Modeling Autonomous Driving Systems-Equipped Vehicle Interactions With Traffic Signs

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Introduction

Motivations

- Prior studies report conflicting impacts of autonomous vehicles (AVs). A study by Li et al. suggests AVs may engage in riskier behaviors compared with human-driven vehicles.[1] A study by Morando et al. highlights AV potential to enhance safety.[2]
- A better understanding of AV behaviors is crucial for safety. This goal calls for an investigation using real-world data.
- Existing freeway-based models may misrepresent AV behaviors at sign-controlled intersections, resulting in unclear impact assessments.
- To date, no known studies have systematically modeled AV responses to traffic signs, leaving a critical research gap.

Contributions

- This study presents the first comprehensive modeling of autonomous driving systems (ADS)-equipped vehicle interactions with traffic signs, covering five key scenarios with six core behavioral modules.
- This study leverages real-world data for model calibration and validation, ensuring that the simulated behaviors closely align with actual ADS behaviors.

[1]Li, T., X. Han, J. Ma, M. Ramos, and C. Lee. 2023. "Operational Safety of Automated and Human Driving in Mixed Traffic Environments: A Perspective of Car-Following Behavior." *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 237, no. 2: 355–366.

[2]Morando, M. M., Q. Tian, L. T. Truong, and H. L. Vu. 2018. "Studying the Safety Impact of Autonomous Vehicles Using Simulation-Based Surrogate Safety Measures." *Journal of Advanced Transportation* 2018: 1–11.

[3]Ettinger, S., S. Cheng,, B. Caine, C. Liu, H. Zhao, S. Pradhan, and D. Anguelov. 2021. "Large Scale Interactive Motion Forecasting For Autonomous Driving: The Waymo Open Motion Dataset." *Proceedings of the IEEE/CVF International Conference on Computer Vision*: 9710–9719.

[4]Erdmann, J., and D. Krajzewicz. 2013. "SUMO's Road Intersection Model." In *Simulation of Urban Mobility User Conference*: 3–17.

Methodology

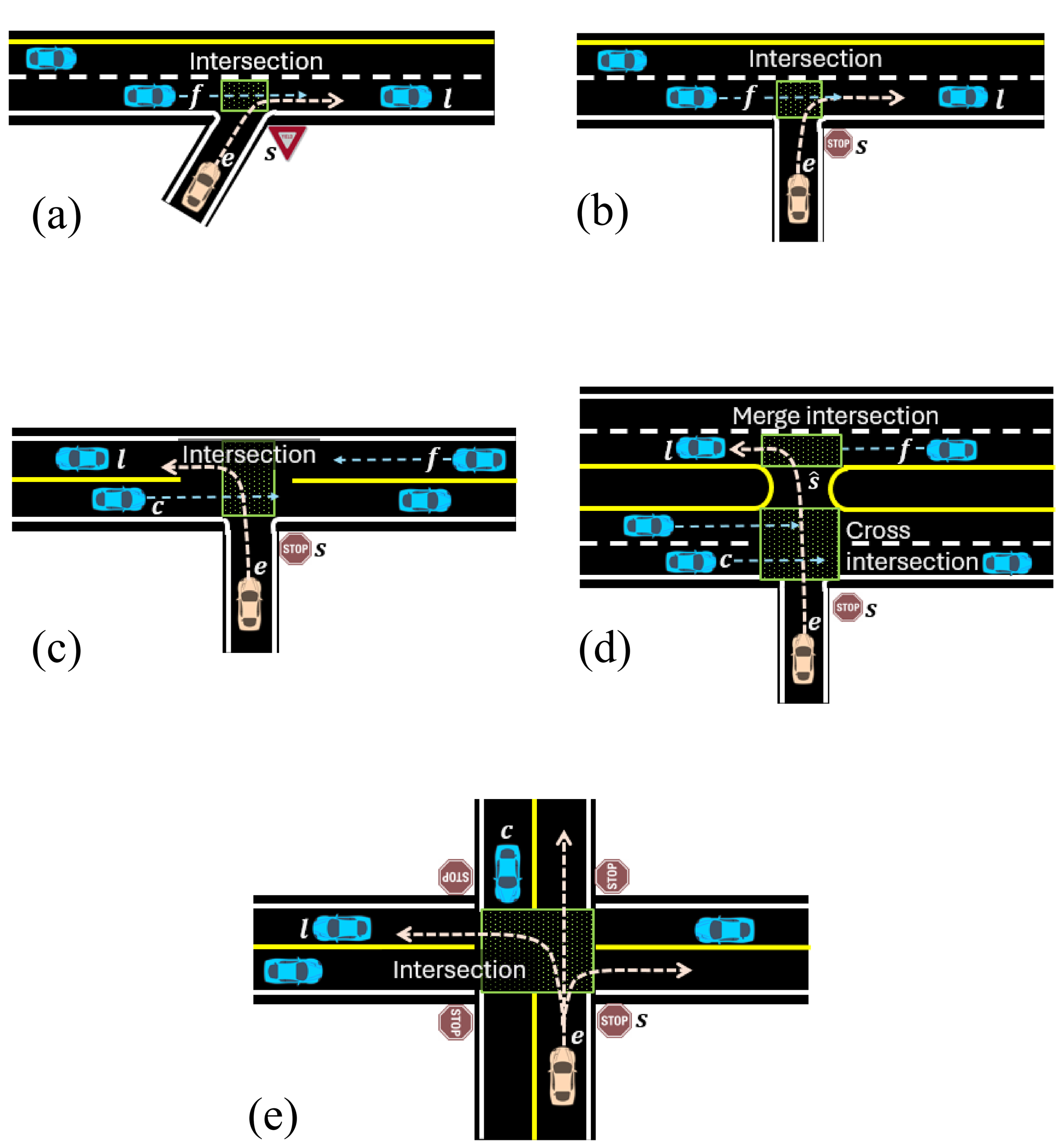
Six key modules:

- Module 1: Approach a traffic sign (car-following model).
- Module 2: Merge decisionmaking (right-of-way rule).
- Module 3: Follow the leading vehicle in the target lane (car-following model).
- Module 4: Cross decisionmaking (right-of-way rule).
- Module 5: Cross the conflict traffic (car-following model).
- Module 6: First come, first served.

Six models for five scenarios (figure 1):

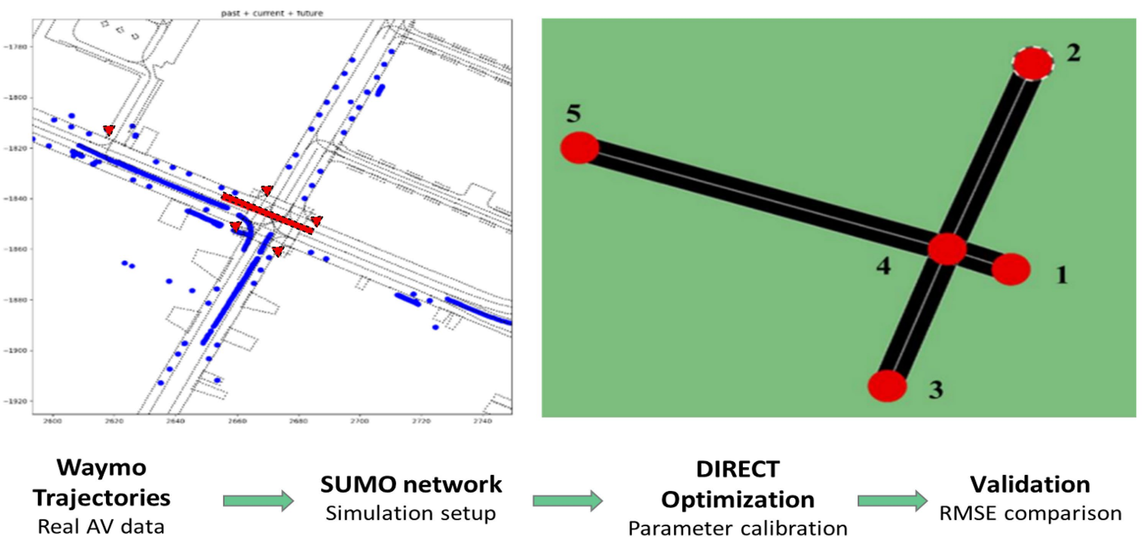
- Model 1: Approach a traffic sign = module 1.
- Model 2: Merge at a yield sign = module 2 + module 3.
- Model 3: Right turn at a stop sign = module 2 + module 3.
- Model 4: One-step left turn at a stop sign = module 4 + module 2 + module 3.
- Model 5: Two-step left turn at a stop sign = module 4 + module 5 + module 2 + module 3.
- Model 6: Operations at an all-way stop = module 6 + module 3.

Figure 1 illustrates traffic scenarios: (a) merge at a yield sign, (b) right turn at a stop sign, (c) one-step left turn at a stop sign, (d) two-step left turn at a stop sign, and (e) all-way stops.



Calibration and Validation

Figure 2 shows the calibration and validation pipeline using Waymo® Open dataset and the SUMO™.[3,4]



Position and speed root mean square errors (RMSEs) were used in the objective function.

$$\min_{\beta^m} \frac{1}{I^m} \sum_{i=1}^{I^m} \left(RMSE_v^{m,i} + RMSE_{x,y}^{m,i}\right)$$

$$RMSE_v^{m,i} = \sqrt{\frac{1}{N^{m,i}} \sum_{n=1}^{N^{m,i}} \left(v_n^{m,i} - \hat{v}_n^{m,i}(\boldsymbol{\beta}^m)\right)^2}$$

$$RMSE_{x,y}^{m,i} = \sqrt{\frac{1}{N^{m,i}} \sum_{n=1}^{N^{m,i}} \left(x_n^{m,i} - \hat{x}_n^{m,i}(\boldsymbol{\beta}^m)\right)^2 + \left(y_n^{m,i} - \hat{y}_n^{m,i}(\boldsymbol{\beta}^m)\right)^2}$$

$N^{m,i}$ = total number of time steps of model m's instance i.

Results

Table 1 shows model calibration results.

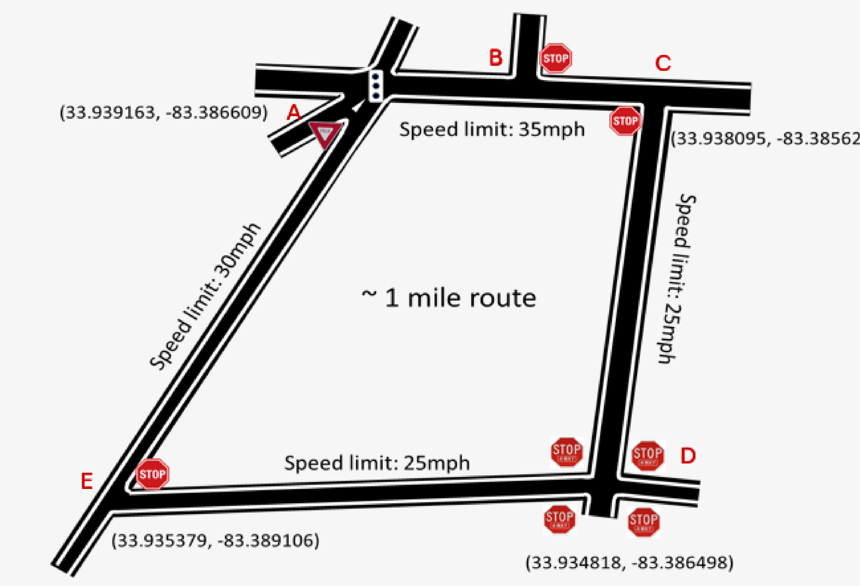
Parameter \ Model	Approach a Traffic Sign	Right Turn at a Stop Sign	One-Step Left Turn at a Stop Sign	Two-Step Left Turn at a Stop Sign	All-Way Stop
Maximum acceleration (m/s^2)	0.59	1.58	1.22	2.17	1.08
Comfortable deceleration (m/s^2)	4.50	2.50	2.75	1.82	4.50
Minimum gap (m)	5.42	2.33	1.11	2.11	4.00
Desired time headway (s)	1.34	0.64	1.47	1.94	2.50
Desired speed on the center turning segment (m/s)	—	—	—	4.94	—
Desired speed on the target segment (m/s)	8.39	13.83	4.22	5.13	12.91
Desired speed within the crossing intersection (m/s)	—	4.67	4.00	4.94	7.00
Desired speed within the merging intersection (m/s)				7.54	
Impatience factor	—	0.35	0.75	0.61	—

—Parameter is not relevant.

All images source FHWA.

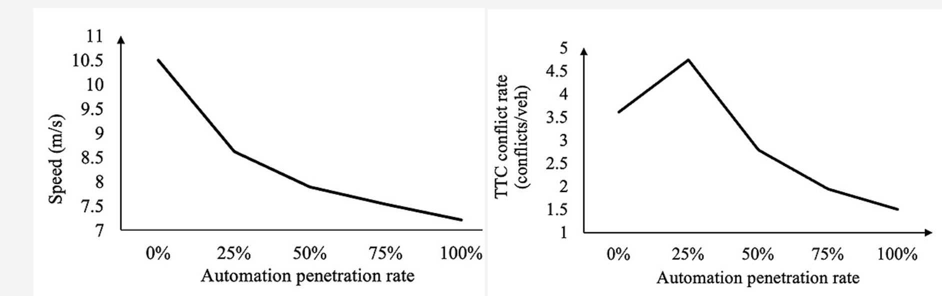
Case Study

Figure 3 shows the case study network in Athens, GA, selected for ADS model implementation.



A: Yield-controlled entry
B: Stop-controlled (no center lane)
C: Stop-controlled (with center lane)
D: All-way stop
E: Stop-controlled (no center lane)

Figure 4 presents network performance with different automation penetration rates, illustrating the mobility-safety tradeoff trend associated with ADS's relatively conservative driving style.



Mobility impact: 25-30% speed reduction at high ADS penetration.

Safety improvement: 60% conflict reduction at high ADS penetration.

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