# Optimization of Signalized Intersections: Analyzing Autonomous Vehicle Behaviors Through Data-Driven Simulations

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**Abstract.** Autonomous vehicles (AVs) present a transformative opportunity to enhance traffic flow, particularly at urban intersections where delays are most frequent. This study investigates how different AV driving behaviors and penetration rates affect traffic efficiency at signalized intersections. Using a microscopic simulation model in PTV VISSIM, the research centers on a four-way intersection in Balgat, Ankara. Five AV driving behaviors—cautious, normal, aggressive, platooning, and mixed—are modeled under various signal cycle lengths. The simulation's accuracy was ensured through calibration and validation with real-world traffic data. The findings reveal that the integration of AVs can significantly improve traffic flow, with aggressive and platooning driving behaviors achieving the most notable reduction in vehicle delays, particularly at shorter cycle lengths (60–70 s). Increased AV penetration rates amplify these positive effects, reducing delays and queue lengths in all tested scenarios. In contrast, cautious AV behaviors led to more significant delays, highlighting the importance of intelligent AV driving strategies for optimizing traffic management. The results underscore that optimizing signal cycle lengths with AV integration can reduce congestion and improve urban traffic flow. While the study demonstrates the potential of AVs to enhance urban traffic management, it also stresses the need for real-world validation and the development of adaptive traffic signal systems capable of accommodating diverse driving behaviors. These insights offer urban planners and policymakers valuable guidance on integrating AVs into current infrastructure to create more resilient and efficient transportation networks.

**Keywords:** Autonomous vehicles · Traffic flow · Signalized intersections · Microscopic simulation · Urban traffic management

## 1 Introduction

The advent of autonomous vehicles (AVs) offers a transformative potential for improving traffic flow, particularly at intersections where delays are most common. Recent studies investigating the influence of AV strategies on traffic delays emphasize systems

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where both human-driven and autonomous vehicles operate. This research is crucial for understanding how effective AV integration can alleviate congestion and optimize signal control [1].

For instance, [2] the impact of connected and autonomous vehicles (CAVs) on traffic stability and throughput was examined. Their research indicates that incorporating CAVs can enhance traffic stability, thereby reducing intersection delays. Similarly, research by [3] CAVs, through their ability to implement proactive control measures, can significantly smooth traffic flow, mitigating congestion at key points.

One approach to traffic improvement is platooning strategies, facilitated by inter-vehicle communication (IVC). Accordıng to [4], that the synchronized movement of AVs can significantly decrease traffic delays by enabling vehicles to communicate and adjust speeds collectively. Building upon this idea, [5] proposed a cooperative platoon control model for mixed traffic (both human-driven and autonomous vehicles), highlighting the potential of such collaboration to optimize intersection traffic management.

Rapid artificial intelligence (AI) advancement has further refined AV strategies. To create efficient driving strategies for CAVs at signalized intersections, [6] introduced a reinforcement learning model. This approach allows vehicles to adjust speeds to align with scheduled arrival times, minimizing delays and enhancing overall traffic flow efficiency. In parallel, Ye and Yamamoto (2018) demonstrated the effectiveness of adaptive algorithms, showing that a carefully structured reward function could train controllers to adapt to varying traffic patterns and signal cycles, ultimately reducing delays.

Eco-driving strategies have also been recognized as effective in enhancing traffic efficiency. An optimal eco-driving control strategy for CAVs, which reduced travel delays by a substantial margin (24.2% to 77.1%) and significantly decreased the number of stops by as much as 99%, was proposed [7]. This strategy also yielded a 40% reduction in fuel consumption, highlighting its dual benefits for traffic efficiency and sustainability. Similarly, a mixed-integer linear programming approach to optimize AV scheduling at intersections, reducing fuel consumption and improving arrival times employed by [8].

Managing mixed traffic flow, which involves interactions between human-driven and autonomous vehicles, introduces additional complexities [9]. tackled this issue by developing sophisticated traffic assignment models that address the different behaviors of diverse vehicle types, demonstrating the need for tailored strategies to manage delays in mixed traffic scenarios. In another study, [10] extended traditional polling system analyses to incorporate constraints specific to AVs, underlining the importance of advanced control mechanisms for managing mixed traffic environments effectively.

Moreover, recent progress in data-driven methodologies has significantly improved the estimation of queue lengths, a critical factor in effective traffic management [11]. offer an extensive review of deep learning models for predicting traffic flow, highlighting how these models can be leveraged to enhance queue length estimation and optimize signal settings. Similarly, [12] conduct a systematic review of shared autonomous vehicle systems, emphasizing their role in smart urban mobility and exploring their potential applications in managing traffic queues. In particular, [13] introduce a novel approach to real-time queue length estimation at signalized intersections using connected vehicles as mobile sensors. This innovative method utilizes the data-gathering capabilities of CAVs, enabling dynamic traffic management strategies that can adapt to changing real-time traffic conditions.

In summary, implementing autonomous vehicle strategies holds significant promise for mitigating traffic delays and queue lengths at signalized intersections [14, 15]. While current research outlines various methods, including platooning, reinforcement learning, and eco-driving strategies, more empirical studies and mixed-traffic explorations are crucial. By addressing these gaps and focusing on practical applications, future research can drive the development of more effective and sustainable traffic management solutions. This study aims to explore the effects of various autonomous vehicle (AV) driving behaviors and their penetration rates on traffic flow efficiency at signalized intersections in urban environments. Through microscopic traffic simulation, the research will examine how different AV driving patterns, combined with varying signal cycle lengths, impact critical traffic metrics such as vehicle delays, queue lengths, and overall throughput. The ultimate objective is to provide valuable insights into optimizing traffic signal timing and effectively integrating AVs to improve traffic management and reduce congestion at urban intersections.

The paper is organized as follows: Section 2 details the methodology used for the microscopic traffic simulations, including descriptions of the simulation environment, vehicle behaviors, and traffic scenarios examined. Section 3 presents the results and discusses the impact of different AV driving behaviors and signal cycle lengths on traffic efficiency. Finally, Section 4 concludes with a summary of the findings, their implications for urban traffic management, and suggestions for future research."

## 2 Methodology

The research for this study was conducted at a signalized intersection in Balgat, Ankara, located at the crossroads of Kızılırmak and Ufuk University Street (Cd No:18, 06520, Çankaya/Ankara). This particular intersection was chosen due to its significant traffic flow, representing typical urban conditions with a mix of vehicles and driving behaviors. The total number of vehicles participating in this study was extracted from traffic counts at this intersection, with data captured for both human-operated vehicles and AVs as per the defined penetration levels. Figure 1 below shows the signalized intersection at Balgat, Ankara (Kızılırmak and Ufuk University Street). The figure shows the total number of vehicles that participated in the study.

The traffic simulation was performed using PTV VISSIM, a well-established traffic microsimulation software. PTV VISSIM allows for detailed modeling of vehicle interactions and the impact of AVs under varying cycle lengths and penetration rates. For this study, we modeled the intersection using accurate geometric data, signal timing plans, and traffic volumes collected from the field. The AVs were categorized into five behaviors: "AV Cautious," "AV Normal," "AV Aggressive," "AV Platoon," and a mixed behavior scenario "MixAllAv." Various AV penetration rates, ranging from 10% to 100%, were considered to analyze the impact under varied scenarios. The types of vehicles modeled were primarily passenger cars, excluding heavy vehicles and non-motorized traffic, to focus on the typical urban vehicle mix. Based on existing literature and theoretical assumptions about AV behaviors, the software calibrated the behavioral models considered in this study to simulate their real-life driving characteristics.

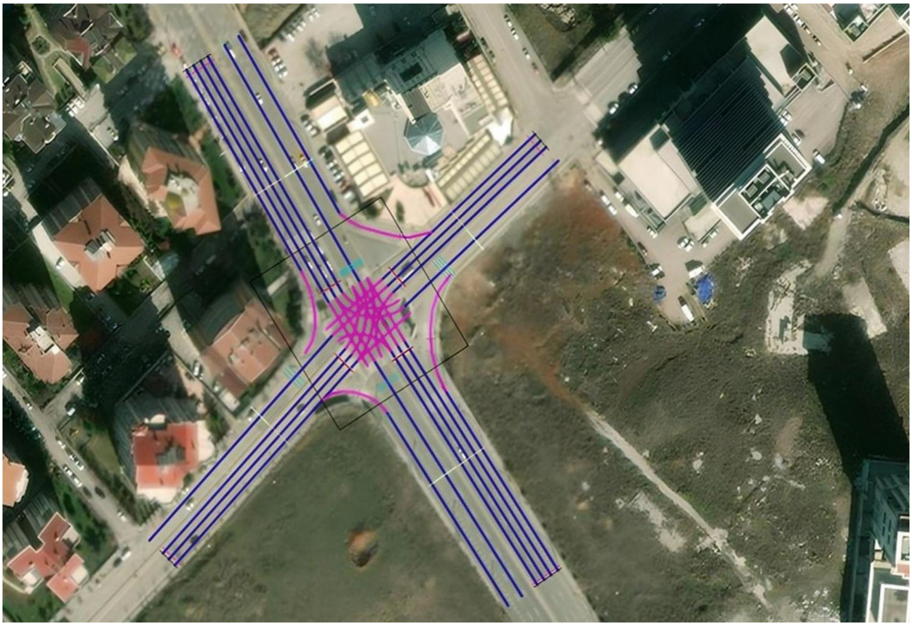


**Fig. 1.** Signalized Intersection at Balgat, Ankara [1]

## 2.1 Calibration and Validation

The calibration process was initiated for accurate simulation modeling by comparing the field data collected at the intersection with the outputs generated by PTV VISSIM. Key traffic parameters, such as vehicle delay, queue length, speed, and throughput, were observed and recorded during peak traffic hours at the Balgat intersection. Table 1 below shows the calculation made for calibration and validation.

**Table 1** Field Data vs. Simulated Data (Calibration and Validation)

| Measures | Field Data (Observed) | Simulated Data (Initial) | Simulated Data (Calibrated) | Error (Initial) | Error (Calibrated) |
|---|---|---|---|---|---|
| Average Vehicle Delay (s) | 35.5 | 40.2 | 36.2 | 13.2% | 1.9% |
| Average Queue Length (Vehicles) | 20 | 24 | 21 | 20% | 5.0% |
| Average Speed (km/h) | 18.4 | 16.5 | 17.9 | 10.3% | 2.7% |
| Throughput (Vehicles/30 min) approx | 2693 | 2545 | 2671 | 5.5% | 0.8% |

The initial simulation run yielded discrepancies between the simulated results and the actual observed data. For example, the average vehicle delay in the field was measured at 35.5 s, while the initial simulation overestimated it at 40.2 s. Similarly, the average queue length in the field was around 20 vehicles, but the uncalibrated simulation predicted 24 vehicles.

Various vehicle behavioral parameters in the simulation were adjusted to address these discrepancies. Factors such as vehicle acceleration, deceleration, desired speeds, and gap acceptance were fine-tuned. After these iterative adjustments, the average vehicle delay in the calibrated simulation decreased to 36.2 s, reducing the error from 13.2% to 1.9%. Similarly, the average queue length was calibrated down to 21 vehicles, with the error reduced to 5% from the initial 20%. These adjustments ensured that the simulated conditions aligned closely with real-world traffic patterns observed at the intersection.

The average vehicle speed and throughput were also part of the calibration process. Initially, the simulated average speed was 16.5 km/h, lower than the observed field speed of 18.4 km/h. After adjustments, the speed increased to 17.9 km/h, reducing the error to 2.7%. For throughput, the field data indicated a half-hourly vehicle flow of 2693 vehicles, whereas the initial simulation recorded 2545 vehicles during the 30-minute simulation. Post-calibration, the simulated throughput increased to 2671 vehicles, yielding a minimal error of 0.8%.

The calibrated model was validated using standard statistical metrics, such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Equations (1) and (2) outline the formulas for RMSE and MAPE and their corresponding calculations.

### 2.1.1 RMSE Calculation

$$RMSE = \sqrt{\frac{(Observed - Simulated)^2}{n}} \tag{1}$$

For vehicle delay:

$$RMSE = \sqrt{\frac{(35.5 - 36.2)^2}{1}} = 0.7 \text{ seconds}$$

### 2.1.2 MAPE Calculation

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Observed_i - Simulated_i}{Observed_i}\right| \times 100 \tag{2}$$

For vehicle delay:

$$MAPE = \left|\frac{35.5 - 36.2}{35.5}\right| \times 100 = 1.97\%$$

For vehicle delay, the RMSE was calculated to be 0.7 s, and the MAPE was approximately 1.97%, both of which fell within acceptable thresholds. This indicated that the calibrated model was a reliable representation of the real-world conditions at the Balgat intersection and could be used for further simulations of AV behaviors and penetration levels.

## 2.2 Measure of Effectiveness

This study's primary measure of effectiveness (MoE) was vehicle delay, measured for different vehicle behaviors (human-operated and various AV types) at varying penetration rates and signal cycle lengths. Vehicle delay is the average time a vehicle waits at the intersection due to traffic congestion or signal control. Other secondary measures included queue length and throughput. However, the focus remained on delay as it is the most significant metric for evaluating the efficiency of intersection control and the influence of AVs on traffic flow.

## 2.3 Assumptions

Several assumptions were made in this study to simplify the modeling process and focus on the core research questions:

1. **Uniform Traffic Composition:** The traffic flow was assumed to consist of standard vehicles (cars) only, with no consideration of heavy vehicles, buses, or non-motorized vehicles such as bicycles or pedestrians. This assumption was made to isolate the impact of AVs and avoid additional variables.
2. **Driver Behavior for Human-Operated Vehicles:** Human-operated vehicles were modeled using average driver behavior settings in PTV VISSIM, based on typical urban driving conditions in Turkey. It was assumed that human drivers exhibit no significant variation in behavior due to factors like time of day, weather conditions, or driver experience.
3. **AV Characteristics:** The AV behaviors were modeled based on theoretical research. Cautious behaviors, characterized by longer headways and more conservative speed profiles, tend to react to traffic signals with increased caution, often slowing down sooner and accelerating later than aggressive behaviors. While enhancing safety, this conservative approach contributes to longer vehicle queues and increased overall delays, especially at intersections with frequent signal changes.

   Conversely, aggressive behaviors are marked by shorter headways and higher speeds, allowing these vehicles to cross intersections more quickly during green phases and reduce time spent idling at red lights. Furthermore, when equipped with advanced inter-vehicle communication systems, aggressive AVs can synchronize their movements more effectively, minimizing the stop-and-go patterns that often exacerbate congestion. This synchronization allows for a smoother flow of traffic and significantly shorter delays. AV platooning was assumed to allow closer following distances between vehicles with coordinated driving strategies. The "MixAllAv" scenario, incorporating a blend of cautious, normal, and aggressive driving behaviors, represents a realistic spectrum of AV integration within urban traffic systems. This scenario is crucial for understanding the nuanced interactions that occur when different AV behaviors coexist within the same traffic ecosystem.
4. **Static Traffic Demand:** The traffic demand during the simulation was assumed to remain constant, representing peak-hour conditions. Variations in demand over time, such as off-peak or fluctuating traffic volumes, were not considered.
5. **Perfect Communication for AVs:** For the platooning scenario, it was assumed that AVs have perfect communication between one another, allowing them to operate

seamlessly as a unit. This assumption simplifies the platooning model but aligns with future expectations of AV technology.

By adhering to these assumptions, the study focused on the core research objective: understanding how AV behaviors and penetration levels affect vehicle delay under varying traffic signal cycle lengths. The simulation results provided insights into how AVs could optimize traffic flow and reduce delays, mainly when aggressive or platoon behaviors were employed at shorter cycle lengths.

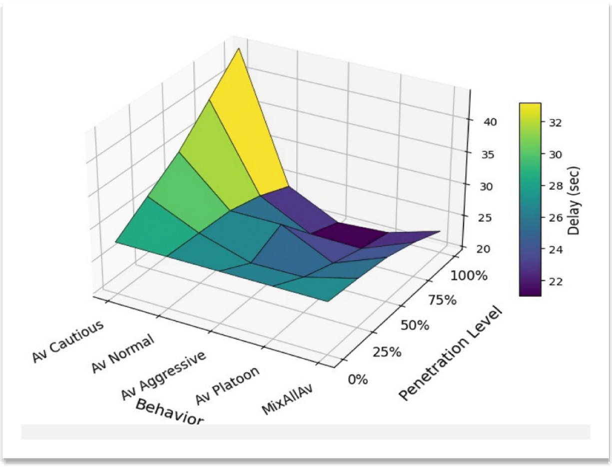
## 3 Results and Discussion

The results from the experiments, beginning with a cycle length of 60 s, show that vehicle delay significantly varies depending on the vehicle behavior and the penetration rate of AVs. As seen in Fig. 2(a), for a 60-s cycle length, aggressive and platoon AV behaviors exhibit the most substantial reduction in vehicle delay, reaching as low as 22 s when the AV penetration rate is 100%. Cautious AVs, in contrast, display higher delays, ranging between 32 and 35 s at full penetration. The mixed behavior scenario, "MixAllAv," also performs well under these conditions, with vehicle delays approaching 26 s at full AV penetration. The results indicate that, at shorter cycle lengths, aggressive and platoon AV behaviors allow for a much more efficient flow of traffic, minimizing delays and enhancing system performance.

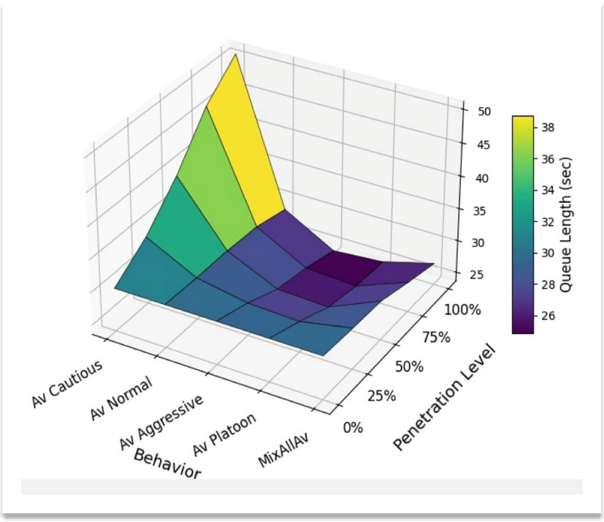
When the cycle length is extended to 70 s, the trends remain similar but with slightly higher vehicle delays across all AV behaviors, as illustrated in Fig. 2(b). At full penetration, cautious AVs experience delays of around 38 seconds, while aggressive and platoon behaviors maintain their superior performance, reducing vehicle delays to approximately 23–25 s. Analysis reveals that the mixed behavior scenario yields variability in delay reduction across different signal cycle lengths. For example, at shorter cycle lengths (60–70 s), the "MixAllAv" scenario demonstrates a moderate decrease in vehicle delays, positioning it between aggressive and cautious behaviors. This suggests that aggressive AVs within the mix can somewhat counterbalance the increased delays caused by cautious AVs, improving traffic flow efficiency. These results reinforce that shorter cycle lengths and higher AV penetration rates provide the best traffic flow efficiency.

At an 80-s cycle length, shown in Fig. 3(a), the system's efficiency declines as vehicle delays increase. Cautious AVs experience delays of around 42 s at full penetration, while aggressive and platoon behaviors manage to keep delays at around 25–27 s. Interestingly, the efficiency of platoon behavior remains high under this cycle length, suggesting that the coordination and communication between AVs in a platoon allow them to navigate the traffic system better, even as cycle lengths increase. The mixed behavior scenario performs moderately well, though not as effectively as aggressive or platoon behaviors.

Moving to a cycle length of 90 s, represented in Fig. 3(b), the vehicle delays increase further. For cautious AVs, delays reach approximately 45 s at full penetration. However, aggressive and platoon behaviors still keep vehicle delays relatively low, at around 28–30 s. The mixed behavior scenario also shows better performance as AV penetration levels rise, which suggests that even in longer cycle lengths, the presence of aggressive or platoon AV behaviors can help reduce overall system delays. However, the general



a) Cycle Length of 60 sec

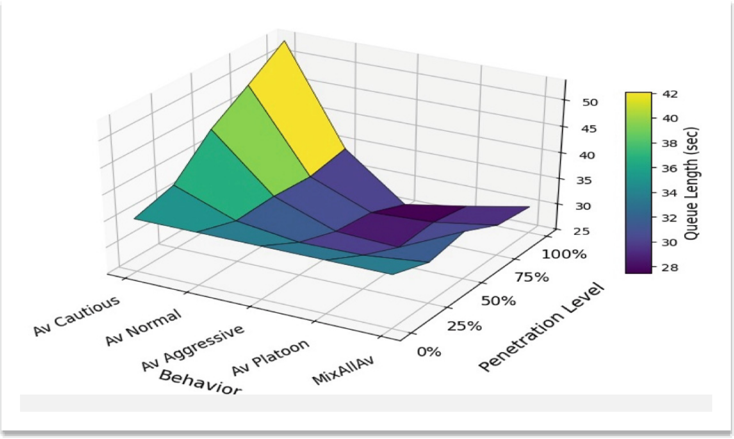


b) Cycle Length of 70 sec

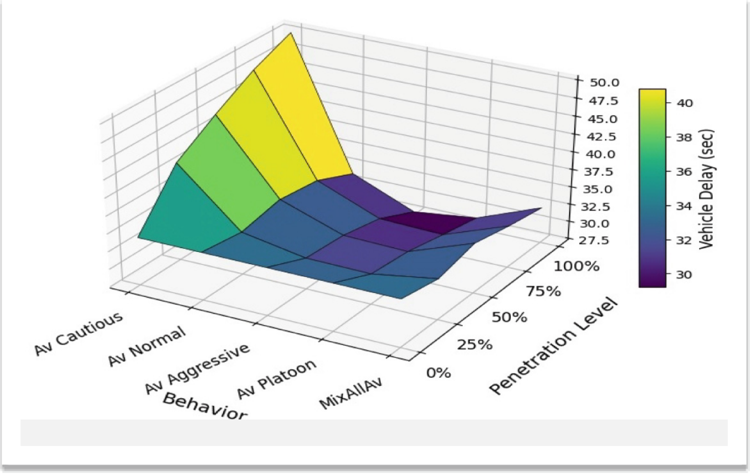
**Fig. 2.** Vehicle Delay at Cycle Lengths of 60 and 70 s.

trend indicates that longer cycle lengths contribute to higher vehicle delays, even as AV penetration increases.

Finally, for a 100-s cycle length, as shown in Fig. 4, the results depict the highest vehicle delays across all AV behaviors. Cautious AVs show the most significant delay, with values nearing 48–50 s at full AV penetration. Conversely, aggressive and platoon behaviors still perform better, with delays dropping below 30 s. The “MixAllAv” scenario demonstrates moderate delays, as expected, given the balance between cautious and



a) Cycle Length of 80 sec



b) Cycle Length of 90 sec

**Fig. 3.** Vehicle Delay at Cycle Lengths of 80 and 90 s.

aggressive behaviors. This final set of results emphasizes the importance of minimizing cycle lengths to achieve optimal traffic flow when AV penetration rates are high. Longer cycle lengths exacerbate vehicle delays, especially for cautious AV behavior.

The bubble plot in Fig. 5 adds another layer of insight by visually representing the vehicle delay across all cycle lengths and penetration rates. The size and color of each bubble correspond to the magnitude of the delay, with larger yellow bubbles representing higher delays and smaller purple bubbles indicating lower delays. The plot shows a clear trend where delays increase with cycle length and AV penetration for certain behaviors, particularly cautious AVs. The higher delay bubbles are clustered around longer cycle lengths and higher penetration rates for cautious behaviors. In contrast, smaller, lower-delay bubbles are concentrated at shorter cycle lengths and for aggressive and platoon

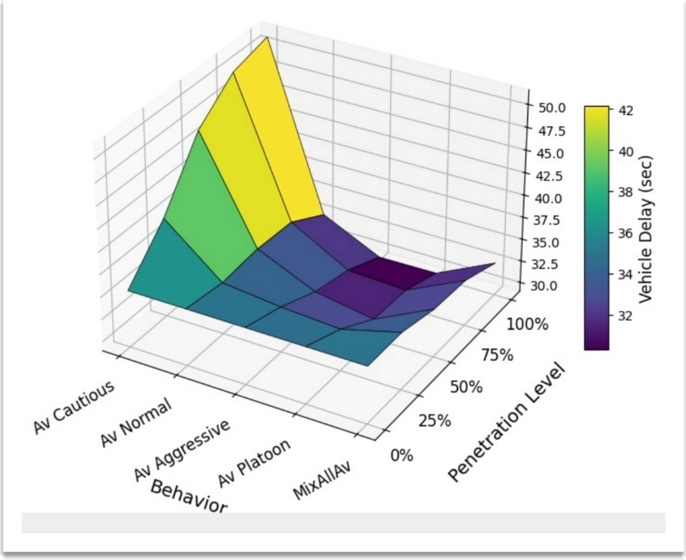


**Fig. 4.** Vehicle Delay at Cycle Length of 100 s

behaviors, especially at higher penetration rates. This visualization further confirms that aggressive and platoon AV behaviors significantly reduce vehicle delays, especially when shorter cycle lengths and AV penetration rates are higher.

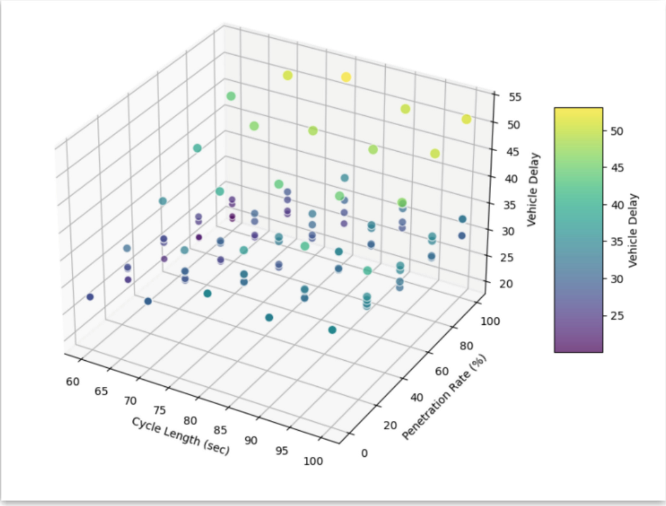


**Fig. 5.** Bubble Plot of Vehicle Delays with Continuous Hues and Sizes.

The overall results reveal that cycle length and AV behavior are key factors in determining vehicle delays in a traffic system. Cautious AV behavior generally results in higher delays, particularly as penetration levels increase, while aggressive and platoon behaviors are much more effective at reducing delays. Shorter cycle lengths, such as 60 or 70 s, provide the best results, particularly when paired with high penetration levels of AVs that exhibit aggressive or platooning behaviors. This outcome is consistent across all scenarios, highlighting the potential for AVs to significantly enhance traffic flow and reduce delays if integrated into traffic systems with shorter signal cycle lengths and more efficient driving behaviors.

The findings also underscore the importance of traffic management strategies in accommodating AVs. As AV penetration levels rise, adjustments to traffic signal cycle lengths may be necessary to maximize the efficiency benefits of AVs, especially those that adopt more aggressive or cooperative behaviors. The ability of platooning AVs to reduce delays is particularly notable, as it suggests that AVs capable of communicating and coordinating with one another can optimize traffic flow, even in more congested environments or under longer cycle lengths. This highlights the need for future traffic systems to not only integrate AVs but also to support technologies that enable vehicle communication to enhance efficiency further.

The results across all cycle lengths show that traffic systems can significantly benefit from higher penetration levels of AVs, especially when cycle lengths are shorter and AVs adopt efficient behaviors such as aggressive driving or platooning. These behaviors lead to the most significant reductions in vehicle delays, ensuring smoother traffic flow and reduced congestion.

## 4 Conclusion

This research uses microscopic traffic simulation to explore the effects of autonomous vehicles (AVs) on traffic flow efficiency at signalized intersections. The study assesses a range of AV driving behaviors—cautious, normal, aggressive, platoon, and mixed—across different penetration rates and signal cycle lengths to identify key strategies for optimizing urban intersection management. The findings demonstrate that higher penetration rates of AVs substantially enhance traffic flow, with aggressive and platooning behaviors leading to the most significant reductions in vehicle delays. For example, at a 60-s cycle length, aggressive and platoon behaviors reduced delays to as low as 22 s at full AV penetration, in contrast to the 35-s delay observed with cautious AV behavior and even with extended cycle lengths, such as 90 s, aggressive and platooning behaviors maintained relatively low delays of approximately 28–30 s. This indicates that combining shorter cycle lengths with higher AV penetration and assertive driving behaviors can significantly minimize delays and congestion.

On the other hand, cautious AV behavior results in increased delays, mainly as cycle lengths and penetration rates grow, emphasizing the need for adaptive AV driving strategies. The study also underscores the importance of optimizing signal cycle lengths to fully harness the efficiency of AVs, with 60–70 s cycles identified as the most effective.

To bridge the gap between theoretical research and practical application, this study suggests a roadmap for real-world validation. Future research should include pilot studies at various urban intersections where AV technologies are being tested. These studies would utilize advanced traffic monitoring technologies to validate simulation outcomes under actual traffic conditions. Collaborations with local traffic authorities will be essential for adjusting traffic signals and directly measuring the impact on traffic flow efficiency. Challenges likely to be encountered include the variability of urban traffic conditions, the integration of real-time data, and ensuring the reliability of communication technologies among diverse AV behaviors. Addressing these challenges will be crucial for accurately assessing the practical viability of AV integration strategies. These insights offer valuable guidance for urban planners and policymakers, illustrating that integrating AVs and well-tuned traffic signal timings can create smoother and more efficient traffic flow. Nevertheless, validating these findings in real-world conditions remains essential. Future research should focus on conducting field experiments in diverse urban environments to test the practicality of these strategies. Additionally, incorporating real-time data and machine learning algorithms could further enhance adaptive traffic signal systems, maximizing the benefits of AVs in urban networks.

In conclusion, adopting autonomous vehicles provides a significant opportunity to transform urban traffic management. By optimizing signal timing and implementing effective AV driving behaviors, cities can reduce congestion by up to 40%, support more sustainable transportation, and establish resilient urban infrastructure.

While this study provides significant insights into the impacts of autonomous vehicle behaviors on traffic efficiency at signalized intersections, it has limitations. The static nature of traffic demand in our simulations may not reflect real-world variability. Also, excluding non-automated vehicles and pedestrians limits the applicability of our findings to simpler urban environments. Future research should include dynamic traffic patterns and a broader mix of traffic participants to validate the robustness of AV integration strategies. Additionally, field tests and the integration of machine learning for traffic management could further enhance the accuracy and practicality of our models.

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