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Effects of Anthropomorphic Driving Vehicles on Traffic Flow

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Abstract: Autonomous driving has many positive impacts, such as improving driver and passenger safety, comfort, and traffic efficiency, but all these advantages are based on people's trust and acceptance of this mode of driving. Anthropomorphic driving can enhance the trust and comfort of drivers and passengers and is seen as a feasible measure to increase people's acceptance of autonomous driving. This paper reports the microscopic traffic simulation of three scenarios around a frequently congested intersection, using non-automated vehicles, autonomous driving vehicles, and anthropomorphic driving vehicles to explore their impact on traffic efficiency. The result shows that, compared to non-automated vehicles, both autonomous vehicles and anthropomorphic driving vehicles can improve traffic efficiency during congested periods, increase traffic volume per unit time, reduce the total travel time and time loss, and have a higher average speed. Compared to autonomous vehicles, anthropomorphic driving has a shorter total travel time and a similar time loss. In terms of average speed, anthropomorphic driving performed better than autonomous driving in terms of both congested and non-congested times. In summary, compared to non-automated vehicles, autonomous driving vehicles have a positive effect on improving traffic efficiency, while, compared to autonomous driving, anthropomorphic driving has more advantages in increasing traffic efficiency and reducing traffic congestion.

Keywords: anthropomorphic driving; microscopic traffic simulation; geographical population distribution; autonomous driving

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1. Introduction

Over the past four decades, the rapid development of autonomous driving has not only increased driving comfort and safety, reduced emissions, and increased convenience for people with disabilities, but has also brought about new hope for optimizing traffic flow and reduce traffic congestion [1–4]. In the realm of autonomous driving, many achievements are centered around autonomous driving decision making and control, involving machine learning, deep learning, and artificial intelligence (AI) [5–7]. At the same time, the implementation and application of connected autonomous vehicles (CAVs) is also a research direction that has received much attention in the field of autonomous vehicles [8–10].

The improvement in mobility is an unintended effect of autonomous vehicles. Vehicles with different levels of automation, including driving-assisted vehicles, partially automated vehicles, and fully autonomous (self-driving) vehicles, all alleviate traffic congestion to different degrees [11–13]. Unlike connected vehicles, which alleviate traffic congestion mainly by reducing or avoiding stop-and-go traffic through vehicle-to-vehicle communication [14,15], the positive effect of autonomous vehicles on traffic is mainly due to the

shortened reaction time and expected distance from the vehicle in front (desired headway) [16,17]. In comparison, the barriers to the implementation of CAVs are greater than those for autonomous vehicles. In addition to price and technical issues, CAVs also present more issues such as vehicle privacy and public acceptance [18–20].

Autonomous vehicles have many advantages, but their implementation also faces many challenges. In the early stages of the implementation of autonomous cars, public acceptance has an important impact on their popularity. Comfort and trust are important indicators that affect public acceptance. The machine-like behaviors of autonomous driving cause many problems that can be solved by anthropomorphic driving. In terms of driving comfort, autonomous vehicles make users lose control and unable to predict future trajectories, causing motion sickness (autonomous carsickness) [21]. In addition, all motion sickness issues represent a concern across all automation levels [22]. Anthropomorphic driving makes human-like driving characteristics possible in terms of trajectory planning [23], lane changing [24], speed maintenance [25], etc. These decision-making tools can be used to mitigate the effects of these driving modes on physiological well-being [26,27]. In terms of user trust and acceptance of autonomous vehicles, many studies show that human-like driving styles also increase user trust in autonomous driving [27,28]. Whether a driver chooses autonomous driving usually depends on their assessment of comfort, safety, and trust [27].

Anthropomorphic driving absorbs the characteristics of human driving to increase comfort and trust without replicating human mistakes. Human driver-related errors have always been a significant contributor to vehicle-related traffic accidents [29–31], accounting for as much as 80–94% of traffic accidents [29]. The risk factors of human drivers that cause accidents, such as alcohol, fatigue, and driver distraction, are all completely avoidable by a machine that does not become drunk, fatigued, or distracted. In addition, other reasons for human driver accidents, including unfamiliarity with a road [32] and poor prediction of other vehicles' behaviors [33,34], are alleviated by anthropomorphic autonomous driving, with machines completing road observation.

Both low-automation driver assistance vehicles and high-automation self-driving cars have been proven to be beneficial in alleviating traffic congestion and increasing traffic capacity [11–13]. The use of anthropomorphic autonomous driving vehicles may become inevitable for the implementation of autonomous driving vehicles. Will anthropomorphic autonomous driving vehicles reduce the positive impact of autonomous driving cars on traffic? And how much positive impact can they have on traffic congestion? This article explores the impact of anthropomorphic autonomous driving cars on traffic by comparing the traffic volume, travel time, time loss, and average speed of non-autonomous driving cars, autonomous driving cars, and anthropomorphic autonomous driving cars in the same traffic scenario.

Among the many differences in driving behaviors between human drivers and autonomous driving vehicles, three have the greatest impact: reaction time, irregular action points [35], and speed maximum longitudinal velocity [36]. The reaction time is affected by factors such as age, gender of the drivers, temperature, altitude of the environment [37], and unexpected situations [38]. However, human drivers' reaction time fluctuates in a relatively small range, from 0.9 s to 1.2 s [38] or 0.5 s to 2 s [39]. For autonomous vehicles, the reaction time is set to 0.5 s [35]. Another important difference between human drivers and machines is the irregular action points of human drivers [35]. The time intervals between the actions (pressing the accelerator and brake pedals) of human drivers follow a very broad distribution, with values between 0.5 and 1.5 s [35].

Another important parameter that distinguishes autonomous driving from human driving is the maximum longitudinal velocity [36]. The purpose of anthropomorphic driv-

ing is to incorporate human characteristics into autonomous driving to increase people's comfort and trust. People want to be driven the way they think they drive, regardless of how they actually drive [36]. Consequently, anthropomorphic driving is different from personalized driving. It does not involve driving according to the driving characteristics of each driver, but rather driving in a way that most people think is comfortable. A too-defensive driving style can reduce people's trust and even lead to the rejection of the autonomous driving system [36]. The strict enforcement of road speed limits may increase unnecessary acceleration and deceleration, reducing comfort. Human drivers are not constantly looking at the speedometer and strictly staying within the speed limit. However, autonomous vehicles set the road speed limit as their maximum speed.

This study selected a frequently congested intersection and used microscopic traffic simulation to restore the real traffic conditions with high precision. In different scenarios (non-autonomous driving scenario, autonomous driving scenario, and anthropomorphic driving scenario), the travel time, average speed, and waiting time of vehicles were compared to explore the impact of autonomous and anthropomorphic driving vehicles on traffic. We posited that, if anthropomorphic autonomous vehicles could maintain or even improve the positive impact of autonomous driving on traffic, this would be of great benefit to its popularization in autonomous driving. Moreover, we hypothesized that, if our results were to show that anthropomorphic autonomous vehicles could increase traffic volume, reduce travel time and time loss, and increase the average speed compared to non-automated driving vehicles, they could provide a reference value for traffic planning departments' inclination towards anthropomorphic autonomous driving.

2. Methodology

In this study, we conducted a traffic simulation in a region of Dalian, China, with a population of about 71,018 and severe traffic problems. The road network, traffic demand, and actual traffic conditions used for verification in this study were all sourced from public information on the Internet. In the traffic simulation of this area, non-automated driving, autonomous driving, and anthropomorphic automatic driving vehicle models were separately implemented to find out the impact of the latter on traffic in congested road conditions.

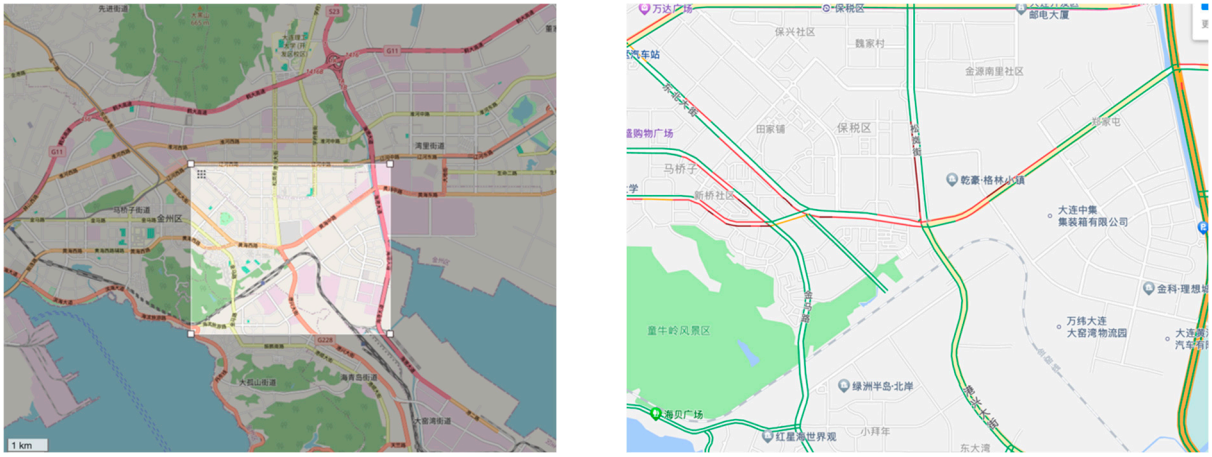
2.1. Road Network Establishment

In traffic simulations, a simulation that reproduces real-world traffic can better represent real traffic scenarios because of its high reproduction accuracy. Real-world traffic scenario reproduction has been carried out in many places, such as in Luxembourg city [40], Kobe city [41], Tokyo [42], Monaco [43], Duisburg [17], etc. Although traffic simulations in any city have their limitations, traffic simulations focusing on traffic-congested sections in large cities have great reference value for traffic congestion problems in other large cities.

A 22 km^2 road network around a frequently congested intersection in Dalian, China, was reproduced using the software SUMO (Simulation of Urban MObility) [44]. This intersection is called "Grimm's Town" Junction by locals, named after "Grimm's Town", the large community (with 3774 households) next to it. During the morning and evening rush hours, traffic at this intersection is always congested (Figure 1). Since all four sides of this intersection are main roads, passerby on these roads cannot avoid this intersection. Therefore, the road network near this intersection was chosen as the research object of this study to explore whether anthropomorphic driving could alleviate traffic congestion at such intersections.

For traffic simulation, the accuracy of the simulation is crucial to the credibility of the simulation results. In this work, the road network was imported from OSM (Open

Street Map) into SUMO and then calibrated through the street-view map on Baidu Maps. During the calibration process, based on the street-view map, the type of lane (public road/company internal road/non-motorized lane/highway/train track, etc.) was identified, while we corrected the number of lanes, the direction of traffic at the intersection (Figure 2), and whether there was a traffic light at the intersection. Since many intersections are large, the original road network imported by OSM often splits one intersection into several intersections (usually equipped with several traffic lights). During the calibration process, these intersections needed to be restored to one intersection.



(**a**) (**b**)

Figure 1. Simulated road network, where the middle intersection is the "Grimm's Town" Junction: (**a**) location of the simulated road network area; and (**b**) traffic conditions in the simulated area during the morning peak on weekdays.

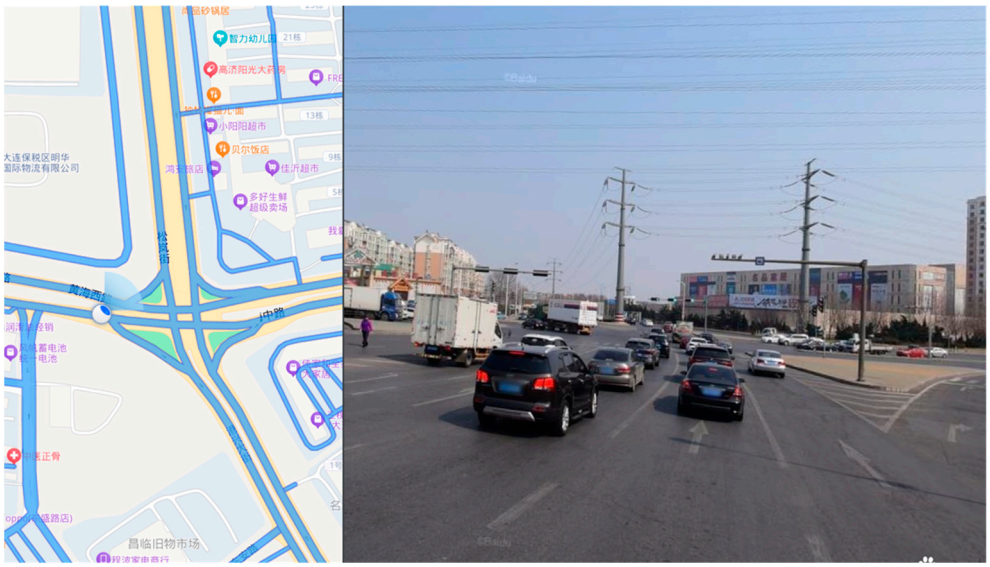


Figure 2. The street-view map in Baidu Maps can determine the direction of the lane at the intersection.

2.2. Traffic Demand Modeling

In order to restore a real traffic scenario, several commonly used sources of traffic demand data can be selected: OD matrices (origin/destination matrices), inductive loop data, and population data. OD matrix data describe the traffic demand between the origin point and the destination point in a road network. Since the OD matrix divides a city into many areas and regards them as points, describing the traffic volume between points, it is relatively accurate for simulating a complete city. Microscopic traffic simulations of

entire megacities often cause large traffic jams due to the large amount of calculations, which reduces the accuracy [45]. Inductive loop detectors buried in the road surface generate a signal indicating the presence of a vehicle over the loop [46]. The inductive loop data contain information such as vehicle length, speed, traffic volume, etc., but since it is impossible to track the vehicle and these detectors are usually not deployed at all intersections, accuracy in generating traffic demand cannot be guaranteed. In the present work, population data were used to generate traffic demand.

A previous work confirmed the accuracy of using population data to generate traffic demand [47], and the current study also used the same method to generate traffic demand. Figure 3 shows the regional division of the population information used to generate traffic demand. The pink areas are the residential areas, and the numbers above are the numbers of households in the area. The data were sourced from Lianjia.com, the largest local real estate agency. The blue areas are workplaces, and the number above is the number of workers. These data were derived from the number of employees that the companies in this area paid social security for [48]; these data were all public data, available on the Internet.

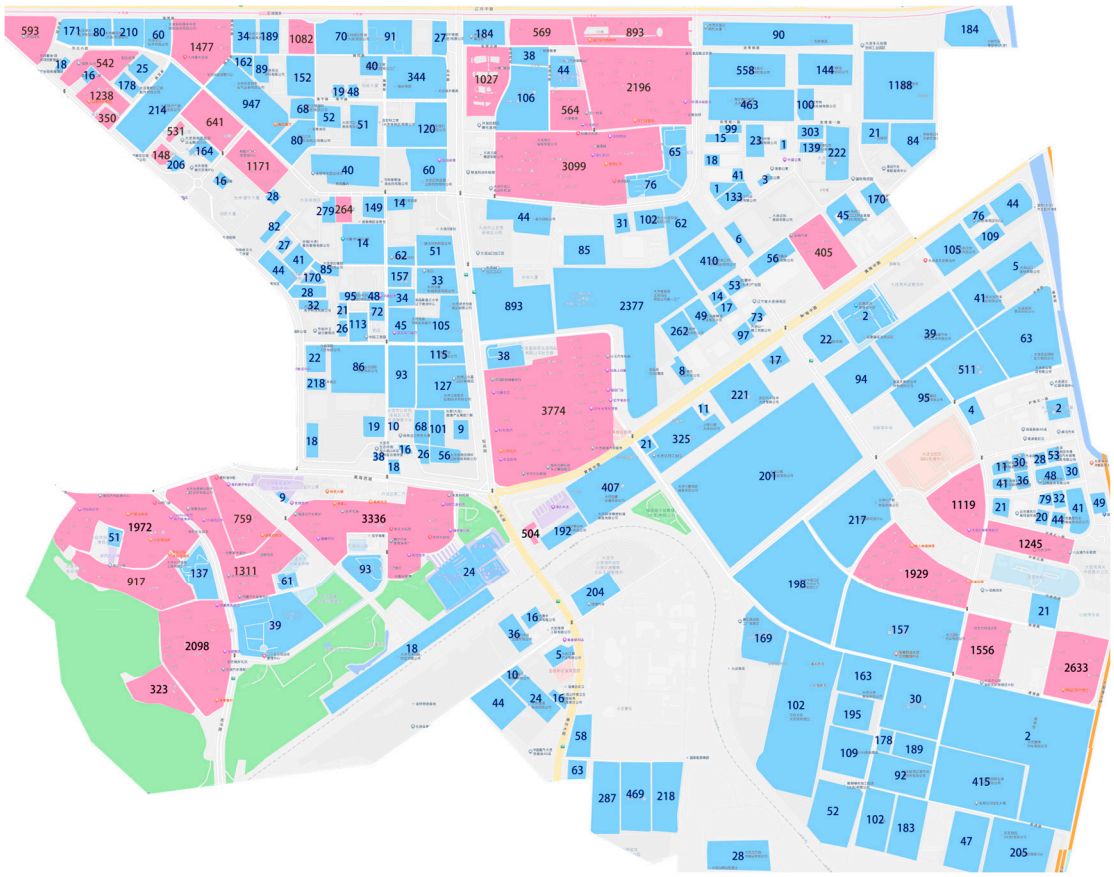


Figure 3. The street-view map in Baidu Maps can determine the direction of the lane at the intersection.

The simulated area is located in the Haiqingdao Sub-District, Jinzhou District, Dalian, China, with a total population of 71,018 people [49]. Taking into account China's average household population of 2.62 people [50], as well as the total number of local households and the total population, the housing vacancy rate was calculated to be 34.7%. In China, the number of temporary workers in a company must not exceed 10% of the total number of employees, so the number of jobs in each company was set to 110% of the number of people paying social insurance, rounded down. Next, the number of people in each area, shown in Figure 3, was allocated to the corresponding road network based on the location of each community entrance and the location of the company entrance on the map. In this study,

since private cars are the main cause of traffic congestion [51], only people traveling by their own car were simulated, and other modes of transportation (such as subways, buses, and company shuttle buses) were not considered in the traffic scenario. According to the results of the 2023 Urban Transportation Questionnaire, 35.89% of people were accustomed to traveling by private car [52].

2.3. Traffic Validation

To verify the traffic situation created by the software, we compared it to the real traffic data. In this study, a macroscopic-scale verification method was used. AutoNavi map [53] is supported by AutoNavi Software Co., Ltd. (Beijing, China), which provides real-time traffic in three colors: red indicates congestion, with an average speed of less than 5 km/h, yellow indicates a low speed, with an average speed of 5–30 km/h, and green indicates smooth traffic, with an average speed over 30 km/h. The traffic data in the AutoNavi map were collected in real time from different sources: 15% of data were from the traffic control department of the city, and AutoNavi map users accounted for the remaining 85% of data. In most cities in China, AutoNavi cooperates with taxi companies to gain their floating car data (FCD). AutoNavi obtains FCD from each user while they are uploading their position during navigation. Though these sources, AutoNavi obtains real-time traffic data with high accuracy and fidelity.

We selected the most representative road section in the road network, which is located at the same position as the inductive loops on the west side in 3.1. For the simulation data, the speed of the vehicles passing this verification point was recorded, and the data from multiple lanes on the same road section were averaged. For real-world data, the forecasted traffic status over 24 h on workdays was recorded. This forecast was provided by the AutoNavi map based on the data from the same day of the week, at the same time of the day. As can be seen from Figure 4, the simulation results were close to the real traffic conditions on weekdays, and the traffic scenario results were quite persuasive.

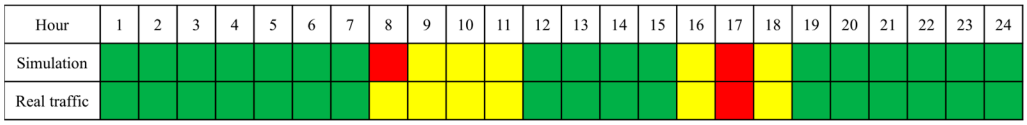


Figure 4. Comparison of simulated traffic and real traffic status. The colors represent the average speed of the vehicle when passing the verification point: green represents more than 30 km/h, yellow represents 5–30 km/h, and red represents less than 5 km/h.

2.4. Anthropomorphic Driving Vehicle Model

In this work, a driver–vehicle separate model was used for the simulation (see Figure 5). A clear benefit of this kind of model is its flexibility. The driver model can be combined with different vehicle models (fuel, electric, hybrid, etc.), and the vehicle model can also be combined with different driver models (autonomous driver, human driver, aggressive driver, etc.). The establishment and detailed parameters of the driver and vehicle model can be found in a previous work [54].

In this work, three scenarios with different vehicle types were constructed for the same road network: Scenario 1 for vehicles with no automation, Scenario 2 for autonomous vehicles, and Scenario 3 for autonomous vehicles with anthropomorphic driving. There are many differences between human driving and machine driving, and in the dynamic and ever-changing scenarios of traffic, the impacts they bring are also ever-changing. Since this study explored the impact of different types of driving (anthropomorphic autonomous driving, autonomous driving, and human driving) on traffic, it used the parameters with the greatest impact on traffic as the parameters of different driver–vehicle models. For

vehicles with different levels of automation, the most influential parameters are reaction time and different action points [35].

In SUMO software, the vehicle information was defined in the route file. Since the driver's reaction time fluctuates from 0.9 to 1.2 s [20] or 0.5 to 2 s [21], the reaction time τ_1 of the vehicles in Scenario 1 was set to 1 s. For the autonomous vehicle in Scenario 2, the reaction time τ_2 was set to 0.5 s [17]. The reaction time τ_3 of the anthropomorphic driving vehicles in Scenario 3 was the same as that of the autonomous vehicle, so it was also set to 0.5 s. Imperfection factor σ describes the irregular action point of human drivers and was set to 0.5 in Scenario 1 and 0 in the other scenarios. The speed factor describes the situation where the maximum speed of the vehicle exceeds the road speed limit. The speed parameter multiplied by the maximum speed limit of the road is the maximum speed that a vehicle can reach. More than half of human drivers exceed the speed limit in daily driving [55]. The speed factor for Scenario 1 and Scenario 3 was set to 1, with 95% of the vehicles driving between 80% and 120% of the legal speed limit. The speed factor for Scenario 2 was set to 0.8, representing a scenario in which the maximum speed of autonomous vehicles did not exceed the road speed limit. The parameters in different scenarios are listed in Table 1.

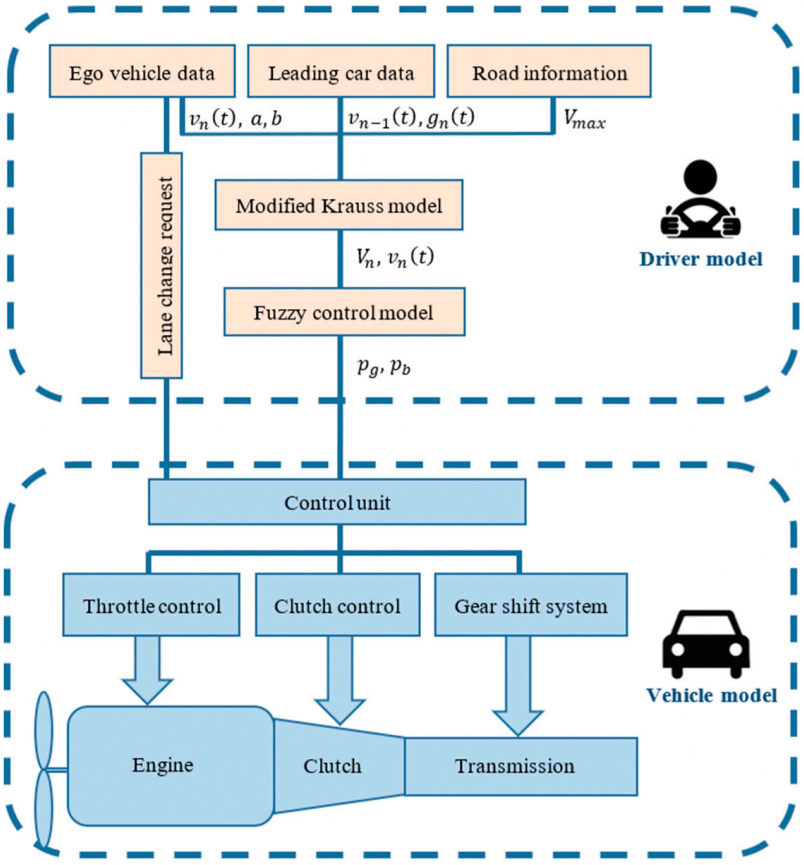


Figure 5. Driver and vehicle model structure used in the simulation.

Table 1. Parameters in different scenarios [17,20,21,55].

	Scenario 1 Non-Automation	Scenario 2 Autonomous	Scenario 3 Anthropomorphic
Reaction time τ	1	0.5	0.5
Imperfection factor σ	0.5	0	0
Speed factor	1	0.8	1

3. Results

In order to compare the vehicle driving conditions in different scenarios, different aspects such as traffic volume at major intersections, total driving and waiting time, and average speed were used for the analysis.

3.1. Traffic Volume

Inductive loops were installed in four directions at the main intersection—"Grimm's Town" Junction—in the road network. The yellow boxes on the black road in Figure 6 represent the locations of the inductive loops.

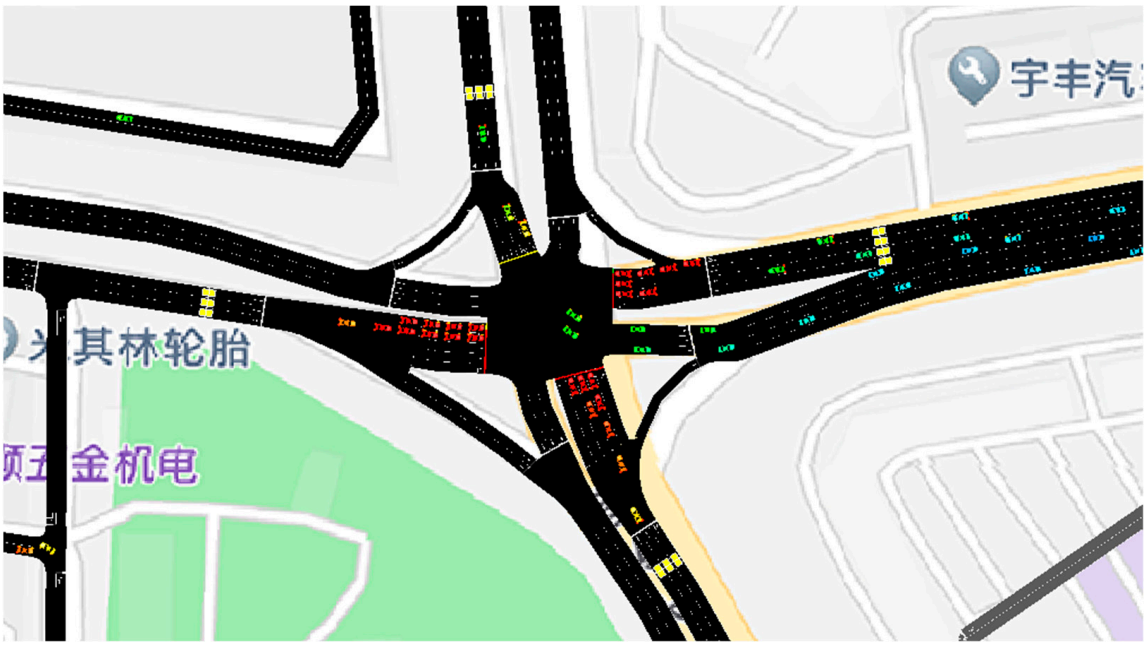
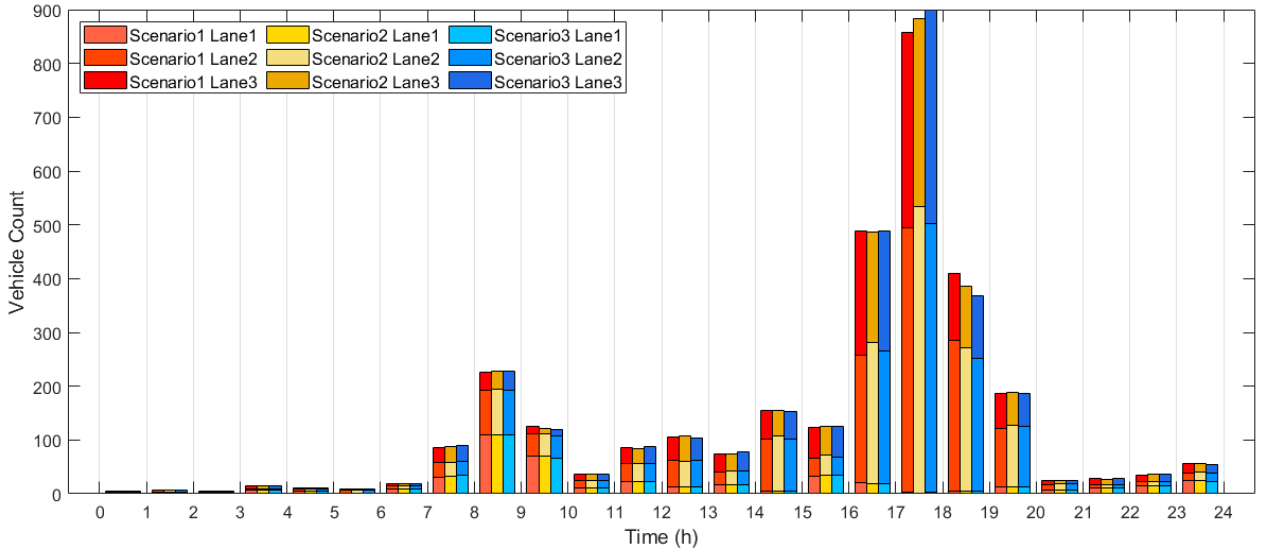


Figure 6. Position of the inductive loops.

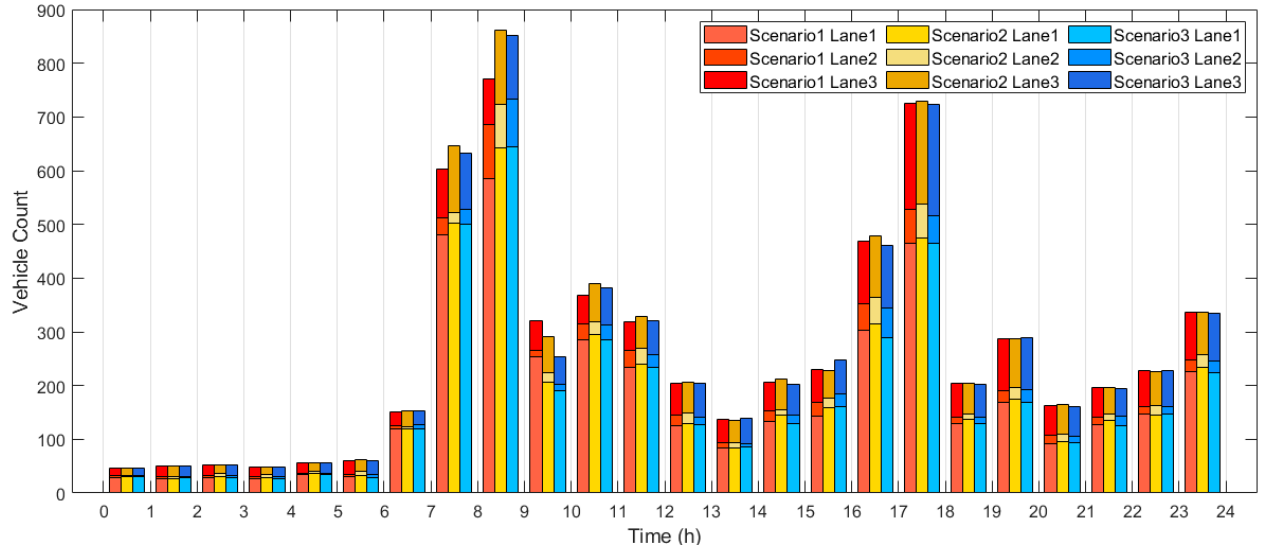
The colors of the vehicles in Figure 4 are displayed according to their speed, with red representing a low speed and blue representing a high speed. Like real inductive loops, the inductive loops in the simulation also recorded the time, speed, vehicle length, and other information for each vehicle passing a specific point and could output the number of vehicles passing said point per minute/hour, according to the time interval set by the user.

Figure 7 shows a set of inductive loop data results. Figure 7a shows the inductive loop data recorded at the bottom (south) of Figure 6, and Figure 7b shows the set recorded to the left (west) of Figure 6. Each column is the sum of the number of vehicles in the three lanes per hour. The route files of the vehicles in each scenario were the same, that is, the paths and departure times of the vehicles were the same, but the number of vehicles passing through this set of inductive loops was different in each scenario. Figure 7a shows that, during the morning peak congestion period (between 8 and 9 o'clock), more vehicles passed through the point in Scenario 2 than in Scenario 1, and the number of vehicles passing through the point in Scenario 3 was essentially the same as in Scenario 2. During the evening rush hour (between 17 and 18 o'clock), when the traffic volume increased significantly, the vehicle count in Scenario 2 was higher than in Scenario 1, and in Scenario 3, it was even higher. This showed that, at this intersection, the traffic efficiency of autonomous vehicles was higher than that of non-automated vehicles, and the traffic efficiency of anthropomorphic driving was higher than that of non-automated vehicles and, at least, not lower than that of autonomous vehicles. Meanwhile, the road section shown in Figure 7b was more congested during the morning rush hour. Between 7 and 9 o'clock, the count of vehicles in Scenarios

2 and 3 was significantly higher than in Scenario 1, but the count in Scenario 3 was slightly lower than in Scenario 2. This shows that the traffic efficiency of both autonomous driving and anthropomorphic driving is higher than that of non-automated vehicles, but the traffic volume of anthropomorphic driving on this road section is slightly lower than that of autonomous driving.



(**a**)



(**b**)

Figure 7. Traffic volume of inductive loops in different scenarios: (**a**) data recorded from the south inductive loops and (**b**) data recorded from the west inductive loops.

3.2. Travel Time and Time Loss

Travel time is the time it takes a vehicle to travel from its departure point to its destination, while time loss describes the time lost due to driving below the ideal speed. Figure 8 shows the travel time and time loss in different scenarios. It is apparent from Figure 8 that the travel time and time loss of Scenarios 2 and 3 were lower than in Scenario 1. In the comparison between Scenario 2 and Scenario 3, the time loss was not much different, but there were more vehicles with a longer travel time in Scenario 2. This shows that anthropomorphic driving is better than autonomous driving in shortening travel time, but its time loss is roughly the same as in autonomous driving.

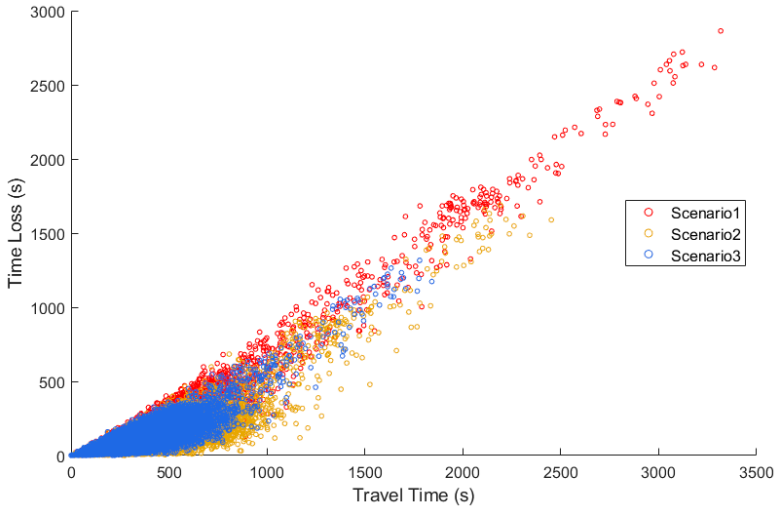


Figure 8. Comparison of travel time and time loss in different scenarios.

3.3. Average Speed

Figure 9 shows the average speed of vehicles at each hour under each scenario, as well as the average number of vehicles running in the simulation in that hour. In terms of average speed, the average speed in Scenario 2 was the lowest most of the time, but the average speed in Scenario 2 was higher than in Scenario 1 during the most congested periods (between 17 and 18 o'clock). This shows that the average speed of autonomous vehicles is lower than that of human drivers most of the time, but in congested road conditions, the average speed of autonomous vehicles is higher than that of human drivers. The average speed of Scenario 3 is higher than that of Scenarios 1 and 2, which shows that anthropomorphic driving has more advantages in terms of average speed. During the particularly congested time period from 17:00 to 18:00, the average speed of anthropomorphic driving was 21.29% higher than that of non-automated driving and 19.05% higher than that of automatic driving.

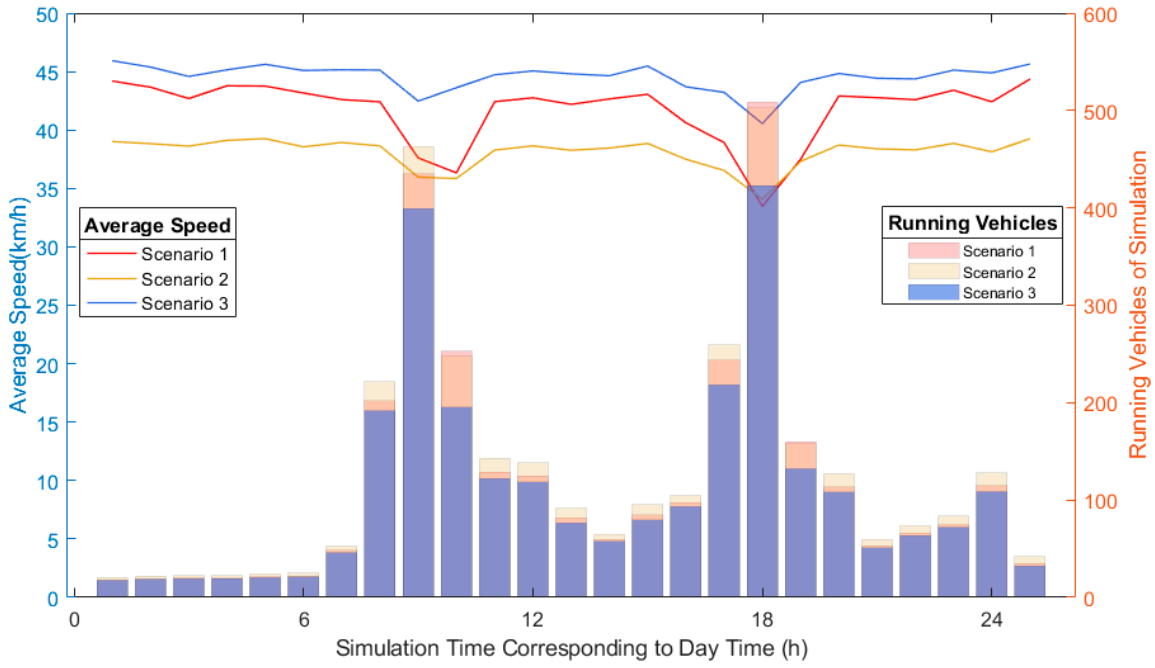


Figure 9. Comparison of average speed and running vehicles in different scenarios.

4. Discussion

Comparing Scenario 1 and Scenario 2, the travel time and time loss of the autonomous vehicle were lower (Figure 7). Under congested road conditions, the traffic efficiency of the autonomous vehicle was higher, which was reflected in there being more vehicles passing through the intersection (more noticeable at 17–18 o'clock in Figure 7a and 7–9 o'clock in Figure 7b) and a higher average speed (Figure 9 17–18 o'clock). Under non-congested road conditions, the average speed of human drivers was higher. Comparing Scenario 1 and Scenario 3, anthropomorphic driving was superior to non-automated vehicles in terms of number of vehicles per unit time, time loss, travel time, and average speed. Comparing Scenario 2 and Scenario 3, the number of vehicles per unit time and time loss of anthropomorphic driving were similar to those of autonomous driving, but anthropomorphic driving vehicles could reduce the travel time and increase the average speed. The advantage of anthropomorphic driving vehicles over non-automated vehicles comes from the former's shorter reaction time and fixed action points, while their advantage over autonomous vehicles comes from their relaxed compliance with speed limit regulations. These advantages can increase the average speed of anthropomorphic vehicles in congested traffic conditions by 21.29% compared to non-automated vehicles and 19.05% compared to autonomous vehicles.

From the results, we can see that, in smooth traffic conditions, anthropomorphic driving vehicles have a higher average speed than autonomous vehicles. This may be due to human drivers' incomplete compliance with the speed limit on the road (strictly complying with the speed limit in places with speed limit cameras and exceeding the speed limit by less than 20% in places without speed limit cameras). However, in congested traffic conditions, autonomous vehicles have more advantages. From the perspective of solving traffic congestion, autonomous vehicles are more beneficial. Anthropomorphic autonomous vehicles combine the advantages of human drivers and autonomous vehicles. In all indicators measured in this study (number of vehicles passing a point per unit time, travel time, time loss, and average speed), anthropomorphic autonomous vehicles were not inferior to autonomous vehicles and human driving. In particular, in terms of average speed in congested roads, they could be 21.29% faster than human drivers and 19.05% faster than autonomous cars.

There are many limitations to this study. First, the road network in this study was based on part of a city, and simulations of traffic in other countries and cities may produce different results. Second, the road network did not consider the impact of road slope, other road users (bicycles, motorcycles, pedestrians, buses), and other road types (railways, light rail, highways) on the road network. Finally, the vehicle model and driver model used in this paper only considered the parameters with the greatest impact on traffic, and other influences (such as driver type, vehicle type, etc.) were not considered.

5. Conclusions

This study used microscopic traffic simulation to reproduce a map of a frequently congested area with geographical population distribution data and simulate non-automated vehicles, autonomous vehicles, and anthropomorphic driving vehicles. The results show that autonomous vehicles and anthropomorphic driving vehicles are better than non-automated vehicles in reducing traffic congestion. In addition, anthropomorphic driving vehicles can reduce travel time and time loss and increase average speed, improving traffic efficiency.

With the expansion of cities and the increase in urban populations, traffic congestion has become a pain point in large cities. Road expansion, public transportation establishment, and shared vehicles all have their limitations. With the development and introduction of

autonomous driving technology, reducing traffic congestion while improving safety and comfort is the outcome that everyone expects. This study used the simulation of a real road network to prove the advantages of anthropomorphic autonomous driving in traffic congestion, which was shown to increase traffic volume, reduce time loss, and increase the average speed by up to 21.29%. This paper has reference significance for traffic planning departments and vehicle manufacturers.

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