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Examining the Influence of Autonomous Vehicle Behaviors on Travel Times and Vehicle Arrivals: A Comparative Study Across Different Simulation Durations on the Kirkuk-Sulaymaniyah Highway

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Research Article

Abstract

This study delves into the effects of autonomous vehicle behaviors on travel times and vehicle arrivals along the Kirkuk-Sulaymaniyah Highway, employing simulations spanning 3600, 5400, and 7200 seconds. Across varied traffic volumes ranging from 350 to 950 vehicles and autonomous vehicle behaviors categorized as cautious, normal, aggressive, aggressive platoons, and a mix alongside human-driven vehicles, the research unveils significant findings. Results highlight substantial reductions in average travel times and heightened vehicle arrivals among autonomous vehicles, particularly those exhibiting aggressive behaviors, compared to their human-driven counterparts. Across all simulation scenarios, aggressive autonomous vehicles consistently demonstrate superior performance, showcasing potential efficiency gains through aggressive driving algorithms. Furthermore, with increasing traffic volume, the advantages of aggressive autonomous behaviors become more pronounced, suggesting their adaptability to congested conditions. However, safety implications and traffic flow dynamics warrant caution, especially in scenarios with high volumes and aggressive behaviors. These insights underscore the importance of further research and policy considerations to leverage the full potential of autonomous vehicles while ensuring safety and efficiency on highways.

Keywords: Autonomous vehicles; Highway simulation; Vehicle behavior; Travel time; Vehicle arrival; Aggressive driving; Cautious driving; Platooning; PTV VISSIM.

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Introduction

Autonomous vehicles (AVs) hold the potential for revolutionizing the transportation system by promoting safety, improving mobility, and increasing efficiency. As the deployment of AVs becomes more feasible, understanding their impact on traffic dynamics and travel behavior is crucial for effectively integrating these vehicles into existing road networks [1-3].

The Kirkuk-Sulaymaniyah Highway is one of the main drivers but has changeable conditions in relation to traffic, due to strategic reasons. This research will use state-of-the-art simulation methods in the analysis of the influence of different AV behaviors on travel times and vehicle arrivals within the Kirkuk-Sulaymaniyah Highway.

Previous research has primarily focused on individual AV behaviors, such as cautious, normal, and aggressive driving, as well as platooning strategies. However, comprehensive comparative analyses across multiple simulation periods and traffic volumes are lacking, hindering a holistic understanding of AV performance under diverse conditions [4].

Cautious Driving: takes into consideration conservative acceleration and deceleration patterns, prioritizing safety over speed. By analyzing how cautious AVs interact with human-driven vehicles and other AVs, researchers aim to understand their role in reducing traffic congestion and enhancing roadway safety [5].

Normal Driving: In addition to cautious driving, the study also explores the normal driving essentially involves a middle-of-the-road style in all its driving behaviors, where AVs obey the standard traffic rules and maintain moderate acceleration/deceleration profiles. The study evaluates the contribution of AVs adopting normal driving behavior to traffic efficiency and improvement of overall travel experience in various traffic scenarios [6].

Aggressive Driving: The other main view in relation to the aggressive driving behavior analysis among AVs on the Kirkuk-Sulaymaniyah Highway is that aggressive driving has been defined as assertive maneuvers, short following distance, rapid acceleration, and deceleration. Though some safety and driver comfort issues might be at stake in such a strategy, evidence shows that aggressive driving can yield optimal flow and reduced travel times, especially in highly congested settings. From an academic perspective, researchers will be looking at the consequences of aggressive AV behaviors to try and understand the cost and benefit, i.e., how effective they really are at reducing the congestion and the efficiency of the roadway [7].

Platooning Strategies: Furthermore, the study delves into the impact of the adopted platooning strategies of the AVs along Kirkuk-Sulaymaniyah Highway. Platooning works in such a way that a set of vehicles move in a synchronized pattern and closely, thereby able to exploit vehicle-to-vehicle communication and automation to keep spacing and optimal speed. It can result in improving aerodynamic efficiency, reduction of fuel consumption, and even improving the traffic flow of one vehicle moving into a gap between other vehicles by reducing inter-vehicular gaps. By evaluating the performance of AVs engaged in platooning, researchers aim to assess their effectiveness in optimizing highway capacity and enhancing overall transportation efficiency [8].

Globally, the deployment of AVs has seen significant progress, with various countries conducting extensive testing and pilot programs. For instance, the United States, China, and several European nations have been at the forefront of AV technology, implementing policies and infrastructure to support AV integration.

These countries have established test beds and regulatory frameworks to facilitate AV development and deployment, highlighting the potential benefits of improved safety, reduced congestion, and enhanced mobility.

In Iraq, the deployment of AV technology is still in its nascent stages, with limited testing and adoption. However, the increasing interest in smart city initiatives and technological advancements presents an opportunity for Iraq to leverage AV technology to address its transportation challenges. Integrating AVs into the Kirkuk-Sulaymaniyah Highway could serve as a pivotal step toward modernizing the country's transportation infrastructure and improving overall traffic management.

by making a comprehensive assessment of AV behaviors from 3600, 5400, and 7200 seconds through simulation. The results from this study will, therefore, serve to help enlighten some of the efficacy and adaptability of AVs in the real world of highway scenarios and provide key input to policymakers, urban planners, and transportation engineers with respect to the potential implications of AV integration.

Finally, the study strongly believes that the enhancement of traffic flow management, congestion, and transportation efficiency through AV technology will serve to remedy the current occurrences in the highlighted phenomena. Ultimately, this research would aim at materializing the possibility of autonomous technology in shaping future transportation in Iraq and beyond, considering and localizing such a necessity within the local context of need.

Literature Review

Table 1 below provides a brief outline of some of the existing studies that have already been undertaken in a view to look at the effects of AVs on travel behavior and transportation systems. These results provide helpful insights about the implications of AV adoption for travel patterns, mode choice, and value of travel time savings. While such studies contribute greatly to understanding the overall effects of AVs, they still leave a gap in the literature for the examination of various AV behaviors and individual impacts on travel times and vehicle arrivals. This research tries to narrow down this gap by trying to focus on the behavioral dynamics of AVs, a concept which entails cautious, normal, and aggressive driving against the concept of aggressive platoons. Further study extended to have scenarios of different traffic volumes and simulation times between one to two hours, therefore giving in-depth understanding of how traffic volumes have been affecting time interactions between AV behaviors and different traffic conditions. This focused analysis aims to offer insights that can inform more tailored strategies for optimizing AV deployment and enhancing traffic management in real-world scenarios.

Methodology

1.1. Study Location & Data Collection

The study is conducted on a highway segment spanning between Kirkuk and Sulaymaniyah, covering approximately 100,019.173 meters, as shown in Figure 1. This segment comprises two links, each consisting of two lanes. The selection of this specific location offers a representative sample of real-world highway conditions, allowing for a comprehensive analysis of autonomous vehicle (AV) behaviors and their impact on travel dynamics. The Kirkuk-Sulaymaniyah Highway is a critical transportation corridor in Iraq, known for its strategic significance and variable traffic conditions. Its importance as a major route for both commercial and personal travel makes it an ideal setting for examining the potential benefits and challenges of integrating AV technology. The diverse traffic patterns and mixed vehicle types on this highway provide a realistic environment to study how AVs can enhance traffic flow, reduce congestion, and improve overall travel efficiency in a region with evolving transportation needs.

Table 1. Summary of studies investigating the impact of autonomous vehicles on travel behavior and transportation systems

Reference	Year	Objective of The Study	Methodology/Tools Used	Key Findings
[25]	2019	Investigate the impact of shared and autonomous vehicles (AVs) on travel behavior.	Generalized ordered logit model for safety perceptions of AVs. Agent-based simulation framework for Autonomous Mobility on Demand (AMoD) services.	1. Changes observed in individual, household, and system-level decisions due to AVs. 2. 31% of current transit riders and 57% of current drivers are willing to adopt AV-based Mobility-on-Demand (MOD) alternatives. 3. Socio-demographics significantly influence preferences for premium, economy, and sharing MOD alternatives. 4. Transformation in the mobility landscape affects behavior, choices, and decisions.
[24]	2019	Conduct a comparative study on the impact of autonomous vehicles (AVs) on travel behavior in Germany and the USA.	Vehicle technology diffusion model. Aspatial travel demand model.	1. AV adoption rates influenced by national context factors. 2. AV penetration rates higher in Germany due to luxury cars. 3. Vehicle mileage increase not significantly different between Germany and the USA. 4. The study compares AV impacts on travel behavior and considers factors influencing AV adoption and travel demand changes in both countries.
[23]	2020	Analyze the impacts of connected and autonomous vehicles (CAVs) on traffic using two city models.	Modification of traditional travel demand models for CAV impacts.	1. Vehicle miles traveled (VMT) and congestion speed increase with CAV deployment. 2. The Madison model consistently showed a VMT increase with CAV adoption scenarios. 3. Average congested speed in Madison was 19 mph higher than in Gainesville. 4. Traditional travel demand models were modified to analyze CAV effects on traffic in Madison, Wisconsin, and Gainesville, Florida.
[22]	2020	Examine the impact of autonomous vehicles (AVs) on auto commuters' value of travel time.	Stated choice experiment. Mixed logit model.	1. Lower value of travel time (VOTT) observed for auto commuters in suburban, urban, and rural areas with AVs. 2. Riding in a private autonomous vehicle reduces the commuting VOTT of suburban, urban, and rural drivers by 32%, 24%, and 18% respectively. 3. Riding in a shared autonomous vehicle reduces the commuting VOTT of suburban, urban, and rural drivers by 14%, 13%, and 8% respectively.
[21]	2021	Analyze the effect of autonomous vehicles (AVs) on travel behavior and urban characteristics.	Analytical derivation of traffic equilibria. Consideration of two right-of-way policies.	1. Frequency-based AVs-priority policy reduces travel costs and alleviates traffic congestion. 2. Increasing AV automation level increases expected trip time for on-demand AVs. 3. Study focuses on a core-suburb city connected by a highway with two AV modes.
[20]	2021	Investigate the potential travel time reduction with autonomous vehicles (AVs) for different types of travelers.	Simulation using MATSim to compare existing and AV scenarios. Data collection: Population, transit network, road network features gathered. Data analysis: Simulation of three groups of travelers conducted.	1. AVs reduce travel time for different types of travelers. 2. Reduction in trip time observed for all three groups. 3. AVs traveled longer distances to pick up and drop off travelers. 4. AVs are expected to change safety, congestion, comfort, reliability, and travel time.
[19]	2021	Discuss the impacts of highly automated vehicles (AVs) on travel demand and evaluate macroscopic modeling methods.	Integration of AV impacts into traditional macroscopic travel demand models.	1. AVs influence traffic flow, travel demand, and modal shift. 2. First-generation AVs may decrease traffic performance, while further developed AVs will improve performance on some parts of the network. 3. Two model extensions are discussed to integrate AV characteristics into traditional macroscopic travel demand models. 4. The first extension assigns specific passenger car unit factors based on roadway type and vehicle capabilities, while the second extension calculates demand changes caused by a different perception of travel time.
[18]	2021	Investigate the impact of autonomous vehicle (AV) technology on long-distance travel behavior.	Analyzed travel survey data. Tested hypotheses using the Pearson method.	1. AV technology impacts long-distance travel behavior for pleasure and business trips. 2. AVs increase pleasure trips, reduce costs, and job-related stress for business travelers. 3. AVs for pleasure trips increase the number of travelers and stimulate longer distances. 4. AV technology reduces travel costs and job-related stress for business trips.
[17]	2021	Investigate the influence of introducing autonomous vehicles (AVs) on conventional transport modes and travel time.	Integration of AVs into activity-based models. Simulation using Multi-Agent Transport Simulation (MATSim) software.	1. AVs can reduce travel time and decrease the usage of cars. 2. Travelers experience a reduction in travel time when conventional transport modes are replaced by AVs. 3. The value of travel time (VOT) affects the usage of AVs and the modal share.
[16]	2022	Evaluate the impacts of connected automated vehicles (CAVs) on travel behavior and demand in Southern California.	Activity-based approach. Stated-preference survey.	1. Work trips contribute significantly to increased car-like mode travel distance in Southern California. 2. Total trip numbers increased by 9%, and car-like mode travel distance grew by 13%. 3. Advanced CAV technology alone doesn't directly benefit transportation systems; policy interventions are critical for future improvements.

Table 1. Summary of studies investigating the impact of autonomous vehicles on travel behavior and transportation systems ***(Cont.)***

[15]	2022	Investigate the impact of connected and autonomous vehicle (AV) technology on market penetration and route choices.	Optimization model for route, mode, and parking lot choices. Iterative solution algorithm to solve the optimization program.	1. Scenarios with AVs increase average travel time by approximately 50%. 2. 14.60% to 32.27% of current parking spaces can be repurposed. 3. Study discusses the impact of automated vehicles on traffic assignment, mode split, and parking behavior.
[14]	2022	Analyze the impacts of autonomous vehicle (AV) driving logics on traffic performance and evaluate transport interventions.	Microscopic traffic simulation using PTV Vissim. Analyzing hypothetical scenarios to evaluate impacts on traffic performance.	1. AV driving logics and physical interventions improve traffic performance. 2. AV-readiness of infrastructures and change in driving behaviors should be assessed for effective transport interventions.
[13]	2022	Investigate how in-vehicle activities in autonomous cars affect travel patterns and welfare.	Activity-based bottleneck model. Analytical and numerical comparisons of supply regimes and pricing rules.	1. In-vehicle activities in autonomous cars impact travel patterns, congestion, supply decisions, and welfare effects. 2. Three supply regimes for autonomous cars are investigated. 3. Autonomous cars allow in-vehicle activities beyond driving. 4. The activity-based bottleneck model studies travel patterns and welfare effects.
[12]	2023	Investigate the impact of autonomous vehicles (AVs) and their driving parameters on urban road traffic.	Simulation of AVs and connected autonomous vehicles (CAVs) with different operational parameters.	1. Reaction times and headway are crucial for traffic optimization with AVs. 2. AVs can be configured to reduce congestion in urban areas. 3. Study examines the influence of operational parameters on traffic flow in Munich. 4. Simulation results highlight the impact of headway and reaction times on urban traffic.
[11]	2023	Explore the impact of autonomous vehicles (AVs) on travel demand, focusing on public perception and acceptance.	Large questionnaire with 5679 participants in Győr, Hungary. Data analyzed using 'R Project for Statistical Computing.'	1. Respondents' prior knowledge of AVs affects travel demand. 2. Providing awareness and education increases the number of trips. 3. Socially desirable answers bias the results. 4. Lack of real-world experience with AVs may affect perceptions and responses.
[10]	2023	Evaluate the behavioral impact of Waymo autonomous vehicles (AVs) on traffic flow.	Empirical analysis comparing AV and human-driven vehicle (HV) behaviors. Calibration of IDM model using Waymo Open Dataset trajectories.	1. Waymo AVs are safer than HVs based on surrogate safety measures. 2. AVs behave conservatively for safety at the cost of traffic efficiency. 3. AVs prioritize safety over traffic efficiency. 4. Limited length of trajectories in Waymo Open Dataset.
[9]	2023	Explore AVs' impact on travel-based activities and ABT, emphasizing emotional well-being and quality of life.	Joint modeling of TBAs and ABT	1. Caution in interpreting "productive" activities in AVs. 2. AVs may cause stress due to non-chill activities. 3. Consideration of psycho-social factors in modeling ABT. 4. Caution against simplistic VTTS factor modifications.

Fig. 1. Aerial view of highway segment between Kirkuk and Sulaymaniyah

Data collection for the study involved gathering information on traffic volume and vehicle speeds. Traffic volume data were collected randomly, encompassing a range of 350 to 950 vehicles illustrated in Table 2. This variability in traffic volume facilitates the examination of how different levels of congestion affect AV performance. Additionally, vehicle speeds were determined based on field speed on the highway shown in Figure 2.

Table 2. Summary of examined traffic volumes

Scenario	Traffic Volume	Vehicle Type
1	350 Veh	Conventional Veh
2	500 Veh	Conventional Veh
3	650 Veh	Conventional Veh
4	800 Veh	Conventional Veh
5	950 Veh	Conventional Veh

Fig. 2. Speed distribution for human-driven vehicles

1.2. Experimental Design

3.2.1 PTV VISSIM

The PTV VISSIM microscopic simulation software is majorly used in the field of transportation engineering and research. It is used to model complex traffic scenarios and dynamic traffic flow, as shown in Figure 3. PTV VISSIM complies with high flexibility and allows personal customization, aiming at maintaining precision in simulating roadways, traffic conditions, and vehicle behaviors. PTV VISSIM employs detailed vehicle movement algorithms to provide precise simulation of vehicle interactions, lane changes, and intersection maneuvers. In addition, its advanced model features take care of the traffic signal control, vehicle routing, and dynamic assignment to give full analysis of the traffic operations and performance under different scenarios. With its user-friendly interface and powerful simulation capabilities, offers its applicability in the study of impacts of autonomous vehicles on traffic flow, travel times, and general transport efficiency.

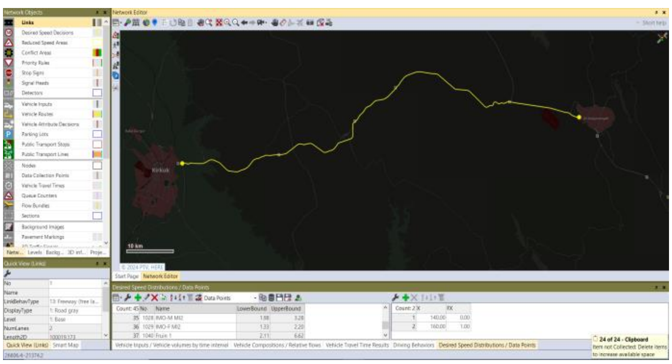

Fig. 3. PTV VISSIM model

3.2.2 Link design

In the design configuration of the highway link under study between Kirkuk and Sulaymaniyah, as shown in the simulation interface and presented in Table 3, the link has been designed carefully with two lanes 3.50 meters wide each. This link follows a behavior type called "Freeway (free lane selection)," which helps to carry out dynamic behavior of lane change among vehicles needed for real simulations on freeways. With a link across the full length of 100,019.173 meters, the link appears perfect for using it within comprehensive traffic flow studies and up to some extent for those of autonomous vehicles. At the basic level, these include the 'Road gray' display type. As indicated in Figure 4, the link has been well designed with detailed geometry points that include curves and sensitive road elements; hence, they are required for accurate reproduction of the physical and operational features of real highways and an increased simulation fidelity during traffic dynamics analysis.

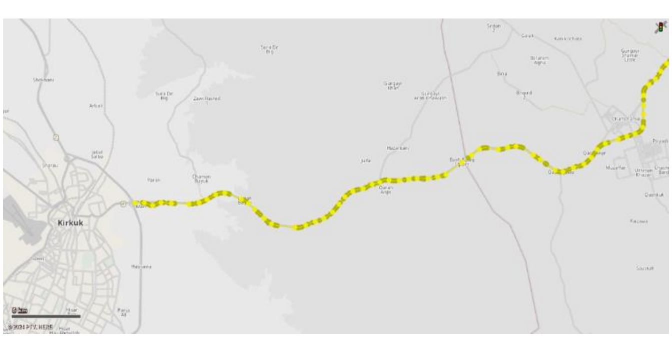

Fig. 4. Detailed route map showing geometry and design features of the highway link

Table 3. Lane specifications for freeway segment between Kirkuk and Sulaymaniyah.

Count	Index	Width	Link Behave	Display Type	Level
1	1	3.5 m	Freeway (free lane selection)	Road Gray	Base
2	2	3.5 m	Freeway (free lane selection)	Road Gray	Base

3.2.3 Travel time measurement

Travel Time Measurement in PTV VISSIM is a major tool for travel time dynamics and efficiency of the transport system. Basically, it allows the researchers to measure how much vehicles take in traveling time from point to point within the selected sections of the simulated road network. This is by locating two points: the start points at the beginning of the specified link and the end at the end of the specified links. Useful information from the travel time measurement includes the level of traffic congestion, network performance, and the predictability of travel time. Besides, the arrival time of the vehicle at the designated endpoint could be extracted using this developed model during the period of simulation, which gives vital information on traffic flow and vehicle arrivals.

3.2.4 Car following model parameters

level 4 autonomous vehicles (AVs) with human drivers in terms of driving behavior. The human agent's driver conforms to traditional basic car-following models sensitive to traffic state and outputting different reaction times.

While AVs had a wide range of car-following behaviors, ranging from cautious to aggressive, which influenced their ability to maintain suitable following distances and adapt to changing traffic situations. These parameters are illustrated in Table 4.

3.2.5 Lane change model parameters

In the study, various lane change model parameters are tailored according to different driving behaviors for autonomous vehicles (AVs), as well as for human drivers, to closely simulate real-world driving scenarios as seen in Table 5. Advanced merging is enabled across all categories, while cooperative lane change is activated for all except human drivers, highlighting a significant distinction in the technological integration between AVs and human-operated vehicles. The safety distance reduction factor varies significantly among the categories, with AV cautious mode maintaining a conservative 1.00 meter, AV normal reducing it to 0.60 meters, AV aggressive further reducing to 0.75 meters, and human drivers set at 0.60 meters. Minimum clearance (front/rear) is another parameter with notable differences; it is set at 1.00 meters for AV cautious mode to promote safer driving behavior, whereas it is reduced to 0.50 meters for the other modes. Furthermore, the maximum deceleration for cooperative braking is distinctly set at -2.50 m/s² for AV cautious, -3.00 m/s² for AV normal, -6.00 m/s² for AV aggressive, and -3.00 m/s² for human drivers, illustrating a varied approach to handling sudden decelerations in traffic flow.

Table 4. Car following model parameters for different driving behavior [27, 28]

Wiedemann 99 following model parameters	AV cautious	AV normal	AV aggressive	Human
CC0 Standstill distance	1.50 m	1.50 m	1.00 m	1.50 m
CC1 Gap time distribution	1.5 s	0.9 s	0.6 s	0.9 s
CC2 'Following' distance oscillation	0.00 m	0.00 m	0.00 m	4.00 m
CC3 Threshold for entering 'Following'	-10.00	-8.00	-6.00	-8.00
CC4 Negative speed difference	-0.10	-0.10	-0.10	-0.35
CC5 Positive speed difference	0.10	0.10	0.10	0.35
CC6 Distance dependency of oscillation	0.00	0.00	0.00	11.44
CC7 Oscillation acceleration	0.10 m/s2	0.10 m/s2	0.10 m/s2	0.25 m/s2
CC8 Acceleration from standstill	3.00 m/s2	3.50 m/s2	4.00 m/s2	3.50 m/s2
CC9 Acceleration at 80 km/h	1.20 m/s2	1.50 m/s2	2.00 m/s2	1.50 m/s2

Table 5. Lane change model parameters for different driving behavior [27, 28]

Parameter's	AV cautious	AV normal	AV aggressive	Human
Advanced merging	on	on	on	on
Cooperative Lane change	on	on	on	off
Safety distance reduction Factor	1.00 m	0.60	0.75	0.60 m
Min clearance (front/rear)	1.00 m	0.50 m	0.50 m	0.50 m
Maximum deceleration for Cooperative braking	-2.50 m/s^2	-3.00 m/s^2	-6.00 m/s^2	-3.00 m/s^2

3.2.6 AVs desired speed distribution

AVs are programmed to accelerate smoothly without having any bias to the preferred speed within this range. The linear trend shown in Figure 5 implies that the speed closer to the upper limit (160 km/hr) or farther from the lower limit (140 km/hr) at which an AV decides to travel is directly proportional to the speed with which it was selected. This simple distribution model is important for simulating high-speed driving circumstances on freeways when vehicles should keep on changing pace in either efficiency or safety. This uniformity in the distribution clearly points to the algorithmic preciseness in speed management, adhered to by AVs, for the systematic optimization of traffic flow and reduction of congestion.

1.3. Experimental Scenarios

The experimental scenarios were meticulously designed to explore the diverse impacts of autonomous vehicles (AVs) under varying conditions. Each scenario represented a unique combination of simulation period, traffic volume, and AV behavior, allowing for comprehensive analysis. For instance, scenarios ranged from a simulation period of 3600 seconds to 7200 seconds, covering different durations of traffic flow observation. Traffic volumes varied from 350 vehicles to 950 vehicles, representing a spectrum of traffic densities as illustrated in Table 6. AV categorized it into four different types of behavior: human-like driving, cautious driving, normal driving, aggressive driving, aggressive platoons, and Mix of All AVs & human. In this way, it was possible to consider how the behaviors of such AVs, together with several traffic volumes and simulation times, impact travel times and vehicle arrivals on the Kirkuk-Sulaymaniyah highway.

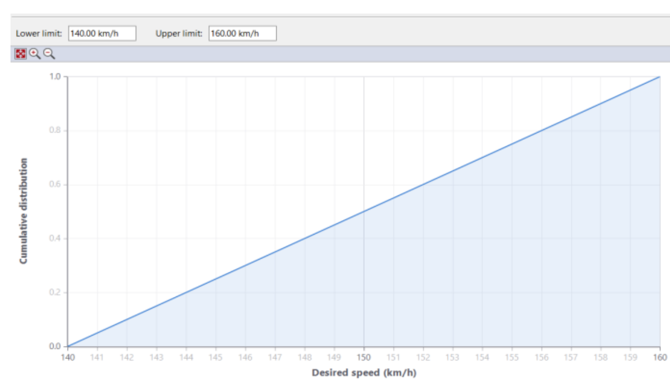

Fig. 5. Speed distribution for AVs vehicles

1.4. Model Validation

The simulation outputs for average travel times show that with the increase in the number of vehicles from 350 to 950, the travel time ranged from 2738.67 seconds (45.64 minutes approximately) for 350 vehicles to 2781.73 seconds (46.36 minutes approximately) for 950 vehicles. As demonstrated by this data from the simulation, with the increase of traffic volumes, travel times increase only slightly, as one would expect from the expected dynamics of traffic.

Table 6. Summary of scenarios with varying AV behaviors, traffic volumes, and simulation periods

Scenario	Simulation Period (Sec)	Traffic Volume (Veh)	Behavior	Scenario	Simulation Period (Sec)	Traffic Volume (Veh)	Behavior
1	3600	350	human	**46**	5400	650	Av Aggressive
2	3600	350	Av Cautious	**47**	5400	650	Av Aggressive Platoons
3	3600	350	Av Normal	**48**	5400	650	Mix of All AVs & human
4	3600	350	Av Aggressive	**49**	5400	800	human
5	3600	350	Av Aggressive Platoons	**50**	5400	800	Av Cautious
6	3600	350	Mix of All AVs & human	**51**	5400	800	Av Normal
7	3600	500	human	**52**	5400	800	Av Aggressive
8	3600	500	Av Cautious	**53**	5400	800	Av Aggressive Platoons
9	3600	500	Av Normal	**54**	5400	800	Mix of All AVs & human
10	3600	500	Av Aggressive	**55**	5400	950	human
11	3600	500	Av Aggressive Platoons	**56**	5400	950	Av Cautious
12	3600	500	Mix of All AVs & human	**57**	5400	950	Av Normal
13	3600	650	human	**58**	5400	950	Av Aggressive
14	3600	650	Av Cautious	**59**	5400	950	Av Aggressive Platoons
15	3600	650	Av Normal	**60**	5400	950	Mix of All AVs & human
16	3600	650	Av Aggressive	**61**	7200	350	human
17	3600	650	Av Aggressive Platoons	**62**	7200	350	Av Cautious
18	3600	650	Mix of All AVs & human	**62**	7200	350	Av Normal
19	3600	800	human	**64**	7200	350	Av Aggressive
20	3600	800	Av Cautious	**65**	7200	350	Av Aggressive Platoons
21	3600	800	Av Normal	**66**	7200	350	Mix of All AVs & human
22	3600	800	Av Aggressive	**67**	7200	500	human
23	3600	800	Av Aggressive Platoons	**68**	7200	500	Av Cautious
24	3600	800	Mix of All AVs & human	**69**	7200	500	Av Normal
25	3600	950	human	**70**	7200	500	Av Aggressive
26	3600	950	Av Cautious	**71**	7200	500	Av Aggressive Platoons
27	3600	950	Av Normal	**72**	7200	500	Mix of All AVs & human
28	3600	950	Av Aggressive	**73**	7200	650	human
29	3600	950	Av Aggressive Platoons	**74**	7200	650	Av Cautious
30	3600	950	Mix of All AVs & human	**75**	7200	650	Av Normal
31	5400	350	human	**76**	7200	650	Av Aggressive
32	5400	350	Av Cautious	**77**	7200	650	Av Aggressive Platoons
33	5400	350	Av Normal	**78**	7200	650	Mix of All AVs & human
34	5400	350	Av Aggressive	**79**	7200	800	human
35	5400	350	Av Aggressive Platoons	**80**	7200	800	Av Cautious
36	5400	350	Mix of All AVs & human	**81**	7200	800	Av Normal
37	5400	500	human	**82**	7200	800	Av Aggressive
38	5400	500	Av Cautious	**83**	7200	800	Av Aggressive Platoons
39	5400	500	Av Normal	**84**	7200	800	Mix of All AVs & human
40	5400	500	Av Aggressive	**85**	7200	950	human
41	5400	500	Av Aggressive Platoons	**86**	7200	950	Av Cautious
42	5400	500	Mix of All AVs & human	**87**	7200	950	Av Normal
43	5400	650	human	**88**	7200	950	Av Aggressive
44	5400	650	Av Cautious	**89**	7200	950	Av Aggressive Platoons
45	5400	650	Av Normal	**90**	7200	950	Mix of All AVs & human

Real-world conditions, the travel times were between 1 hour and 1 hour and 20 minutes for a similar route. This discrepancy between the simulated and actual travel times could perhaps be accounted for by further delays at three traffic clearance points encountered on the road. Each clearance point might have another five to ten minutes each, per checkpoint. With the inclusion of these delay times in the simulation results, the adjusted simulated travel times brought the simulated travel times almost in line with observed real travel times, thereby confirming that the simulation model used was accurate and reliable to represent human driving behaviors under varying traffic volumes. This sustains the realism of the effectiveness of the model in reflecting realistic traffic conditions and thus provides a strong underpinning for further exploration of autonomous vehicle impacts in such traffic scenarios.

Results

1.5. Simulation Period Influence on AV Arrival Rates

The impact of the simulation time span on AV arrival rates is very important when considering the understanding of the behavior and impacts of AVs on traffic dynamics. From other characteristics set by other simulation periods, traffic volume, and the behavior of AVs, there was a large difference in the number of AVs that reached the endpoint, as shown by Figure 6. For example, in Scenario 1, where the simulation period is 3600 seconds and the traffic volume is 350 vehicles, the number of arrivals from AVs running under cautious mode (Scenario 2) was 118, slightly higher than those under human driving conditions, which had 86 vehicles. Similarly, AVs in normal driving behavior (Scenario 3) and aggressive driving behavior (Scenario 4) exhibited arrival rates of 120 and 132 vehicles, respectively, while AVs forming aggressive platoons (Scenario 5) arrived at a slightly lower rate of 113 vehicles. In the Mix scenario (Scenario 6), the number of arrivals was 119 vehicles. As the traffic volume increased to 500 vehicles (Scenarios 7-12), 650 vehicles (Scenarios 13-18), 800 vehicles (Scenarios 19-24), and 950 vehicles (Scenarios 25-30), the arrival rates for AVs across different behaviors also increased. For instance, at 500 vehicles, the arrival rates for AVs were 161 (cautious), 168 (normal), 202 (aggressive), 147 (aggressive platoons), and 164 (Mix scenario), compared to 122 for human-driven vehicles. At 650 vehicles, the arrival rates for AVs were 208 (cautious), 222 (normal), 279 (aggressive), 199 (aggressive platoons), and 215 (Mix scenario), compared to 154 for human-driven vehicles. At 800 vehicles, the arrival rates were 262 (cautious), 275 (normal), 350 (aggressive), 236 (aggressive platoons), and 268 (Mix scenario), compared to 175 for human-driven vehicles. Finally, at 950 vehicles, the arrival rates were 317 (cautious), 341 (normal), 404 (aggressive), 301 (aggressive platoons), and 329 (Mix scenario), compared to 238 for human-driven vehicles. Notably, AVs in aggressive driving behavior consistently exhibited higher arrival rates compared to cautious and normal driving behaviors across all traffic volumes. This trend persisted as the simulation period remained constant at 3600 seconds.

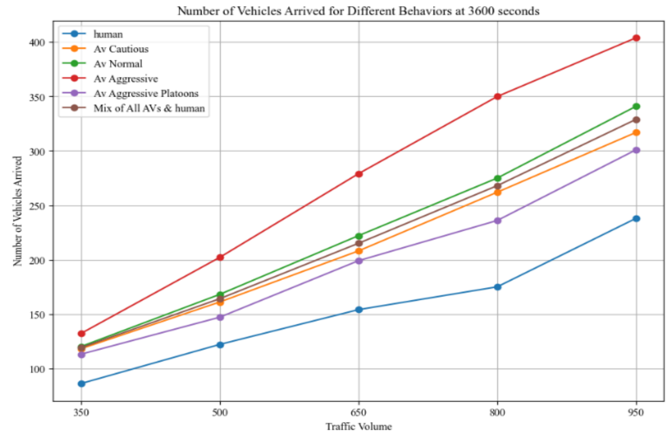

Fig. 6. Comparative arrival rates of different driving behaviors at various traffic volumes over a 3600-second simulation period

However, with a simulation period of 5400 seconds, a noticeable divergence emerges in the arrival rates of autonomous vehicles (AVs) across various behaviors and traffic volumes, as illustrated in Figure 7. Despite the longer observation duration, the arrival rates of AVs continue to fluctuate, reflecting the dynamic nature of traffic flow and AV interactions. For instance, under Scenario 37 with a traffic volume of 500 vehicles, human-driven vehicles witnessed an arrival rate of 388, while AVs in cautious mode (Scenario 38) exhibited a slightly higher arrival rate of 423 vehicles. This trend persisted across different behaviors, with AVs displaying varying arrival rates based on their driving modes. AVs in normal driving behavior (Scenario 39) and aggressive driving behavior (Scenario 40) exhibited arrival rates of 426 and 449 vehicles, respectively, while AVs forming aggressive platoons (Scenario 41) arrived at a rate of 415 vehicles. In the Mix scenario (Scenario 42), the arrival rate was 425 vehicles. As the traffic volume increased to 650 vehicles (Scenarios 43-48), 800 vehicles (Scenarios 49-54), and 950 vehicles (Scenarios 55-60), the arrival rates for both human-driven vehicles and AVs across different behaviors also increased. For instance, at 650 vehicles, the arrival rates for AVs were 548 (cautious), 553 (normal), 587 (aggressive), 536 (aggressive platoons), and 551 (Mix scenario), compared to 508 for human-driven vehicles. At 800 vehicles, the arrival rates for AVs were 665 (cautious), 668 (normal), 705 (aggressive), 650 (aggressive platoons), and 667 (Mix scenario), compared to 608 for human-driven vehicles. Finally, at 950 vehicles, the arrival rates for AVs were 792 (cautious), 798 (normal), 849 (aggressive), 777 (aggressive platoons), and 795 (Mix scenario), compared to 714 for human-driven vehicles. Notably, aggressive driving behaviors (Scenarios 40, 46, 52, and 58) consistently resulted in higher AV arrival rates compared to cautious or normal behaviors, indicating a potential impact of driving style on traffic dynamics. This trend highlights the significant influence of AV driving behavior and traffic volume on arrival rates within the extended simulation period of 5400 seconds.

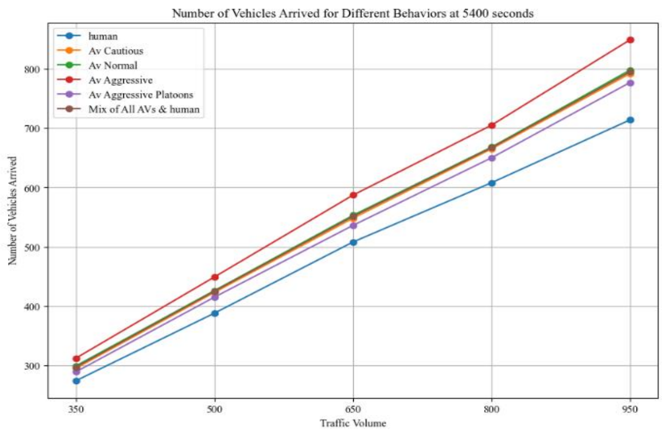

Fig. 7. Comparative arrival rates of different driving behaviors at various traffic volumes over a 5400-second simulation period

With a simulation period of 7200 seconds, significant fluctuations in the arrival rates of autonomous vehicles (AVs) are observed across different driving behaviors and traffic volumes as illustrated in Figure 8. Extending the observation time to such a long duration proves that AV arrival rates remain consistent, demonstrating that the dynamic process of traffic flow and AV interaction exhibits stable characteristics over time. For instance, under Scenario 61 with a traffic volume of 350 vehicles, human-operated vehicles had an arrival rate of 425, whereas for Scenario 62, with AVs in cautious mode, the arrival rate was slightly higher at 450 vehicles. This trend persisted across all behaviors, with AVs showing different arrival rates depending on their driving nature. AVs in normal driving behavior (Scenario 63) and aggressive driving behavior (Scenario 64) exhibited arrival rates of 453 and 499 vehicles, respectively, while AVs forming aggressive platoons (Scenario 65) arrived at a rate of 439 vehicles. In the Mix scenario (Scenario 66), the arrival rate was 452 vehicles. As the traffic volume increased to 500 vehicles (Scenarios 67-72), 650 vehicles (Scenarios 73-78), 800 vehicles (Scenarios 79-84), and 950 vehicles (Scenarios 85-90), the arrival rates for both human-driven vehicles and AVs across different behaviors also increased. For instance, at 500 vehicles, the arrival rates for AVs were 649 (cautious), 653 (normal), 680 (aggressive), 643 (aggressive platoons), and 651 (Mix scenario), compared to 612 for human-driven vehicles. At 650 vehicles, the arrival rates for AVs were 833 (cautious), 838 (normal), 885 (aggressive), 825 (aggressive platoons), and 836 (Mix scenario), compared to 790 for human-driven vehicles. At 800 vehicles, the arrival rates were 1041 (cautious), 1045 (normal), 1091 (aggressive), 1034 (aggressive platoons), and 1043 (Mix scenario), compared to 971 for human-driven vehicles. Finally, at 950 vehicles, the arrival rates were 1228 (cautious), 1247 (normal), 1311 (aggressive), 1223 (aggressive platoons), and 1238 (Mix scenario), compared to 1167 for human-driven vehicles. Importantly, aggressive driving styles (Scenarios 64, 70, 76, 82, and 88) consistently resulted in higher AV arrival rates compared to cautious or normal driving behaviors, indicating a potential effect of driving style on traffic flow. This analysis underscores the significant impact of AV driving behavior and traffic volume on arrival rates within the extended simulation period of 7200 seconds.

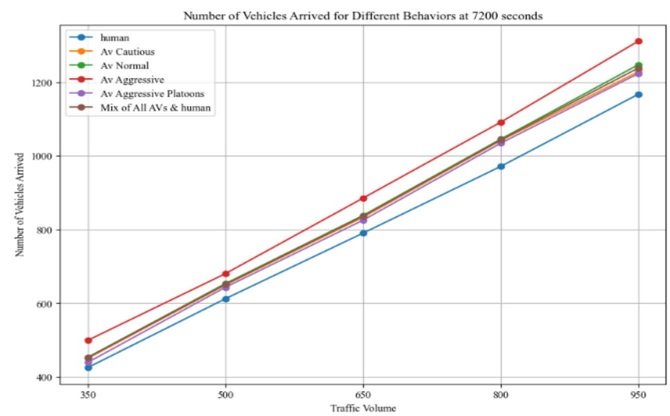

Fig. 8. Comparative arrival rates of different driving behaviors at various traffic volumes over a 7200-second simulation period

1.6. Simulation Period Influence on AV Travel Time

The influence of the simulation period on autonomous vehicle (AV) travel time is evident across various driving behaviors and traffic volumes. As depicted in the results, the average travel time for AVs varies significantly depending on the simulation duration, as shown in Figure 9. For instance, under Scenario 1 with a simulation period of 3600 seconds and a traffic volume of 350 vehicles, human-driven vehicles exhibited an average travel time of 2738.67 seconds. However, AVs operating in cautious mode (Scenario 2) demonstrated a notably lower average travel time of 2431.61 seconds, indicating improved efficiency in travel under AV operation. This trend persisted across different behaviors and traffic volumes, with AVs consistently displaying shorter average travel times compared to human-driven vehicles. For example, AVs in normal driving behavior (Scenario 3) and aggressive driving behavior (Scenario 4) exhibited average travel times of 2408.61 and 2129.29 seconds, respectively, while AVs forming aggressive platoons (Scenario 5) had an average travel time of 2503.06 seconds. In the Mix scenario (Scenario 6), the average travel time was 2420.11 seconds. As the traffic volume increased to 500 vehicles (Scenarios 7-12), 650 vehicles (Scenarios 13-18), 800 vehicles (Scenarios 19-24), and 950 vehicles (Scenarios 25-30), there was a general upward trend in average travel time for both human-driven vehicles and AVs, suggesting potential congestion effects. For example, at 500 vehicles, the average travel times for AVs were 2443.99 (cautious), 2410.95 (normal), 2139.63 (aggressive), 2514.88 (aggressive platoons), and 2427.47 (Mix scenario), compared to 2734.34 for human-driven vehicles. At 650 vehicles, the average travel times for AVs were 2467.02 (cautious), 2411.23 (normal), 2131.60 (aggressive), 2522.77 (aggressive platoons), and

2439.12 (Mix scenario), compared to 2740.96 for human-driven vehicles. At 800 vehicles, the average travel times were 2492.01 (cautious), 2414.54 (normal), 2146.62 (aggressive), 2534.16 (aggressive platoons), and 2453.28 (Mix scenario), compared to 2759.70 for human-driven vehicles. Finally, at 950 vehicles, the average travel times were 2483.99 (cautious), 2409.34 (normal), 2162.35 (aggressive), 2528.39 (aggressive platoons), and 2446.67 (Mix scenario), compared to 2781.73 for human-driven vehicles. Notably, aggressive driving behaviors (Scenarios 4, 10, 16, 22, and 28) consistently resulted in shorter average travel times for AVs compared to cautious or normal behaviors, indicating a potential trade-off between travel time and driving style.

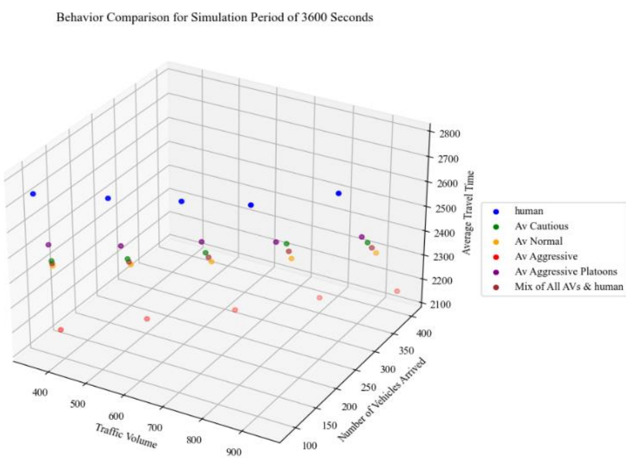

Fig. 9. 3D visualization of average travel time, number of vehicles arrived, and traffic volume by driving behavior over a 3600-second simulation period

However, with a simulation period of 5400 seconds, the dynamics of autonomous vehicle (AV) travel time demonstrate notable shifts across different driving behaviors and traffic volumes, as shown in Figure 10. As illustrated in the data, AVs exhibit varying average travel times under different driving modes and traffic conditions. For instance, under Scenario 31 with a traffic volume of 350 vehicles, human-driven vehicles recorded an average travel time of 2744.94 seconds. In contrast, AVs operating cautiously (Scenario 32) displayed a reduced average travel time of 2425.39 seconds, indicating enhanced efficiency in travel under AV control. This trend continued across different behaviors and traffic volumes, with AVs consistently showing shorter average travel times compared to human-driven vehicles. For example, AVs in normal driving behavior (Scenario 33) and aggressive driving behavior (Scenario 34) exhibited average travel times of 2412.56 and 2145.73 seconds, respectively, while AVs forming aggressive platoons (Scenario 35) had an average travel time of 2508.52 seconds. In the Mix scenario (Scenario 36), the average travel time was 2418.98 seconds. As the traffic volume increased to 500 vehicles (Scenarios 37-42), 650 vehicles (Scenarios 43-48), 800 vehicles (Scenarios 49-54), and 950 vehicles (Scenarios 55-60), there was a general upward trend in average travel time for both human-driven vehicles and AVs, suggesting potential congestion effects. For example, at 500 vehicles, the average travel times for AVs were 2438.92 (cautious), 2408.25 (normal), 2147.31 (aggressive), 2517.79 (aggressive platoons), and 2423.58 (Mix scenario), compared to 2742.21 for human-driven vehicles. At 650 vehicles, the average travel times for AVs were 2452.15 (cautious), 2411.93 (normal), 2165.78 (aggressive), 2524.83 (aggressive platoons), and 2432.04 (Mix scenario), compared to 2749.51 for human-driven vehicles. At 800 vehicles, the average travel times were 2480.16 (cautious), 2413.44 (normal), 2164.01 (aggressive), 2527.46 (aggressive platoons), and 2446.80 (Mix scenario), compared to 2768.54 for human-driven vehicles. Finally, at 950 vehicles, the average travel times were 2496.24 (cautious), 2418.40 (normal), 2209.67 (aggressive), 2528.53 (aggressive platoons), and 2457.32 (Mix scenario), compared to 2789.05 for human-driven vehicles. Notably, aggressive driving behaviors (Scenarios 34, 40, 46, 52, and 58) consistently resulted in further reductions in average travel time for AVs.

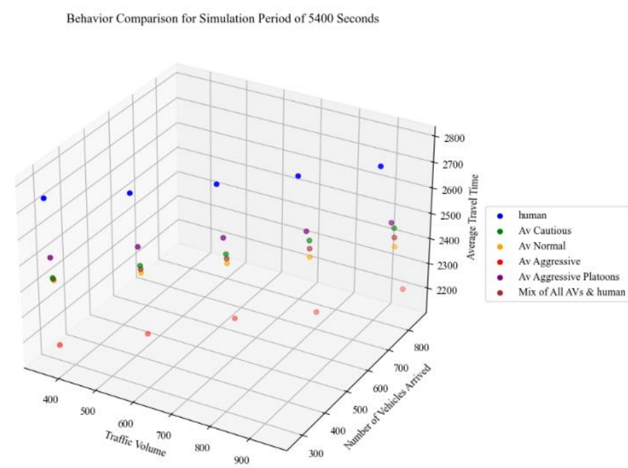

Fig. 10. 3D visualization of average travel time, number of vehicles arrived, and traffic volume by driving behavior over a 5400-second simulation period

With a simulation period of 7200 seconds, the impact on the average travel time of autonomous vehicles (AVs) becomes more pronounced across various driving behaviors and traffic volumes, as shown in Figure 11. In Scenario 67, where human-driven vehicles are predominant, the average travel time is recorded at 2746.04 seconds for a traffic volume of 500 vehicles. In comparison, AVs operating cautiously (Scenario 68) demonstrate a slightly reduced average travel time of 2435.98 seconds, highlighting the efficiency of AVs in managing travel time. Similarly, AVs operating under normal and aggressive behaviors exhibit average travel times of 2406.37 seconds and 2142.48 seconds, respectively, indicating variations in travel efficiency based on driving style. Interestingly, aggressive platoons of AVs (Scenario 71) display an average travel time of 2515.63 seconds, suggesting potential congestion effects or differences in platooning dynamics. As traffic volume increases, both human-driven vehicles and AVs experience longer average travel times, with AVs generally maintaining shorter travel times across different behaviors. For instance, at 650 vehicles (Scenarios 73-78), the average travel times for AVs were 2456.34 (cautious), 2410.33 (normal), 2165.72 (aggressive), 2519.72 (aggressive platoons), and 2433.33 (Mix scenario), compared to 2770.50 for human-driven vehicles. At 800 vehicles (Scenarios 79-84), the average travel times for AVs were 2473.27 (cautious), 2415.48 (normal), 2179.31 (aggressive), 2526.42 (aggressive platoons), and 2444.37 (Mix scenario), compared to 2780.55 for human-driven vehicles. Finally, at 950 vehicles (Scenarios 85-90), the average travel times for AVs were 2494.50 (cautious), 2418.67 (normal), 2200.62 (aggressive), 2530.38 (aggressive platoons), and 2456.58 (Mix scenario), compared to 2792.62 for human-driven vehicles. Notably, aggressive driving behaviors (Scenarios 70, 76, 82, and 88) consistently resulted in shorter average travel times for AVs compared to cautious or normal behaviors, indicating a potential trade-off between travel time and driving style. This analysis underscores the significant influence of AV driving behavior and traffic volume on average travel time within the 7200-second simulation period.

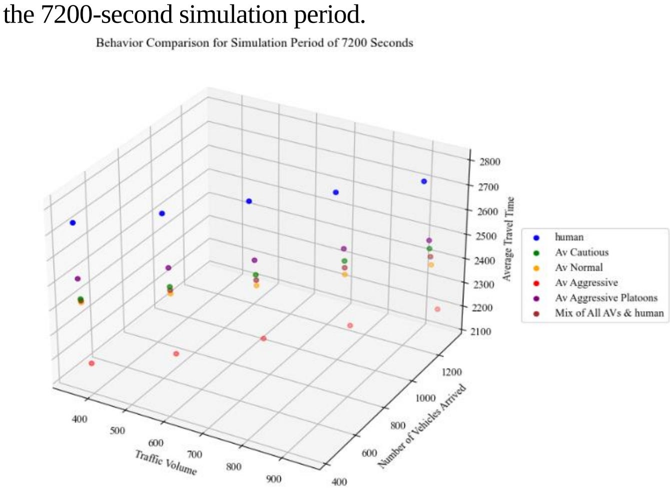

Fig. 11. 3D visualization of average travel time, number of vehicles arrived, and traffic volume by driving behavior over a 7200-second simulation period

Discussion

Such results, which have been obtained analytically in this study, provoke investigations into the deeper implications of the integration of AVs in the traffic dynamics. These discrepancies in the rate of arrival of AVs and travel times, observed under various simulation periods and driving behaviors, underline the interaction of technology, infrastructure, and human factors in shaping transportation systems. Notably, AVs operating cautiously recorded smooth running with shorter travel times compared to scenarios with human drivers. This study also highlights the existing challenges and opportunities regarding the deployment of AVs in managing aggressive driving behaviors and optimizing platooning strategies to minimize congestion and improve overall traffic performance. Based on the findings, AVs reduce travel time and enhance roadway capacity, but these benefits are contingent on traffic volume, driving behavior, and simulation time conditions. The inclusion of a mix of AVs and human drivers presents an additional layer of complexity, reflecting real-world conditions where different vehicle types and driving styles coexist. This mixed scenario shows that integrating AVs into the current transportation system can lead to varying outcomes based on the proportion of AVs and their driving behaviors. The wider implications for urban mobility and transport planning are also significant. As autonomous vehicle technologies continue to mature, policymakers and urban planners will need to be prepared for changes in travel behavior, mode choice, and infrastructure needs. Regulatory frameworks, safety standards, and public acceptance are crucial for integrating AVs into the existing transport system to maximize the benefits of this revolutionary technology. This research contributes to the nascent literature on autonomous vehicles and traffic dynamics, shedding light on the challenges and opportunities involved in integrating AVs within the transportation ecosystem. By investigating the interactions between AVs, human drivers, and traffic conditions, this study provides a foundation for decision-making and policy development in the future of mobility within a rapidly changing urban landscape.

Conclusion

This study examined the impact of autonomous vehicles (AVs) on traffic dynamics, focusing on arrival rates and travel times across different simulation periods, traffic volumes, and driving behaviors. The findings revealed that AVs, particularly those operating in cautious mode, consistently demonstrated improved travel efficiency and reduced travel times compared to human-driven vehicles. This suggests that the adoption of AV technology has the potential to enhance traffic flow and alleviate congestion.

Nonetheless, the research also highlighted challenges related to aggressive driving behaviors and the optimization of platooning strategies. These challenges underscore the need for continued research and development to optimize AV integration into traffic systems. Additionally, the study emphasized the importance of regulatory frameworks, safety standards, and public acceptance in the successful deployment of AVs.

In conclusion, this research provides valuable insights into the effects of AVs on traffic dynamics and the broader implications for urban mobility and transport planning. By addressing the complex interactions between AVs, human drivers, and traffic conditions, the study offers a foundation for policymakers and urban planners to develop strategies that maximize the benefits of AV technology. Based on the study's findings, future research should focus on several key areas. Investigate the safety impacts of aggressive AV driving behaviors. Optimize platooning strategies and their effects on traffic flow. Conduct long-term simulations and pilot projects to understand AV influence over time. Integrate AVs with smart infrastructure to improve traffic management. Study public acceptance and interaction with AVs. Develop comprehensive regulatory frameworks. Assess and maximize the environmental benefits of AVs. These directions will help harness AV technology's potential and ensure successful integration into urban mobility.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

CRediT Author Statement

Mustafa Albdairi: Conceptualization, Writing-original draft, Validation, Data curation, Formal analysis
Ali Almusawi: Conceptualization, Supervision

References

[1] Dannemiller KA, Mondal A, Asmussen KE, Bhat CR. Investigating autonomous vehicle impacts on individual activity-travel behavior. Transp Res Part A Policy Pract. 2021;148:402-422. https://doi.org/10.1016/j.tra.2021.04.006

[2] Narayanan S, Chaniotakis E, Antoniou C. Factors affecting traffic flow efficiency implications of connected and autonomous vehicles: A review and policy recommendations. In: Milakis D, Thomopoulos N, van Wee B, editors. Advances in Transport Policy and Planning. Vol. 5. Academic Press; 2020. p. 1-50. https://doi.org/10.1016/bs.atpp.2020.02.004

[3] Parsa AB, Shabanpour R, Mohammadian A (Kouros), Auld J, Stephens T. A data-driven approach to characterize the impact of connected and autonomous vehicles on traffic flow. Transp Lett. 2020;13(10):687-695. https://doi.org/10.1080/19427867.2020.1776956

[4] Garrow LA, German BJ, Leonard CE. Urban air mobility: A comprehensive review and comparative analysis with autonomous and electric ground transportation for informing future research. Transp Res Part C Emerg Technol. 2021;132:103377. https://doi.org/10.1016/j.trc.2021.103377

[5] Utriainen R, Pöllänen M. Prioritizing Safety or Traffic Flow? Qualitative Study on Highly Automated Vehicles' Potential to Prevent Pedestrian Crashes with Two Different Ambitions. Sustainability. 2020;12(8):3206. https://doi.org/10.3390/su12083206

[6] Calvi A, D'Amico F, Ferrante C, Calcaterra G. A Driving Simulator Study on the Effects of Autonomous Vehicles on Drivers Behaviour Under Car-Following Conditions. In: Advances in Transportation. 2022;60:60-68. https://doi.org/10.54941/ahfe1002434

[7] Adamidis FK, Mantouka EG, Vlahogianni EI. Effects of controlling aggressive driving behavior on network-wide traffic flow and emissions. Int J Transp Sci Technol. 2020;9(3):263-276. https://doi.org/10.1016/j.ijtst.2020.05.003

[8] Zhang L, Chen F, Ma X, Pan X. Fuel Economy in Truck Platooning: A Literature Overview and Directions for Future Research. J Adv Transp. 2020;2020:2604012. https://doi.org/10.1155/2020/2604012

[9] Dannemiller KA, Asmussen KE, Mondal A, Bhat CR. Autonomous vehicle impacts on travel-based activity and activity-based travel. Transp Res Part C Emerg Technol. 2023;150:104107. https://doi.org/10.1016/j.trc.2023.104107

[10] Hu X, Zheng Z, Chen D, Sun J. Autonomous Vehicle's Impact on Traffic: Empirical Evidence From Waymo Open Dataset and Implications From Modelling. IEEE Trans Intell Transp Syst. 2023;24(6):6711-6724. https://doi.org/10.1109/TITS.2023.3258145

[11] Mohammed D, Horváth B. Travel Demand Increment Due to the Use of Autonomous Vehicles. Sustainability. 2023;15(11):8937. https://doi.org/10.3390/su15118937

[12] Kaltenhäuser B, Hamzehi S, Bogenberger K. The Impact of Autonomous Vehicles and Their Driving Parameters on Urban Road Traffic. In: Antoniou C, Busch F, Rau A, Hariharan M, editors. Proceedings of the 12th International Scientific Conference on Mobility and Transport. Lecture Notes in Mobility. Singapore: Springer; 2023. p. 3-19. https://doi.org/10.1007/978-981-19-8361-0_2

[13] Yu X, van den Berg VAC, Verhoef ET. Autonomous cars and activity-based bottleneck model: How do in-vehicle activities determine aggregate travel patterns?. Transp Res Part C Emerg Technol. 2022;139:103641. https://doi.org/10.1016/j.trc.2022.103641

[14] Desta R, Tóth J. Impacts of Autonomous Vehicle Driving Logics on Heterogenous Traffic and Evaluating Transport Interventions with Microsimulation Experiments. In: Krömker H, editor. HCI in Mobility, Transport, and Automotive Systems. HCII 2022. Lecture Notes in Computer Science. Vol. 13335. Cham: Springer; 2022. p. 355-370. https://doi.org/10.1007/978-3-031-04987-3_24

[15] Xie T, Liu Y. Impact of connected and autonomous vehicle technology on market penetration and route choices. Transp Res Part C Emerg Technol. 2022;139:103646. https://doi.org/10.1016/j.trc.2022.103646

[16] He BY, Jiang Q, Ma J. Connected automated vehicle impacts in Southern California part-I: Travel behavior and demand analysis. Transp Res Part D Transp Environ. 2022;109:103329. https://doi.org/10.1016/j.trd.2022.103329

[17] Hamadneh J, Esztergár-Kiss D. The Influence of Introducing Autonomous Vehicles on Conventional Transport Modes and Travel Time. Energies. 2021;14(14):4163. https://doi.org/10.3390/en14144163

[18] Maleki M, Chan Y, Arani M. Impact of Autonomous Vehicle Technology on Long Distance Travel Behavior. Presented at: Institute of Industrial and Systems Engineers (IISE) Annual Conference and Expo 2020; 2021. https://doi.org/10.48550/arXiv.2101.06097

[19] Sonnleitner J, Friedrich M, Richter E. Impacts of highly automated vehicles on travel demand: macroscopic modeling methods and some results. Transportation. 2022;49:927–950. https://doi.org/10.1007/s11116-021-10199-z

[20] Hamadneh J, Esztergár-Kiss D. Potential travel time reduction with autonomous vehicles for different types of travellers. Promet-Traffic&Transportation. 2021;33(1):61-76. https://doi.org/10.7307/ptt.v33i1.3585

[21] Liu P, Xu SX, Ong GP, Tian Q, Ma S. Effect of autonomous vehicles on travel and urban characteristics. Transp Res Part B Methodol. 2021;153:128-148. https://doi.org/10.1016/j.trb.2021.08.014

[22] Zhong H, Li W, Burris MW, Talebpour A, Sinha KC. Will autonomous vehicles change auto commuters' value of travel time? Transp Res Part D Transp Environ. 2020;83:102303. https://doi.org/10.1016/j.trd.2020.102303

[23] Hungness D, Bridgelall R. Model Contrast of Autonomous Vehicle Impacts on Traffic. J Adv Transp. 2020;2020:8935692.

https://doi.org/10.1155/2020/8935692

[24]Kröger L, Kuhnimhof T, Trommer S. Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. Transp Res Part A Policy Pract. 2019;122:146-161. https://doi.org/10.1016/j.tra.2018.03.033

[25]Eluru N, Choudhury CF. Impact of shared and autonomous vehicles on travel behavior. Transportation. 2019;46:1971-1974. https://doi.org/10.1007/s11116-019-10063-1

[26]Öner J, Ersoysal H. Uşak İlinde Meydana Gelen Trafik Kazalarının İncelenmesi. Avr Bilim Ve Teknol Derg. 2021;(31):298-308. https://doi.org/10.31590/ejosat.996702

[27]Osman A. Evaluation of The Impact of Automated Driven Vehicles on Traffic Performance at Four-leg Signalized Intersections [Dissertation]. Linköping University; 2023. https://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-192382

[28]Almusawi A, Albdairi M, Qadri SSSM. Microscopic insights into autonomous vehicles' impact on travel time and vehicle delay. In: IET Conference Proceedings, 4th International Conference on Distributed Sensing and Intelligent Systems (ICDSIS 2023); 2023. p. 442-450. https://doi.org/ 10.1049/icp.2024.0525