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Research Article

Modeling, Calibrating, and Predicting Traffic Jam Lengths Under Mixed Aggressive AVs and Human Driving Scenarios

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Keywords

Autonomous vehicles, Aggressive driving behavior, Traffic congestion, Signalized intersection, Regression modeling.

Abstract

This study evaluates the impact of varying penetration rates of aggressive autonomous vehicles (AVs) on traffic congestion at a four-legged signalized intersection in Al-Qadisyah, Kirkuk City, Iraq. A simulation using SUMO and regression modeling quantified the relationship between penetration rates and congestion metrics. Introducing 25% aggressive AVs reduced the Mean Max Jam Length by approximately 7% compared to 100% human-driven scenarios, while a full transition to 100% aggressive AVs achieved a 30% reduction. Linear and quadratic regression models were calibrated to represent these relationships, with quadratic models demonstrating superior accuracy based on validation metrics like Coefficient of determination. (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). Predictions for intermediate penetration rates aligned with observed trends, offering actionable insights for traffic planning. This research highlights the potential of aggressive AV behavior in reducing congestion, optimizing intersection performance, and informing AV deployment strategies, supported by rigorous calibration and validation of predictive models.

1. Introduction

The integration of autonomous vehicles (AVs) into modern traffic systems is anticipated to bring transformative changes to urban mobility [1, 2]. It will reduce human errors, increase efficiency in the flow of traffic, and ensure safety overall [3, 4]. With their advanced sensors and techniques for communication, such cars can adapt to real-time conditions of traffic flow and thus are considered a solution for congestion mitigation and traffic optimization [5-7]. Since most towns in the world have grown and have placed high demands on transportation, there is great attention regarding research and development participation of AVs in terms of shaping the future of mobility [1].

Among these different driving behaviors, the aggressive driving style has unique importance to exploring traffic throughput [8]. The most apparent features distinguishing an aggressive AV from cautious or normal driving are higher accelerations, reduced reaction times, and decisiveness over lane change or gap acceptance maneuvers [9, 10]. This can provide delays as little as possible for the aggressive AV and give a wider use of road capacity [11, 12].

This study aims to evaluate the impact of varying penetration rates of aggressive AVs on traffic congestion metrics, specifically Mean Max Jam Length (meters) and Max Jam Length (vehicles), at a four-legged signalized intersection. The study will focus on quantifying the relationship between the penetration of AVs and congestion with the help of a simulation-based approach combined with regression modeling; it also must identify the optimal rates of penetration, which can go a long way in providing insightful inputs for planning traffic and formulating strategies concerning the deployment of AVs.

Adoption of AVs has been well received in most parts of the world because of the associated benefits like minimizing human mistakes, better managing traffic, and reducing emissions [13]. Most of the extensive research into AVs thus far has aimed at understanding AVs that have cautious, normal, and aggressive behaviors driving styles of AVs These behaviors, characterized by proactive lane-changing and rapid acceleration, can significantly influence traffic dynamics, particularly in urban settings with complex intersection geometries [14].

Growing penetration of AVs into traffic systems inspires in-depth research in relation to their impacts on stability, congestion, and capacity of traffic flow [15]. [16] explored the impacts of aggressive driving on mixed traffic flows, further focusing on characteristics of stability and capacity. In their study, a car-following model was developed and calibrated by using a genetic algorithm, and it was underlined that aggressive driving improves traffic capacity when its proportion is below 35%. However, higher proportions lead to instability. Furthermore, they identified that the penetration rate of AVs over 49% will enhance the stability and efficiency of mixed traffic flow.

[17] have proposed a stochastic temporal queueing model to estimate traffic breakdown probabilities in mixed flows of AVs and human-driven vehicles, especially at bottleneck areas such as on-ramps. They used Monte Carlo simulations and Newell's car-following model in showing that higher AV penetration can shift traffic breakdown probability curves for the better in terms of traffic efficiency. This work effectively models breakdown probabilities.

[18] studied mixed traffic flow by a cell transmission model with mixed traffic flow CAVs and HDVs. Indeed, their result clearly proves that CAV significantly improves congestion because headways will shorten under this condition due to the use of CAV technology and improve road traffic capacity accordingly. It remains focused, though, upon investigation on characteristics of congestion and the respective time lengths of

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bottle-necking-on and without referring to the topic relationship between the rates of AVs or even the relations for the traffic-jam metrics given in queue lengths at signalized intersections.

[19] investigated how CAVs stabilize mixed traffic flow by suppressing the propagation of the "phantom jam" triggered by erratic human driving behaviors; they developed an improved controller to enhance stability considering driver heterogeneity and perception-reaction time delays for the CAVs. While their findings underline the role of AVs in enhancing stability and safety, the focus of this study has been the stabilization of traffic flow, while there is no focus on any congestion metric, including jam lengths at intersections.

Although much understanding has been developed on the impacts of AVs regarding traffic flow stability and capacity, only a very limited number of studies have so far addressed issues directly related to modeling, calibration, and prediction of lengths of traffic jams under mixed aggressive AV and human driving. Most of this focus either on the bottleneck characteristics or breakdown probabilities at signalized intersections, or on issues related to the way the flow of traffic can be stabilized, without providing any rigorous analysis about the jam lengths. This work fills this gap by quantifying the relationship between the penetration rates of aggressive AVs and congestion metrics such as Mean Max Jam Length-in Meter and Max Jam Length-in vehicles. Utilizing simulation and regression modeling, this research not only assesses the impacts of aggressive AV behaviors but also delivers calibrated and validated predictive models to help in traffic planning and AV deployment strategies.

2. Methodology

2.1. Study Framework

This study uses a simulation-based approach to assess the impacts of aggressiveness of AVs with different penetration rates on the traffic jam length. In more detail, the integration of traffic simulation and regression modeling methods indicates the relationship between the variation in penetration rate and traffic performance metrics, as illustrated by Figure 1.

A four-legged junction was simulated on the traffic simulation tool SUMO, which is widely used for various complex traffic simulation scenarios and customizable vehicle behaviors. Complementary to the output of the simulations, data analyses and regression modeling were done in Python.

The framework focuses on the following:

- Simulating realistic traffic scenarios with varying AV penetration rates, ranging from 0% to 100% in increments of 25%, and later refined to 10% increments for prediction.
- Measuring two key traffic performance metrics:
  - Mean Max Jam Length (meters): Average maximum length of vehicle queues.
  - Max Jam Length (vehicles): Maximum number of vehicles in a queue.

Employing regression models (linear and quadratic) to formulate relationships between penetration rates (independent variable) and jam length metrics (dependent variables).

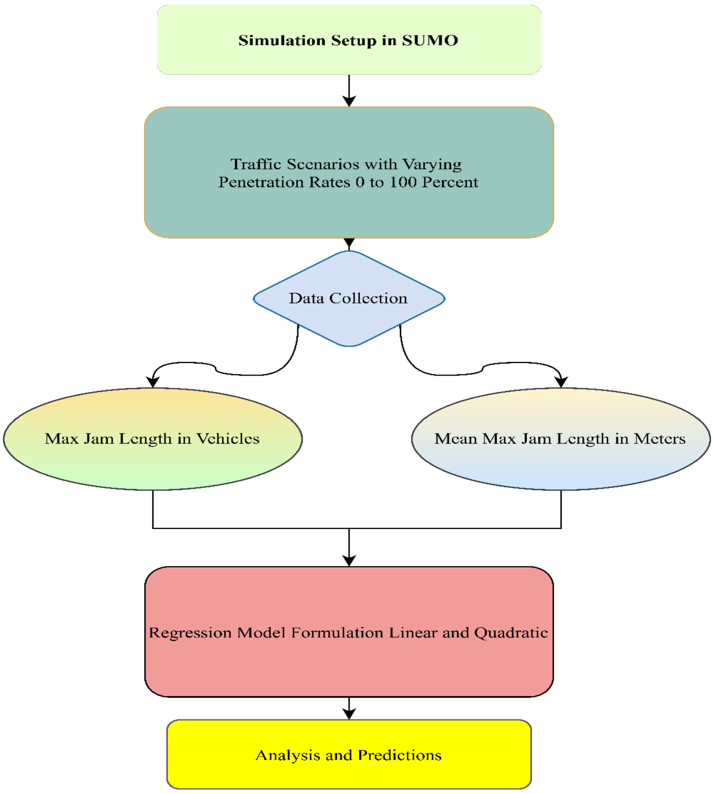
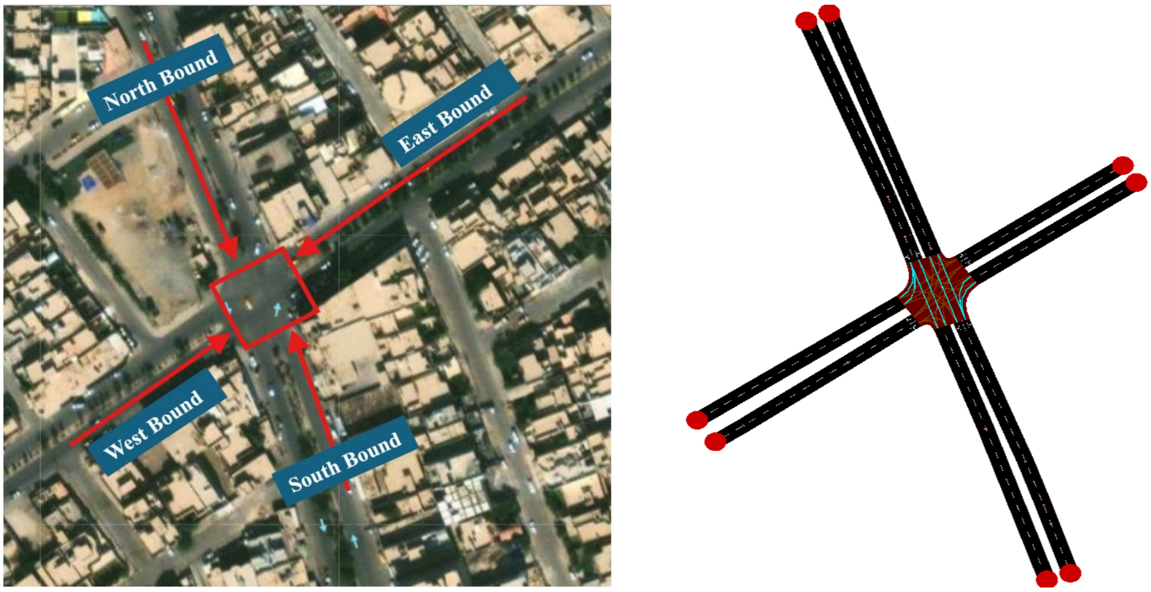


Figure 1. Framework for Modelling and Predicting Traffic Jam Lengths under Mixed Aggressive AV and Human Driving Scenarios

2.2. Study Location

The traffic volumes were selected randomly to match the unique characteristics of the studied intersection. The case study is a four-legged signalized intersection in Al-Qadisyah, Kirkuk City, Iraq, as shown in Figure 2(a, b). This intersection is in a low-developed area were traffic signals work inconsistently due to frequent shutdowns of electricity. This is the reason for selecting an existing signal timing program which works but does not operate consistently.

Relatively high volumes of traffic were selected to meet the objective of the study in the worst scenarios under different conditions of traffic. In this respect, differences in performance in mixed traffic will then be clearly observable, even when no heavy congestion is found under normal conditions.



(a) (b)

Figure 2. (a) Satellite view of the studied four-legged intersection. (b) Modelled intersection layout in SUMO

The intersection operates under the signal timing program and traffic volume shown in Table 1.

Table 1. Examined Traffic Volumes and Signal Timing

Bound	Vehicles (Veh/h)	Movement (Veh/h)			Green Time (s)	Yellow Time (s)
		Right	Straight	Left		
North	1100	200	600	300	21	3
South	1200	300	500	400	23	3
East	800	250	200	350	21	3
West	1000	150	450	450	23	3

2.3. Simulation Setup

The simulation environment was developed using the SUMO platform to model and evaluate traffic performance under mixed driving scenarios. Traffic flows included penetration rates of aggressive AVs at varying levels (0%, 25%, 50%, 75%, and 100%) to study the impact of aggressive AV behavior on intersection performance. Two types of vehicle behaviors were modeled as shown in below xml configuration:

xml configuration. Behaviors of vehicle types modeled.

```
<!—Vehicle Type →
   <vType id="aggressive_av" accel="3.0" decel="5.0" sigma="0.3" maxSpeed="13.9" minGap="1.0" tau="1.0" laneChangeModel="LC2013" lcStrategic="7.0" lcCooperative="0.8" lcSpeedGain="0.8" lcKeepRight="0.2" color="1,0,0"/>
             <vType id="normal_human" accel="2.5" decel="4.5" sigma="0.5" maxSpeed="13.9" minGap="2.5" tau="1.5" laneChangeModel="LC2013" lcStrategic="3.0" lcCooperative="1.0" lcSpeedGain="0.5" lcKeepRight="0.7" color="0,0,1"/>
```

2.4. Key Metrics Analyzed

2.4.1. Mean Max Jam Length (meters)

This metric represents the average of the maximum jam lengths recorded in meters across the simulation duration. It provides an indication of the spatial extent of traffic congestion on each bound or approach.

- Importance: This metric is critical for understanding how far traffic queues extend under different penetration rates and vehicle behavior scenarios.

- Calculation: The simulation records the maximum jam length (in meters) at each time step, and the mean of these values is computed over the simulation duration.
- Use in Decision-Making: Planners can use this metric to identify bounds where excessive congestion may require additional signal optimization or infrastructure improvements.

2.4.2. Max Jam Length (vehicles)

This metric refers to the peak number of vehicles queued in a jam during the simulation. It captures the worst-case traffic congestion scenario for each approach.

- Importance: The peak jam length in vehicles reflects the intersection's inability to process high volumes of traffic efficiently under certain conditions.
- Calculation: The maximum number of vehicles in a jam is recorded at each time step, and the highest value is noted for the entire simulation duration.
- Use in Decision-Making: High values for this metric indicate the potential need for measures like signal retiming, lane additions, or traffic flow redistribution to mitigate congestion.

By combining these two metrics, the study ensures a comprehensive understanding of the spatial (meters) and numerical (vehicles) impact of congestion under varying traffic and aggressive AV penetration scenarios.

2.5. Model Formulation

2.5.1. Linear Regression

Linear regression is a simple statistical model that assumes a straight-line relationship between the independent and dependent variables. It can be defined as equation (1):

$$y = a \cdot b + x \quad (1)$$

where y represents the dependent variable (jam length metrics), x is the independent variable (penetration rate), and a and b are regression coefficients. Linear regression provides a straightforward interpretation of the relationship, making it an effective baseline model to understand the fundamental interaction between penetration rates and traffic congestion metrics.

2.5.2. Quadratic Regression

Quadratic regression is a more flexible model designed to account for non-linear relationships, where the effect of the independent variable, penetration rate, may change at higher levels. It can be defined as equation (2):

$$y = a \cdot x^2 + b \cdot x + c \quad (2)$$

In this equation, y represents the dependent variable (jam length metrics), "x" is the independent variable (penetration rate), and a, b and c are the regression coefficients. Quadratic regression is particularly useful for capturing curvatures in relationships, such as diminishing or accelerating impacts of penetration rates on traffic congestion metrics, providing a more nuanced understanding compared to linear regression.

3. Results and Discussion

3.1. Simulation Results for Jam Lengths

Figure 3 presents the simulation results for Mean Max Jam Length (meters) and Max Jam Length (vehicles) under different penetrations of aggressive AVs. The observed trend provides significant insights into the traffic congestion management of different traffic compositions. Average queue length was at 6.85 vehicles when human driver-only comprised the case in 100%, translating into Mean Max Jam Length of 49.43 meters, underlined normal levels of congestion which AVs will tackle solely from the human-driven side. Then Mean Max Jam Length went down to 46.07 meters upon adding 25% aggressive AVs when average queue length fell to 6.68 vehicles, signifying the positive capabilities of the presence of AVs in maximizing flow. When the proportion of aggressive AVs increased to 50%, the Mean Max Jam Length further decreased to 42.65 meters, with an average queue length of 6.49 vehicles, suggesting that balancing traffic compositions can improve efficiency. A dominant presence of aggressive AVs at 75% reduced the Mean Max Jam Length to 38.39 meters and the average queue length to 6.18 vehicles, demonstrating the growing impact of AV behavior as their penetration rate rises. The final full replacement of human-driven vehicles with aggressive AVs gave the lowest Mean Max Jam Length of 34.45 meters and an average queue length of 5.86 vehicles and these results align with the finding of [2], once again underlining the capability of aggressive AV behavior in mitigating congestion and optimizing the performance at intersections by a large margin. The results tended to show a consistent trend of reduced jam lengths with increasing penetration rates of aggressive AVs, underlining the contribution that autonomous driving technologies can make to improve the flow of traffic and reduce congestion. The findings provide important insights for urban planners and policymakers in devising a strategy for the gradual integration of AVs into traffic systems.

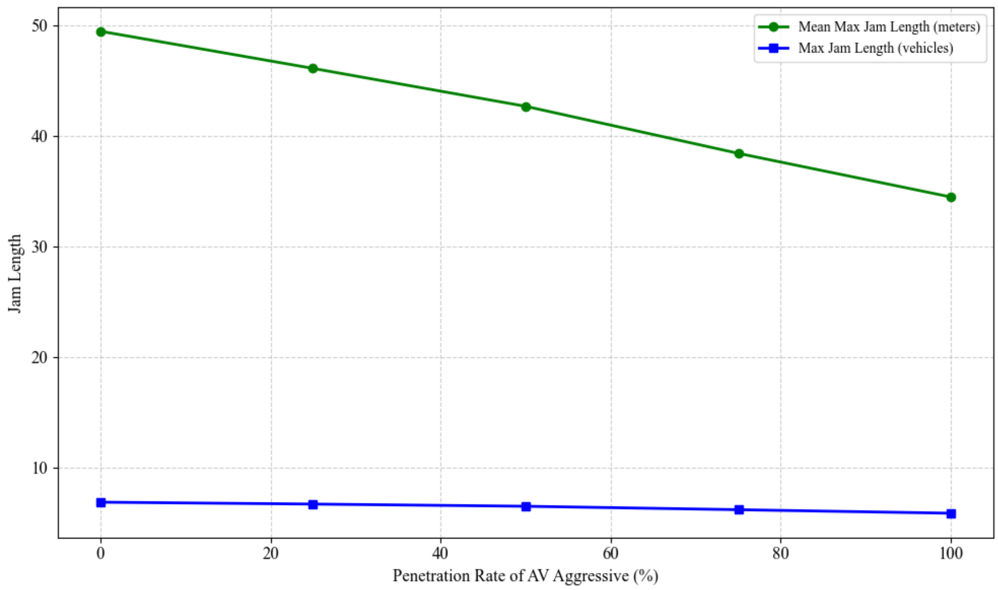


Figure 3. Simulation results showing the Mean Max Jam Length (meters) and Max Jam Length (vehicles) across varying penetration rates of aggressive AVs

3.2. Calibration of Formulas

Regression models were calibrated based on the observed data from simulation. Thus, both a linear and a quadratic model represented the relation between the penetration rates of aggressive AVs and lengths of traffic jams. The linear regression models provided a straightforward relationship with equations capturing the dependency of both Mean Max Jam Length (meters) and Max Jam Length (vehicles) on penetration rates. However, the quadratic models demonstrated improved accuracy by capturing potential non-linear trends in the data, as seen in the diminishing impact of penetration rates at higher levels.

The calibrated linear model for Mean Max Jam Length is given in Equation (3):

$$\text{Mean Max Jam Length (meters)} = -\,0.1506\,x + 49.7294 \tag{3}$$

While the quadratic model is expressed in Equation (4):

$$\text{Mean Max Jam Length (meters)} = -\,0.0002\,x^2 - 0.1277\,x + 49.4435 \tag{4}$$

Similarly, for Max Jam Length (vehicles), the linear model is shown in Equation (5):

$$\text{Mean Max Jam Length (vehicles)} = -\,0.0100\,x + 6.9133 \tag{5}$$

And the quadratic model is presented in Equation (6):

$$\text{Mean Max Jam Length (meters)} = -\,0.0000\,x^2 - 0.0053\,x + 6.8548 \tag{6}$$

These formulas provide a mathematical framework to quantify the relationship between penetration rates and traffic congestion, with quadratic models designed to capture potential variations more effectively than linear ones.

3.3. Validation of Models

Observed data was compared with the predicted values using linear and quadratic regression equations to validate the regression models. Validation has been done to check the accuracy of the models in representing the observed trend for Mean Max Jam Length (meters) and Max Jam Length (vehicles).

Figure 4a Observed versus Predicted for Mean Max Jam Length (meters). The quadratic model has a better fit for the observed data and captures nonlinear variation. Figure 4b Validation of Max Jam Length (vehicles). For the most part, the same trends are repeated in that the quadratic model outperforms the linear model in terms of accuracy.

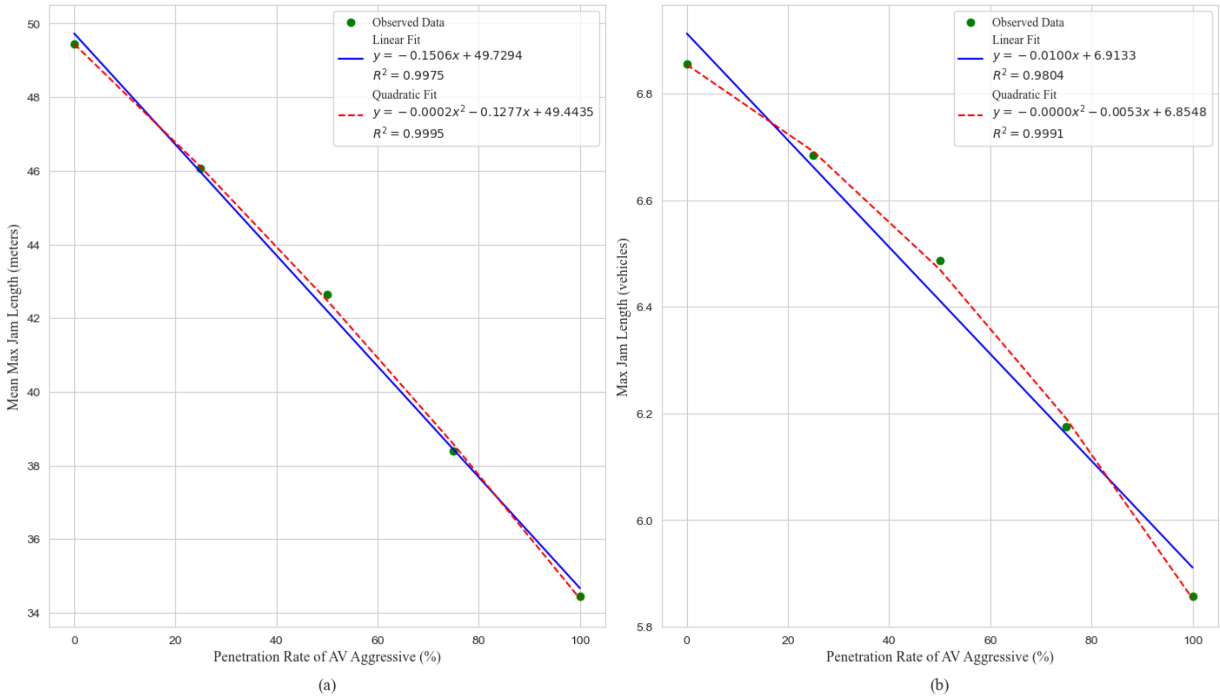


Figure 4. (a) Validation of Mean Max Jam Length (meters) and (b) Validation of Max Jam Length (vehicles)

Validation metrics of R², for the two models. Figure 5. These metrics will comprehensively assess the performance of both models:

- Coefficient of determination (R^2): Indicates the proportion of variance explained by the model, with higher values reflecting better accuracy.
- Mean Square Error (MSE): Measures the average squared difference between observed and predicted values, with lower values indicating better performance.
- Mean Absolute Error (MAE): Represents the average magnitude of errors, providing an interpretable measure of accuracy.

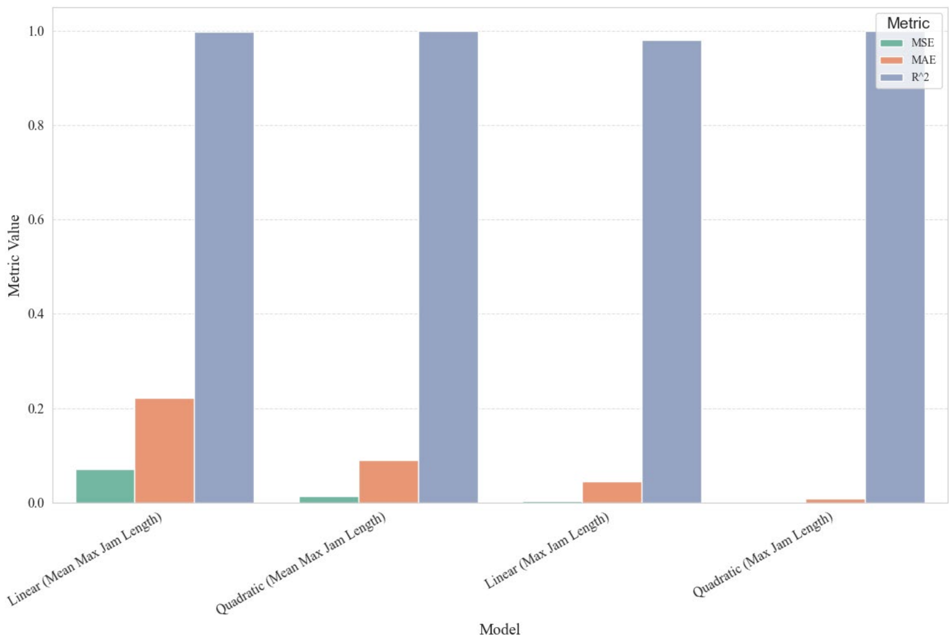


Figure 5. Validation metrics (R^2, MSE, and MAE) for linear and quadratic regression models

These models provided better validation metrics, reflecting their strength in the capture of subtle nonlinear patterns in the data. This underlines the importance of the quadratic model for giving a realistic and nuanced representation of traffic congestion dynamics under mixed traffic scenarios.

3.4. Prediction of Jam Lengths

The calibrated regression models have been used to predict jam lengths for additional penetration rates, with steps from 10% up. This includes the Mean Max Jam Lengths (in meters) and Maximum Jam Length)in vehicles(using Linear and Quadratic Models.

The results align with the trends observed in the simulation data, which are that with increasing penetration of aggressive AVs, both Mean Max Jam Length (in meters) and Max Jam Length)in vehicles(decrease. It reflects the role of AVs in reducing traffic congestion due to optimized driving behavior even at high traffic flow conditions.

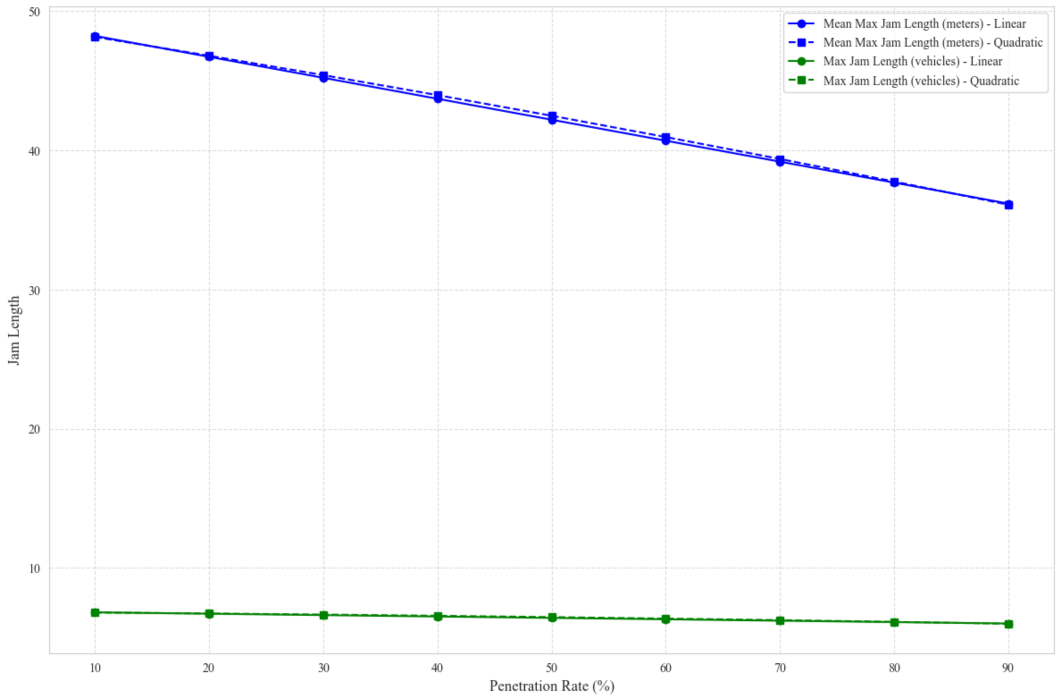


Figure 6. Predicted Mean Max Jam Length (meters) and Max Jam Length (vehicles) for various penetration rates using linear and quadratic regression models

The linear model predicts that jam lengths would decrease steadily with increasing penetration rates. This reflects its ability to capture the general trend. On the other hand, the quadratic model offers some adjustments to predictions in the capture of non-linear changes of congestion at extreme values of penetration rate-for instance, the decreasing benefits when the penetration rate approaches 100%.

Both models foresee a decrease in the number of vehicles in jams for higher penetration rates. However, the quadratic model predictions better match the observed subtle variations, therefore highlighting its capability to model complex relationships.

These predictions have several implications for traffic planning and AV deployment strategies:

- Traffic Congestion Management: The identification of the congestion reduction rates by penetration rates will help planners in focusing the policies on adopting AVs beyond thresholds where significant reductions in congestion will indeed be achieved or have already commenced.
- Signal Timing Optimization: Integrating AV deployment strategies with adaptive signal timing could further enhance the benefits observed in reduced jam lengths.
- AV Deployment and Policy Making Strategies: The findings further confirm the incremental and strategic deployment of aggressive AVs in highly congested areas for the full exploitation of their useful potential. Such models could underpin policy decisions like incentives for AV adoption, where congestion reductions become measurable at specific penetration levels.

4. Conclusion

The aim of this research is to evaluate the impact of aggressive AV penetration rates on the flow at a four-legged signalized intersection. Accordingly, as revealed from simulation and regression modeling, there are significant improvements in traffic performance measures like Mean Max Jam Length-in meters and Max Jam Length-in vehicles with increased AV penetration rates. The key finding revealed that a higher jam length reduction rate at higher AV penetration rates could signal the possibility of aggressive AV behaviors in mitigating congestion and optimizing the efficiency of intersections. Quadratic regression models are seen to be better than linear regression models in describing the subtle nonlinear relationship between the penetration rate and congestion metrics; this again ensures their utility in traffic analysis and planning. Model predictions showed that strategic increases in AV penetration rates can bring substantial congestion relief even under challenging traffic conditions. The findings could be useful guidelines for policymakers and urban planners in designing traffic management policies and promoting autonomous driving technologies. In future work, it would be relevant to go beyond the findings of this article by taking more realistic traffic data, other behavioral models, and complicating the geometry of the crossroads for greater validation and generalization of results. This research brings out the potentially transformative influence that AVs have on the prospects of urban mobility by providing practical guidelines in terms of integrating them gradually and effectively into already existing traffic.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest.

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