, with emissions reduction of more than 50% at full AV adoption.
- Modest emission improvement at low penetration rates, while the steepest benefits occurred between 70% and 100% adoption.
- Low levels of AV integration may yield only incremental improvements, while full automation could introduce new challenges, particularly if overly cautious driving behaviors or induced demand leads to increased travel.
- Full benefits of AVs require high adoption plus supportive infrastructure, realistic driving profiles, and strong policy frameworks.
- The findings highlight the importance of coordinated planning, where technological advances in automation are integrated with traffic management strategies, upgrades to both physical and digital transportation infrastructure and built environment, and policies that prevent rebound effects.

> Limitations and Future work

•Broader Scope of Analysis

Extend the analysis to multiple intersections and scenarios.

•Comparative Evaluation

Compare Bosch ESTM+VISSIM with VISSIM+MOVES to provide broader insights.

•Digital Twin Development

Develop a digital twin of the modeled intersection to enhance validation.

•Passenger Comfort Assessment

Evaluate human comfort in relation to the AV calibration used in this study.

> Acknowledgment

This work was supported in part by the National Science Foundation (NSF) EPSCoR RII Track-2 Program under Grant No. OIA-2119691, and in part by the U.S. Department of Transportation through a University Transportation Center for multimodal mobility in urban, rural, and tribal areas. The authors thank the PTV Group for providing technical support with the VISSIM and BOSCH License used in this study.

> Reference

- 1. P. Bansal and K. M. Kockelman, "Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies," *Transportation Research Part A*, vol. 95, pp. 49–63, Jan. 2017, doi: 10.1016/j.tra.2016.10.013.
- 2. A. Alessandrini, A. Cattivera, F. Filippi, and F. Ortenzi, "Driving style influence on car CO2 emissions," *U.S. Environmental Protection Agency*, p. 11, 2012, Accessed: Jun. 16, 2025. [Online]. Available: https://www3.epa.gov/ttnchie1/conference/ei20/session8/acattivera.pdf
- 3. A. Olia, "Modelling and assessment of the transportation potential impacts of connected and automated vehicles," Jul. 2016.
- 4. C. Stogios, D. Kasraian, M. J. Roorda, and M. Hatzopoulou, "Simulating impacts of automated driving behavior and traffic conditions on vehicle emissions," *Transp Res D Transp Environ*, vol. 76, pp. 176–192, Nov. 2019, doi: 10.1016/J.TRD.2019.09.020.
- 5. J. Conlon and J. Lin, "Greenhouse Gas Emission Impact of Autonomous Vehicle Introduction in an Urban Network," *Transp Res Rec*, vol. 2673, no. 5, pp. 142–152, May 2019, doi: 10.1177/0361198119839970.
- 6. M. Szumska and R. Jurecki, "The effect of aggressive driving on vehicle parameters," *Energies (Basel)*, vol. 13, no. 24, Dec. 2020, doi: 10.3390/en13246675.
- 7. M. Miotti, Z. A. Needell, S. Ramakrishnan, J. Heywood, and J. E. Trancik, "Quantifying the impact of driving style changes on light-duty vehicle fuel consumption," *Transp Res D Transp Environ*, vol. 98, no. August, p. 102918, 2021, doi: 10.1016/j.trd.2021.102918.

> Reference

- 8. J. Suarez *et al.*, "Benchmarking the driver acceleration impact on vehicle energy consumption and CO2 emissions," *Transp Res D Transp Environ*, vol. 107, pp. 9–12, Jun. 2022, doi: 10.1016/J.TRD.2022.103282.
- 9. "Bosch and PTV Group: Alliance for better air Bosch Media Service." Accessed: Jan. 07, 2025. [Online]. Available: https://www.bosch-presse.de/pressportal/de/en/bosch-and-ptv-group-allicance-for-better-air-226240.html
- 10. P. Sukennik, "Micro-simulation guide for automated vehicles-final," Feb. 2020.
- 11. M. Nasim Khan, A. Das, and M. M. Ahmed, "Non-Parametric Association Rules Mining and Parametric Ordinal Logistic Regression for an In-Depth Investigation of Driver Speed Selection Behavior in Adverse Weather using SHRP2 Naturalistic Driving Study Data," *Transp Res Rec*, vol. 2674, no. 11, pp. 101–119, Sep. 2020, doi: 10.1177/0361198120941509.
- 12. UDOT Automated Traffic Signal Performance Measures." Accessed: Jul. 24, 2025. [Online]. Available: https://udottraffic.utah.gov/atspm/
- 13. C. Chen, X. Zhao, H. Liu, G. Ren, Y. Zhang, and X. Liu, "Assessing the Influence of Adverse Weather on Traffic Flow Characteristics Using a Driving Simulator and VISSIM," *Sustainability 2019, Vol. 11, Page 830*, vol. 11, no. 3, p. 830, Feb. 2019, doi: 10.3390/SU11030830.
- 14.WSP Michigan Inc. and MDOT, "VISSIM Protocol Manual," Detroit, Aug. 2020.
- 15. PTV Group- Knowledge Base, "Warm-Up Period for Vissim Simulation", Accessed: Sep. 28, 2024. [Online]. Available: https://support.ptvgroup.com/en-us/knowledgebase/article/KA-04927