Hindawi
Journal of Advanced Transportation
Volume 2019, Article ID 7878042, 16 pages
https://doi.org/10.1155/2019/7878042

Research Article

Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model

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Received 8 July 2019; Revised 21 October 2019; Accepted 5 November 2019; Published 16 December 2019

Academic Editor: Giulio E. Cantarella

Automated vehicles used as public transport show a great promise of revolutionizing current transportation systems. Still, there are many questions as to how these systems should be organized and operated in cities to bring the best out of future services. In this study, an agent-based model (ABM) is developed to simulate the on-demand operations of shared automated vehicles (SAVs) in a parallel transit service (PTS) and a tailored time-varying transit service (TVTS). The proposed TVTS system can switch service schemes between a door-to-door service (DDS) and a station-to-station service (SSS) according to what is best for the service providers and the travelers. In addition, the proposed PTS system that allows DDS and SSS to operate simultaneously is simulated. To test the conceptual design of the proposed SAV system, simulation experiments are performed in a hypothetical urban area to show the potential of different SAV schemes. Simulation results suggest that SAV systems together with dynamic ridesharing can significantly reduce average waiting time, the vehicle kilometres travelled and empty SAV trips. Moreover, the proposed optimal vehicle assignment algorithm can significantly reduce the empty vehicle kilometres travelled (VKT) for the pickups for all tested SAV systems up to about 40% and improve the system capacity for transporting the passengers. Comparing the TVTS system, which has inconvenient access in peak hours, with the PTS systems, which always makes available door-to-door transport, we conclude that the latter could achieve a similar system performance as the former in terms of average waiting time, service time and system capacity.

1. Introduction

It is being said that we are at the dawn of the next mobility revolution with the introduction of automated driving. However, there are aspects of the automated vehicles (AVs) that still need to be understood, for example, there are many legal, regulatory and technical problems that are delaying the deployment of AVs. A fleet of shared automated vehicles (SAV), which functions as a centralized taxi service system, will probably bring the most disruptive changes in urban mobility. The real potential of SAVs is that they make the implementation of an entirely new public transportation system possible. That is, SAVs might have the power to fundamentally transform transportation mobility and revolutionize the transport system given the added degrees of freedom of operating shared taxi systems [1–10].

A fleet of SAVs operated in a centralized way in SAV systems could function as an efficient taxi system to provide demand-responsive service for travel demand during a day, especially in urbanized areas. The SAV system could be used to provide station-to-station (stop-to-stop) service (SSS) to transport as many people as possible in busy routes in a demand-responsive fashion. However, the SAV system could also be operated as a door-to-door service (DDS) giving great convenience to travellers as of today's Transport Network Companies such as Uber, Lyft, and Didi Chuxing. In this paper, we aim to take into consideration these two ways of operating urban automated transport systems, both in parallel and in sequence, and propose a simulation tool to assess their impact on an urban network.

In addition, SAV systems could facilitate the implementation of dynamic ride-sharing which aims to pool multiple travelers with similar origins, destinations, and departure times in the same vehicle. Dynamic ridesharing has the potential to improve the performance of proposed SAV systems in terms of energy saving, waiting time reduction, VKT reduction, etc. [11–17]. More importantly, the dynamic ridesharing could enable the SAV system in accommodating more travel demand with the same number of vehicles. The proposed SAV systems offering various service schemes with dynamic ridesharing could eliminate the problems in past attempts to provide demand-responsive transit services [18].

Building upon the on-demand DDS and on-demand SSS, two extra on-demand transit service systems are proposed and simulated. Time-varying transit service (TVTS) that can switch service schemes between DDS and SSS depending on the time of day (peak hours and off-peak hours for example), and the simultaneous operation of DDS and SSS, allowing both of them to operate in parallel (designated as parallel transit service: PTS).

Few studies have explored the operation of variations in the service schemes of SAV systems. As a first attempt to investigate this problem, the paper constructs an agent-based model (ABM) to study different scenarios of operations of different service schemes. With the help of ABM, conceptual design and a preliminary study are presented for different SAV systems as defined above: SSS system, DDS system, TVTS system, and four PTS systems. The ABM describes the SAV system with its details and complexity by modelling the travel requests and vehicle movements, and especially interactions between vehicles and travelers. The model allows us to understand how the system components of the SAV system behave over time and find the potential of SAV systems by studying the most efficient ways of operating them under different service schemes. Therefore, the preliminary look at system performance of SAV systems could provide useful information for transport operators when deciding to adopt a SAV system in the future. But it also provides support for future more detailed simulation studies whereby these schemes might be important to test.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature related to SAV systems and dynamic ridesharing. Section 3 presents the model specifications. Section 4 gives a detailed description of the experiments that have been run. Section 5 provides an analysis of the simulation results. Conclusions are drawn in Section 6. The final section lists some model limitations and envisions future work.

2. Background Literature

Given that the possible future existence of SAV will bring the most potentially disruptive changes in the urban transport system, the exploration of the implementation of these systems has been a focal point of transportation research in recent years [19–23].

Burns et al. examined the performance of an SAV system and cost to explore the feasibility of a fleet of SAVs to serve the existing travel demand, they found that the SAV systems are compelling due to the shorter waiting time and low operational cost [24]. Spieser et al. examined the problem of fleet sizing of Automated Mobility-on-Demand Systems using the actual transportation data of Singapore and found out that the fleet sizes of SAVs that serve the entire mobility needs between stations in Singapore can be 1/3 of previous passengers' vehicles while keeping an acceptable waiting time [25]. Fagnant et al. investigated the benefits and environmental implications of SAV systems in an Austin-sized city, Texas. Their study results indicate that each SAV can substitute 11 and 9 conventional vehicles in order to serve 3.5% and 1.3% of regional trips respectively. Although approximately 11% extra empty VKT was generated, energy savings and emission reductions may overcome those effects [26, 27].

Several studies focus on investigating the potential benefits of SAV systems when considering shared rides. Fagnant et al. investigated the impact of the dynamic ridesharing in SAV systems on vehicle mile travelled (VMT), waiting times and travel costs for SAV users. They concluded that the dynamic ridesharing could result in a reduction of generated VMT up to 4.2% and the reduction of the waiting time and average total service time up to 4.5 minutes and 0.3 minutes respectively [11]. Zhang et al. focused on the potential impact of SAV fleet size, dynamic ridesharing and clients' preference, and vehicle cruising on urban parking demand by considering 2% of the population as the users of the SAV system in a hypothetical city. Their study indicated that the SAV system could facilitate the reduction of parking demand of about 90%, and the reduction could be further expanded by 1% by considering dynamic ridesharing in the SAV system [28].

Other works concern multi-mode transportation in the analysis of the impact of an SAV system. Martinez in the International Transport Forum investigated the performance of shared automated taxis as a supplement to serve requests for shared buses offering inter-stop service with prebooking. The benefits of shared taxis and bus systems are the reduction of emissions and VKT, peaking at 40% and 30% respectively [29, 30]. Zachariah et al. investigated the operation of a fleet of autonomous taxis supplementing the transit train service among fixed taxi stands in New Jersey. Simulation results revealed that shared rides could significantly reduce the VMT. In addition, they found that temporal and spatial demand variations influence the ride-sharing success rate. Therefore, the favorable distribution of the SAV fleet based on the demand variations can significantly improve the sharing rate and reduce congestion [31]. SAVs as a feeder service to train stations have been explored from an operational point of view looking at how many vehicles are needed, defining an area of operation, and how to charge the vehicles in case they are electric [32, 33].

Although studies on SAV systems are now booming, there are a limited number of research papers that explore the implementation of efficient on-demand SAV systems in terms of the different service schemes in which they could be operated and the potential synergies among those. That is, it is unclear what kind of service schemes the SAV systems should provide in a demand-responsive fashion. This paper attempts to fill that gap through a simulation study in a hypothetical city as a first approach to the problem. An ABM is used to explore the trade-offs in different SAV systems between the service levels, captured by the waiting time and service time (in-vehicle travel time) and the system efficiency in terms of VKT, system capacity, and served trips.

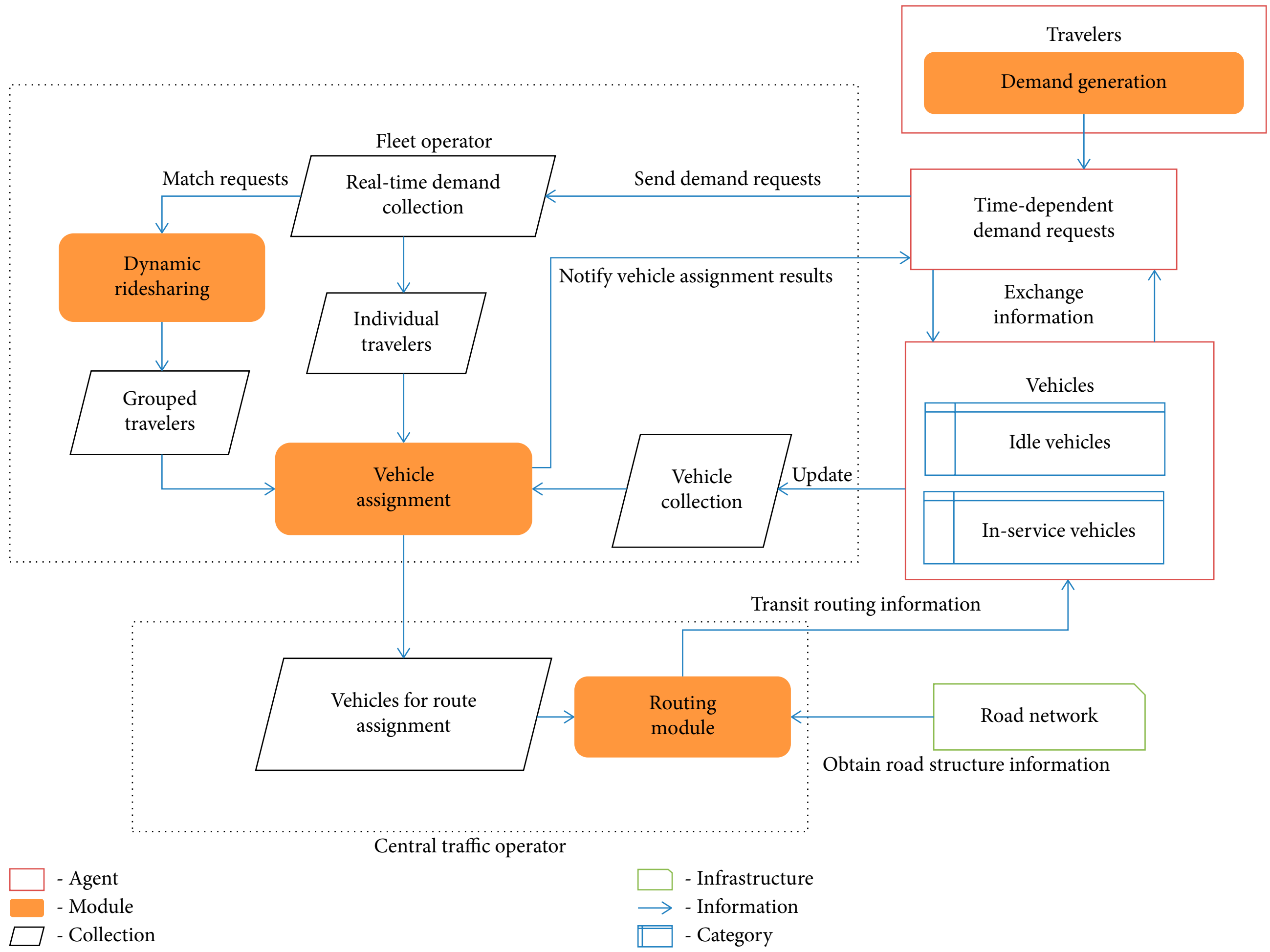


FIGURE 1: Interaction between system components.

3. Model Specifications and Operations

The ABM is intended to simulate the operations of SAVs and their interactions with travelers' real-time requests within a hypothetical city area. We simulate tailored on-demand SAV systems with various service schemes as already described. In this study, the fleet operator has no information about the travel requests in advance. In other words, the fleet operator has no information about travelers before they request service. After a traveler requests a vehicle, the fleet operator knows the information of the traveler. The fleet operator only assigns the idle vehicles to serve the travelers in a real-time fashion, and therefore scheduled assignment in a prebooking fashion is not possible. As shown in Figure 1, the fleet operator is responsible for real-time vehicle assignment, dynamic ridesharing, and managing and monitoring information of travel requests and vehicles. In addition, the central operator is designed for route assignments for SAVs. Vehicle assignment means that the fleet operator finds idle vehicles to serve real-time travel requests. The route assignment is to find a route either for en-route pickup vehicles or en-route drop-off vehicles. We distinguish the functions between the fleet operator and the central operator, enabling the designed system to keep an expanded capability for multiple operators.

The interaction of system components in Figure 1 between SAVs and time-dependent travel requests are illustrated. The fleet operator controls the assignment of SAVs to serve real-time travel requests. After the assignment of SAVs, communications will take place between travel requests and SAVs until travellers arrive at their destination. That is, after SAVs received the essential information (origin, destination, identification) of travel requests, each SAV will communicate with targeted travel requests for pickups and drop-offs. The dynamic ridesharing module in the fleet operator aims to group travellers, according to the matching rules. The routing module in the central operator is responsible for the route calculation for real-time vehicle routing. The central operator will transit routing information to the in-service vehicles. The model contents include dynamic generation of time-dependent requests, real-time vehicle assignment, and dynamic ridesharing. To deal with the lack of some essential information, we list the detailed description of model assumptions:

(i) No induced travel demand is taken into account;
(ii) All the travelers are willing to share rides with strangers;
(iii) The battery capacity can support full-day operations for each SAV;

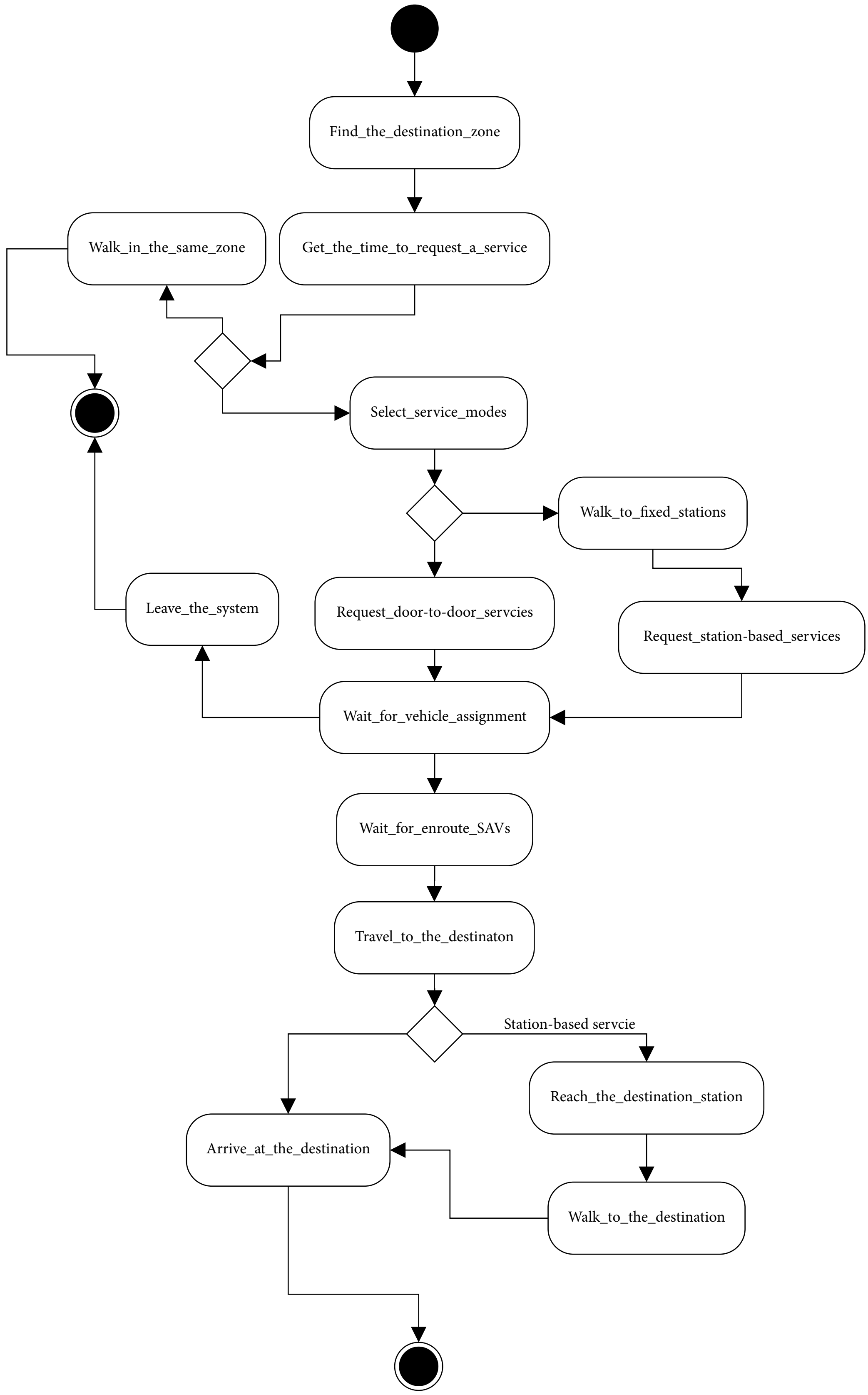


Figure 2: The state chart that represents the behavior of a travel request.

(iv) The parking spaces are enough for all the SAVs in each station.

For easier model implementation, we simplify the following model specifications:

(i) SAV speed is predefined on road segments and updated for peak hours and off-peak hours respectively;
(ii) Cancellation of assigned SAV is not allowed;
(iii) Travelers will give up a request when the waiting time for being assigned a vehicle exceeds a specific time threshold;
(iv) Travelers' choices between door-to-door service and station-based service are based on a fixed willingness to use a certain service, which is an experimental parameter (20%, 40%, 60%, and 80%).

3.1. Real-Time SAV Assignment. In this model, two assignment methods are designed. The first vehicle assignment method is to assign the nearest idle vehicles to serve the real-time travel requests according to the first-come, first-served (FCFS) principle. We define the first vehicle assignment method as the FCFS vehicle assignment method. The second is an optimal assignment method that assigns a group of idle vehicles to bundled travel requests with the objective of minimizing the total empty travel distance for the pickups.

3.1.1. FCFS Vehicle Assignment Method. We design a fleet operator to assign the idle and nearest SAVs to serve real-time travel requests. The rules of the design are as follows:

(i) The fleet operator will find an idle and nearest SAV in the same sub-region as the request departure location based on the FCFS principle;
(ii) If there is no available SAV close to the request, the fleet operator will find an idle SAV from the whole study area to serve it;
(iii) The fleet operator only gives top priority to shared riders. That is, the travelers who will share their rides are sorted from the waiting list, and assigned an idle and nearest SAV as soon as possible.

3.1.2. Optimal Vehicle Assignment Method. The optimal vehicle algorithm method can assign a group of idle vehicles $V = \{v_{1,} \cdots , v_n\}$ to bundled travel requests $R = \{r_{t1,} \cdots , r_{tn}\}$. That means that the fleet operators can bundle a certain number of travel requests, each of which is specified with a timestamp, assign a group of available vehicles to them with the objective of minimizing the total empty travel distance of the assignment. The size of bundled travel requests varies along the day according to the demand that coincides in the same time interval. The collection of idle vehicles participating in the optimal assignment is found by searching for the nearest vehicles for each travel request in the set R. The assignment problem can be formulated as a bipartite matching problem between bundled travel requests and selected idle vehicles in every dispatching time interval. The Hungarian algorithm [34] is used to solve the problem.

Nevertheless, a travel request can be assigned a vehicle by FCFS principle without calling the Hungarian algorithm only when the fleet operator failed in finding adequate idle vehicles as input for the Hungarian algorithm or when there is only one request for vehicle assignment in a certain dispatching time interval.

After the SAV assignment, the vehicle will have the essential information about requests (location, requested service, ridesharing status), and communicate with travellers by sending an assignment message. After that, the traveler waits for the SAV's arrival. Therefore, the waiting time can be composed of waiting time for vehicle assignment (due to the unavailability of a SAV) and waiting for the SAV' arrival while it is en-route for picking up the traveller.

3.2. Dynamic Generation of Time-Dependent Travel Requests. Based on the aggregate travel demand, individual travel requests are generated with spatial-temporal characteristics. In this study, the demand generation process can be divided into the following two steps.

(1) Generating a fixed number of time-dependent travel requests for each zone over each time interval.

Total production of travel requests for each zone is calculated based on an origin-destination (OD) matrix, and then demand production per one-hour interval for each zone is estimated by using the departure time distribution and total demand production per zone for 24 hours. At the beginning of each time interval, a fixed number of travel requests are generated, and then the generated travel requests are distributed within this time interval by following a discrete uniform distribution. As a result, all the generated requests for each time interval will be associated with a specified time.

(2) Finding a destination zone for each travel request.

It is assumed that observations of travel requests in each zone over other traffic analysis zones in the whole study area are known in the OD matrix table. That is to say, the number of requests ending in every other zone is known. Based on these observations of travel requests over traffic analysis zones in the OD matrix table, the destination zone of each travel request will be drawn by using the Monte Carlo simulation process. In the end, each request will have a destination zone. We give a detailed overview of departure time distribution and total travel requests for each zone in the section of detailed travel demand.

As shown in Figure 2, statechart diagram as one of the five Unified Modeling Language diagrams is used to model the dynamic nature of the travellers. The statechart diagram can define different states of a traveler during its lifetime and these states are changed by events. By using statecharts, traveler behavior can be visually shown. The statechart has states and transitions. Transitions may be triggered by user-defined conditions (timeouts or rates, agent's arrival, messages received by the statechart, and Boolean conditions). For example, after the SAV assignment, the vehicle will have the essential information about requests (location, requested service, ridesharing status), and communicate with the clients by sending an assignment message (state transition by receiving a message). After that, the traveler waits for the SAV's arrival (state transition by vehicle arrival). The travel request will give up waiting for vehicle assignment when waiting assignment time exceeds a time threshold (state transition by timeout event).

3.3. Fleet Size. The fleet size is an experimental parameter in the ABM. We simulate the operations of SAV systems with different fleet sizes. In addition, in order to illustrate the relations between multiple system characteristics, we estimate a small fleet size for keeping an acceptable service quality for SAV systems.

3.4. Dynamic Ride-Sharing. The SAV can facilitate the implementation of dynamic ride-sharing. Dynamic ridesharing aims to pool multiple travelers with similar temporal and spatial characteristics.

In this model, we design a set of rules for the implementation of the dynamic ridesharing. Travelers who have common OD zones are allowed to share a SAV. Note that the grouped travelers with common OD zone may have different departing and arriving specific locations within each zone. The travel requests can be served at a service station or at their doorstep.

From the service scheme point of view, we design a set of rules for dynamic ridesharing.

(i) If both of the shared rides need to be served at a station, the assigned SAV will pick them up at the origin station, and then drop them off at the destination station.

(ii) If both of the shared rides need to be served in a door-to-door fashion, the assigned SAV will first pick up the passenger who is closer to it and then pick up another one. Based on the trip distance of the passengers, the SAV will first drop off the passenger who has a shorter trip distance, and then it will drop off the second passenger at its specific destination of the same zone. If the assigned SAV has the same estimated travel distance from the two passengers in two different locations, the SAV will first pick up the passenger who sent the request earlier, and then pick up the second passenger at his or her doorstep. After reaching the first passenger's destination, the second passenger will be dropped off.

(iii) If one of the shared rides needs to be served at a station and the other one is to be served at the doorstep, the SAV will first pick up the passenger who is closer to it and then pick up the other passenger. Based on the trip distance of the passengers, the SAV will first drop off the passenger who has a shorter trip distance, and then it will drop off the second passenger at its destination (designated station or specific location) of the same zone. If the assigned SAV has the same estimated travel distance from the two passengers in two different locations, the SAV will first pick up the passenger who sent the request earlier, and then pick up the second passenger at his or her doorstep. After reaching the first passenger's destination, the second passenger will be dropped off.

In this ABM, a ridesharing agent type is introduced to delegate the grouped travel requests. That is, once the ridesharing agent is created, it is responsible for the interaction with an assigned vehicle. Each ridesharing agent records the information of grouped travellers, the OD of the travellers, and the assigned vehicles for grouped travellers. According to the designed rules for dynamic ridesharing, the fleet operator dynamically adds and removes ridesharing agents in the simulation process.

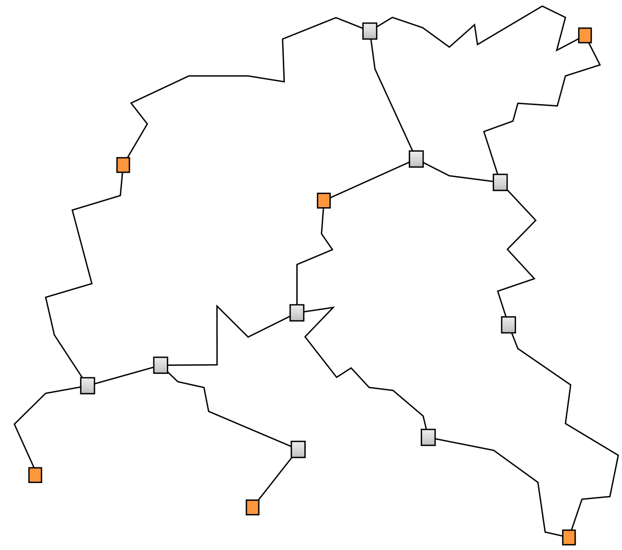


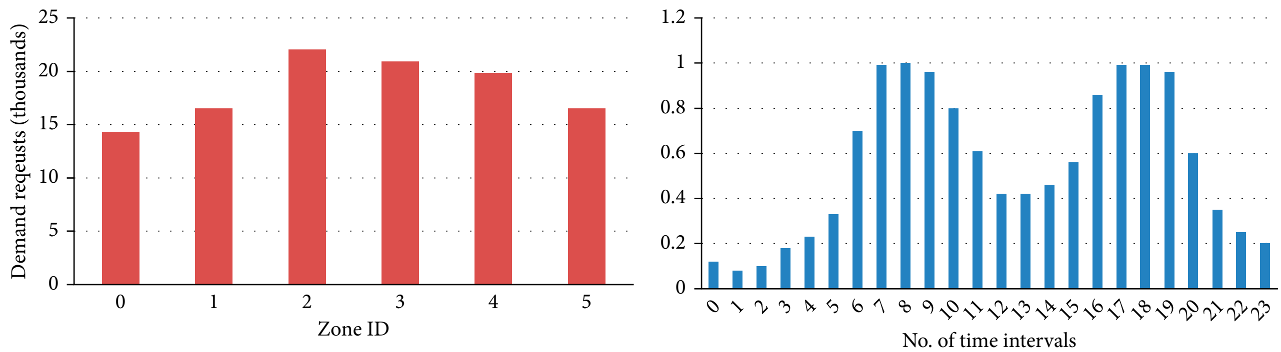
Figure 3: The road network.

3.5. Service Scheme. We have defined four types of on-demand SAV systems in terms of variations of service schemes as described above: DDS system, SSS system, TVTS system, and PTS system. In all SAV systems, we did not simulate user choices for different services based on attributes such as price or travel distance; however, we assume that individual requests have various levels of willingness to use the station-to-station service in the proposed PTS systems. According to the willingness to choose the station-to-station service, the PTS system can be divided into PTS-20%, PTS-40%, PTS-60%, and PTS-80%. This would result from the prices of both services; otherwise, travelers would naturally prefer to use the door-to-door system only because it is more convenient.

4. Model Application and Implementation

The simulation model was developed from scratch in Anylogic proprietary ABM platform with Java programming language, which is available for research purposes. In this study, SAV systems with different service schemes are tested in a hypothetical urban road network.

4.1. Urban Road Network. The road network of a city in the scale of 5 km × 5 km (roughly the size of Delft in the Netherlands) is used for testing the operations of different SAV systems. The network is taken from the UDES (Urban Dynamics Educational Simulator) model (https://www.researchgate.net/project/The-Urban-Dynamics-Educational-Simulator-UDES). The road network topology includes 78 links and 77 nodes (see Figure 3). Stations for the drop-off



(a) (b)

Figure 4: The detailed overview of departure time distribution and total demand for each zone. (a) Departure time distribution. (b) Total demand for each zone.

and pickup service in SAV systems are uniformly distributed among the traffic analysis zones (TAZs) in the whole study area. The scale is graphically defined in the agent simulation environment as: one pixel corresponds to ten meters. The SAVs shortest paths are computed using the Dijkstra algorithm.

4.2. Detailed Travel Demand. The SAV systems will serve a total demand of 110 000 trips in a full day. Figure 4 depicts the departure time distribution of the demand and the total production of travel requests for each zone that are used as input in the simulation model as explained in Section 3.

To mimic the commuting patterns, OD matrices with different assumed observations are used: one in the first half of the day and the other for the rest of the day. The destination zones are found by using the Monte Carlo simulation process. Therefore, heterogeneous observations in the trip table enable the simulation to generate different results.

Travel demand is not only generated and attracted in the centroid of each TAZ but specific points inside the zones are used, in order to simulate the operation of different service schemes. That means that travellers would walk from/to the station when using the station-based service or waiting for their pickup at their places of residence if there is a door-to-door service.

4.3. Simulation Parameters. Table 1 shows basic input parameters for the SAV simulation. The vehicle speed is predetermined in all SAV systems in peak hours and off-peak hours respectively. Based on the research conducted by Wang et al. [35] in terms of speeds during the different times of the day, the reduction of the speed in peak hours range between 10% and 30%. Therefore, we assume that the speed of the SAV is 20% lower than that in off-peak hours. In this ABM, we assume the SAV speed in off-peak hours is 36 km/h. The energy efficiency of different electrical vehicles roughly ranges from 1 kWh per 7.16 km to 1 kWh per 4.82 km (https://pushevs.com/electric-car-range-efficiency-nedc/). Therefore, for energy consumption, we adopt a rate of electricity consumption of 1 kWh per 7 kilometers that is reasonable for a two-seat, light-weight vehicle. We assume that travelers will give up requesting a SAV when the waiting time for a vehicle assignment exceeds 5 minutes. In this paper, we assume that the maximum number of travelers in a shared car is two. The time interval being used for the assignment is 5 seconds.

Table 1: Input parameters.

Category	Value
City scale	5 km × 5 km
Road links	78
Road nodes	77
Travel requests	110 000
Vehicle off-peak speed	36 km/h
Vehicle peak-hour speed	28.8 km/h
Vehicle capacity	2 persons
Time threshold for client dropout	5 minutes
Time interval for optimal assignment	5 seconds
Operation hours	Around the clock
AM peak	7 AM–9 AM
PM peak	4 PM–6 PM
Fleet size	[2000, 4500]
Fleet size step	500

5. Results and Discussion

5.1. Analysis of the Impact of Vehicle Assignment Methods. To look at how the optimal vehicle assignment method impacts the performance of different SAVs systems, 70 scenarios for different SAV systems with variations of fleet size are simulated (see in Table 2).

The simulation results in Figure 5 indicate that the optimal vehicle assignment algorithm can reduce empty VKT. The fleet operator can optimally assign idle vehicles to serve the travelers while minimizing the total empty travel distance for the pickups. The degree of reduction of empty VKT greatly depends on the fleet size. In Figure 5(a), the optimal assignment can reduce the empty VKT for all the SAV systems in about 40%, while there is almost all of the same empty VKT for both assignment methods with a 4000-SAV fleet size in Figure 5(e).

Table 2: Combinatorial scenarios for the simulation of optimal vehicle assignment.

Assignment method	Optimal assignment method			FCFS assignment method			
SAV systems	DDS	SSS	TVS	PTS-20	PTS-40	PTS-60	PTS-80
Fleet size	2000		2500	3000	3500		4000

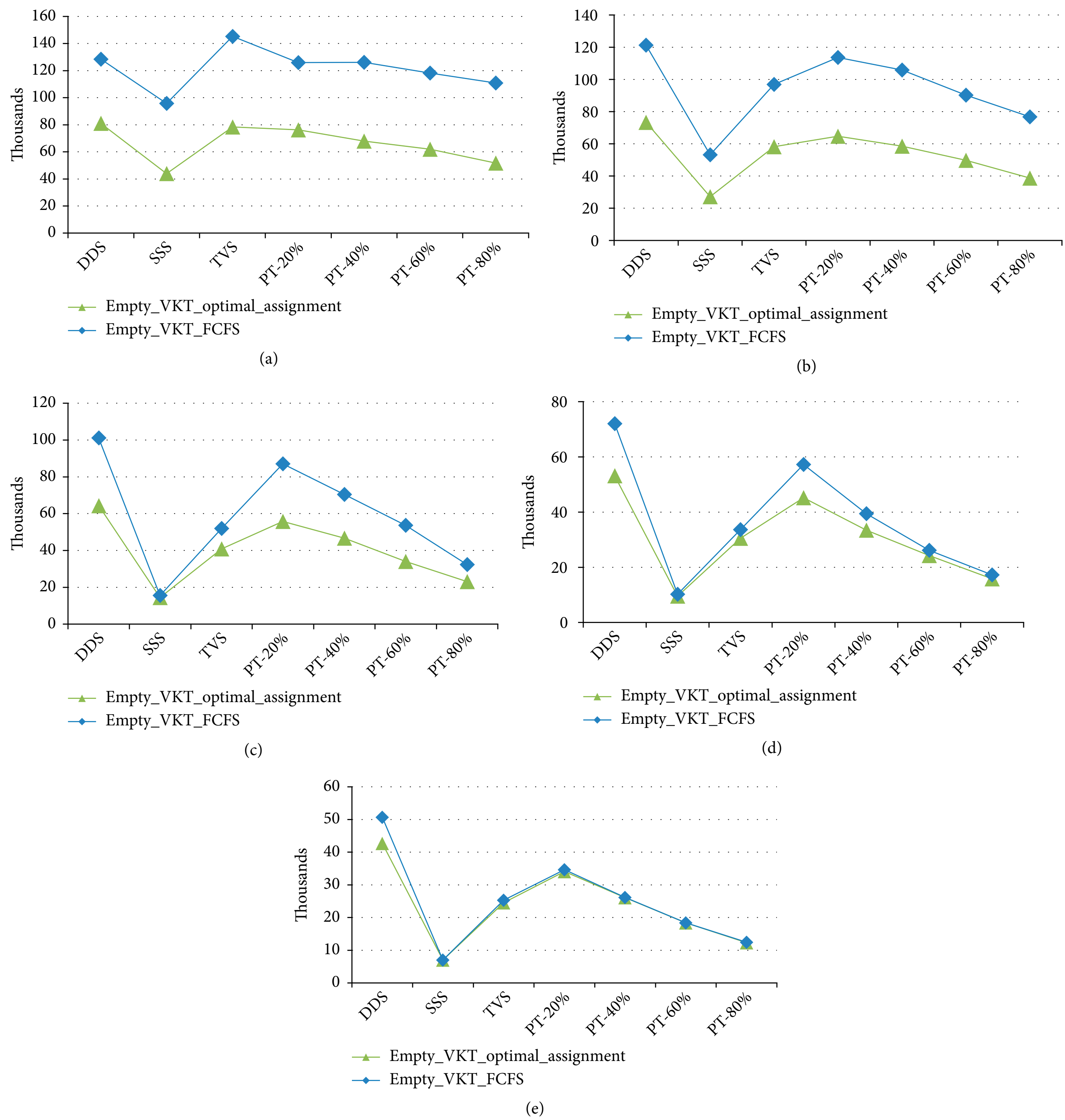


Figure 5: Comparisons of generated empty VKT for different assignment methods with variations of fleet size. (a) Comparisons of VKT with the 2000-SAV fleet size. (b) Comparisons of VKT with the 2500-SAV fleet size. (c) Comparisons of VKT with the 3000-SAV fleet size. (d) Comparisons of VKT with the 3500-SAV fleet size. (e) Comparisons of VKT with the 4000-SAV fleet size.

Table 3: Performance indicators for DDS, SSS, and TVTS systems with a 2000-SAV fleet size.

SAV system	DDS		SSS		TVTS	
Ridesharing	No	Yes	No	Yes	No	Yes
Avg. waiting time (min)	14.79	7.21	9.84	4.41	12.87	6.43
Avg. peak-hour waiting time (min)	20.53	11.22	16.82	8.68	19.68	9.08
waiting time > 10 minutes (trips)	47 849	29 766	42 962	16 624	48 188	23 773
Avg. service time (min)	26.76	19.01	19.15	11.95	23.67	15.311
Avg. peak-hour service time (min)	33.65	24.34	26.94	16.99	28.56	16.22
Total VKT (km)	769 099	681 432	673 892	600 751	661 443	617 767
Energy consumption (KWh)	109 871	97 347	96 270	85 821	94 491	88 252
Total SAV trips	131 355	117 999	141 076	125 544	138 487	131 901
Requests dropouts	24 328	24 554	12 358	12 027	19 066	16 322
Percentage of dropouts (%)	22.1%	22.3%	11.2%	10.9%	17.3%	14.8%
Percentage of shared rides (%)	0%	34.4%	0%	15.6%	0%	20.1%

Table 4: Performance indicators for four-PTS systems with a 2000-SAV fleet size.

SAV system	PTS-20%		PTS-40%		PTS-60%		PTS-80%	
Ridesharing	No	Yes	No	Yes	No	Yes	No	Yes
Avg. waiting time (min)	15.07	6.61	14.33	5.78	13.53	5.06	12.06	4.71
Avg. peak-hour waiting time (min)	22.48	13.20	21.79	11.92	21.08	11.11	19.54	9.77
waiting time > 10 minutes (trips)	5 108	2 408	5 078	2 331	5 129	2 123	4 820	1 921
Avg. service time (min)	26.49	16.32	25.22	15.11	23.88	14.01	21.85	13.12
Avg. peak-hour service time (min)	34.88	23.11	33.58	22.14	32.35	20.67	30.18	18.77
Total VKT (km)	651 423	568 632	659 864	564 712	674 841	565 322	675 645	589 666
Energy consumption (KWh)	93 060	81 233	94 266	80 673	96 405	82 022	96 520	84 238
Total SAV trips	136 548	118 441	138 086	118 301	141 295	119 849	141 729	121 721
Requests dropouts	22 130	21 095	20 083	19 290	17 842	17 085	15 103	14 233
Percentage of dropouts (%)	20.1%	19.2%	18.3%	17.5%	16.2%	15.5%	13.7%	12.9%
Percentage of shared rides (%)	0%	18.7%	0%	19.6%	0%	20.1%	0%	25.9%

The shape of the polyline depicting the results of the optimal assignment displayed in Figure 5 is similar to that representing the results of the FCFS assignment. It is evident that the trend of the generated empty VKT over different SAV systems for both vehicle assignment methods is similar to each other. That means that although the optimal assignment method can reduce the generation of empty VKT, the difference of generated empty VKT across SAV systems remains the same to some extent.

Considering the number of drop-outs (unsatisfied trips), it is possible to see the simulation results in Figures 6 and 7 for the total number of dropouts with both vehicle assignment methods and for all tested systems. Results indicate that the optimal vehicle assignment can enable the SAV systems to transport considerably more travelers. This can be explained because of a reduction in the waiting time due to the higher efficiency of the optimal vehicle assignment method.

5.2. Analysis of Fleet Size Variations. We provide a performance analysis of the SAV system for different fleet sizes. In addition, a small fleet size for the base scenario to keep an acceptable level of service quality is determined to analyze the other characteristics of different SAV systems. Simulation results in Tables 3 and 4 indicate that the average peak-hour waiting time in all systems with dynamic ridesharing ranges from 8.68 minutes to 13.17 minutes when we adopt the 2000-SAV fleet size. For smaller fleet sizes, the service quality would be lower. Furthermore, there is little difference in the average waiting time in the four-PTS system when the fleet size is reduced from 3500 to 2000 as shown in Figure 8. Therefore, we could analyze the SAV systems' performance starting from the estimated 2000-SAV fleet size.

5.3. Analysis of the Impact of Dynamic Ridesharing. SAV systems allow travellers to share their rides according to the designed rules. In this analysis, we analyse the impact of dynamic ridesharing in the SAV system. Compared with a nonridesharing system in Tables 3 and 4, SAV systems with ridesharing significantly reduce at least 50% of the average waiting time, 6.0% of VKT and 4.7% of total SAV trips. The dynamic ridesharing could improve the performance of all proposed systems.

The DDS system reaches a peak of approximately 34.4% of shared rides, while the SSS system has the lowest percentage of shared rides (around 15.6%). Four-PTS systems have slightly high percentages of shared rides from 18.7% to 25.9%.

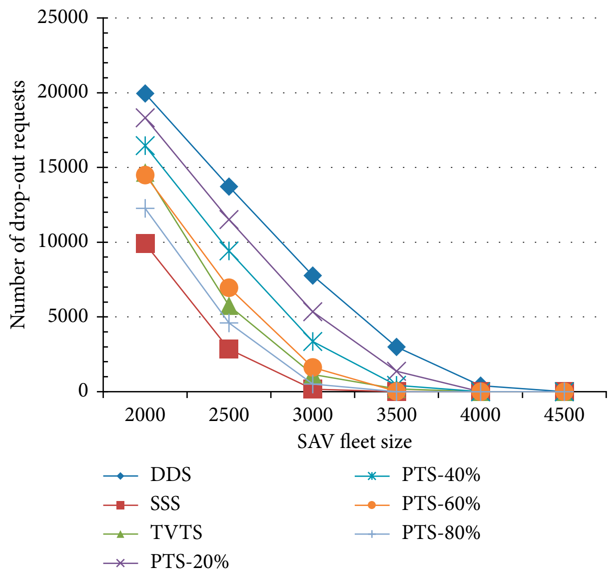


Figure 6: Unsatisfied requests for different SAV systems with variations in fleet sizes by optimal vehicle assignment.

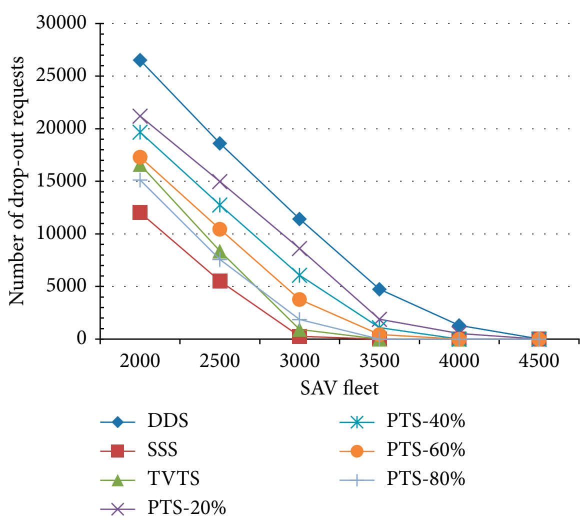


Figure 7: Unsatisfied requests for different SAV systems with variations of fleet sizes by FCFS vehicle assignment.

Especially, the TVTS system is about the same as the PTS-60% for the percentage of shared rides with a 2000-SAV fleet size, reaching 20.1% of total serviced trips. The PTS systems and TVTS system, providing two service schemes, can achieve a relatively high sharing rate of trips. Although the simulation results for dynamic ridesharing may not give conclusive evidence under designed matching rules to group travelers, the preliminary investigations of the impact of dynamic ridesharing on different SAV systems provide useful insights into the deployment of different SAV systems.

5.4. Analysis of Waiting Time and Service Time. Simulation results in Figure 8(a) indicate that the average waiting time in the four PTS systems with dynamic ridesharing has little difference, approximately 40–42% of average service time (in-vehicle travel time) in case of the 2000-SAV fleet size. TVTS system has a similar performance in terms of average waiting time and service time with the PTS-20% and PTS-40% system. We can infer that the SAV systems, e.g., PTS-20% and PTS-40% system, that allows two service schemes to operate in parallel with a degree of restricted access to the door-to-door service could provide a similar system performance than the TVTS system which only offers station-based service in peak hours.

When a total fleet size of 3500 SAVs is adopted (Figure 8(d)), the average waiting time in the PTS systems with 80% willingness to request station-based services could achieve a similar value with that of TVTS system with approximately 22.8% of average service time. This means that the system performance in terms of average waiting time and average service time achieved by the sequential operational rules in the TVTS system can be obtained by the proposed parallel modes of service schemes in the PTS-80% system.

5.5. Analysis of VKT and Energy Consumption. The DDS system has more VKT and energy consumption than other SAV systems as can be seen in Figures 9(c) and 9(d). Except for the DDS system, other proposed systems converge to the same amount both in VKT and energy consumption respectively, when fleet size approaches 4000 vehicles. Both VKT and energy consumption experience is a growing trend in four PTS systems with an increase in fleet size from 2000 to 2500, while the TVTS system has a high level of energy consumption and VKT. Nevertheless, with the continued growth of fleet size to 4000, the TVTS system decreases the energy consumption and VKT to a relatively low level compared to the energy consumption on the PTS systems. TVTS system could operate a relatively large fleet size to provide quality service while consuming less energy.

Figure 9(a) showing the number of total SAV trips indicates that total SAV trips rise first, then fall for each system with an increment of fleet sizes for each SAV system. One of the possible explanations is that with the increase of the SAV fleet size, fewer travel requests drop out of the SAV system. Therefore, the SAV system satisfies many more trips that result in the increase in the total number of SAV trips. On the other hand, the gradually increased fleet size will potentially reduce the empty SAV trips for pickup. The decline of empty (unoccupied) SAV trips for en-route pickups appears to reduce the total SAV trips. As a result, the total SAV trips rise first and decline for each SAV system. The peak number of total SAV trips is about 131342 trips in the TVTS system, while the DDS, PTS-20% and PTS-40% systems only reach about 118000 trips with the 2000-SAV fleet size.

Results in Figure 9(b) indicate that the empty trips with a 2000-SAV fleet size for each SAV system occupy 30–40% of the total trips served. The percentage of empty trips in the SSS system has a minimum of 28.1% of the total served 97973 trips with 2000-SAV fleet size, while the DDS reaches a peak of 42.0% with a total of 83480 trips. The percentage of extra empty trips in the TVTS system is the second-largest percentage (40.6%). With a total fleet size of 2000 SAVs, SAV systems seem to generate a higher percentage of empty trips. The high

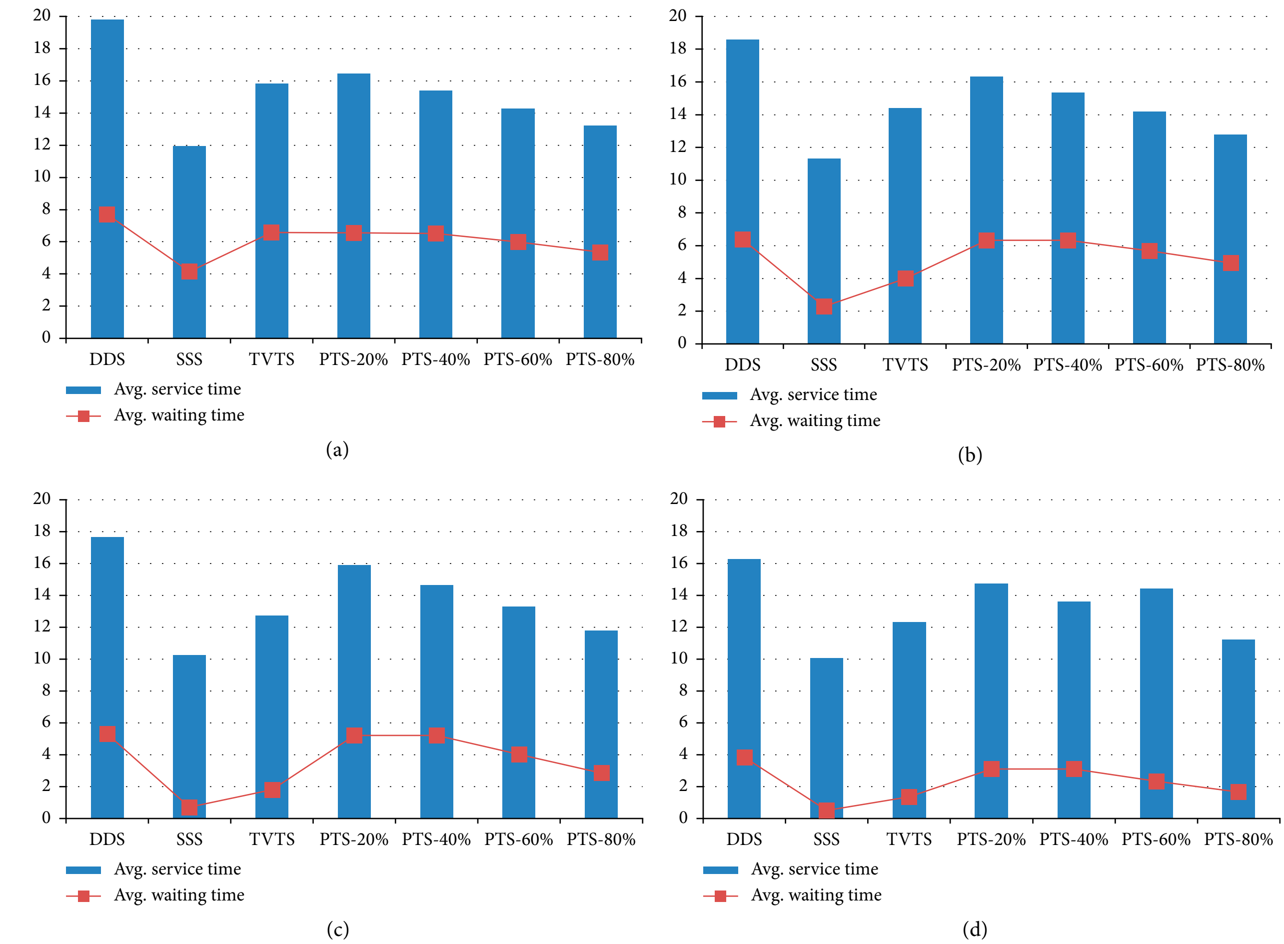


FIGURE 8: Avg. waiting time and Avg. service time with variations of fleet sizes for seven SAV systems. (a) 2000-SAV fleet size. (b) 2500-SAV fleet size. (c) 3000-SAV fleet size. (d) 3500-SAV fleet size.

percentage of empty vehicle trips in DDS and TVTS has the potential to cause heavy traffic congestion.

5.6. Analysis of System Capacity and Drop-Out Requests. With the 2000-SAV fleet (Tables 3 and 4), the peak number of drop-outs is 24554 trips corresponding to 22.3% of the total number of requests (110000) in the DDS system, while in the SSS system this number goes down to 12027 drop-outs, only accounting for 10.9% of the 110000 requests. The dropout rate in TVTS system approximates that of PTS-60% system with a 2000-SAV fleet size, reaching 15% of the total number of requests (110000). The PTS-80% system has the lowest number of dropouts. It is evident that the PTS system with a relatively high percentage of willingness to choose station-based service would be able to accomplish the performance of the TVTS system.

Results in Figure 10 indicate that the number of trips whose waiting time exceeds 10 minutes is between 29493 trips and 16624 trips, going down from 35.3% to 16.9% of system capacity (total number of served trips) with a 2000-SAV fleet size. The percentage of trips whose waiting time exceeds 10 minutes is about 25% in both PTS-40% and TVTS system, which are slightly larger than that of PTS-60% and PTS-80%. Both the TVTS system and PTS system with a relatively smaller fleet size can roughly keep 75% of the travelers waiting 10 minutes or less. With the shifts of SAV fleet size to 3500, DDS system still has a peak of 14.1% requests whose waiting time is larger than 10 minutes. Results indicate that PTS-20% still maintains a high percentage of travelers whose waiting time exceeds 10 minutes with a 3000-SAV fleet size (21%). Therefore, we can infer that the PTS system with a low willingness to choose the station service will lead to a long wait.

Simulation results in Figure 7 indicate that the number of travelers who give up waiting for a SAV assignment has a significant descending trend with the increase of SAV flee sizes in seven SAV systems. Except for the system with DDS, a fleet of 3500 SAVs can accommodate almost all of the requests. The fleet size that accommodates the total 110000 requests in the DDS is approximately 4500 SAVs. Therefore, The SAV system only with door-to-door service needs many more SAVs to handle the high demand. A large number of vehicles in the fleet, has the potential to reduce vehicle utilization. In fact, the simulation results in Figure 11 reveals that the DDS system has the lowest number of the served trip per SAV in all scenarios.

In addition, the numbers of served trips per SAV in Figure 11 are from 41.7 trips to approximately 49.0 trips in the SAV system with a 2000-SAV fleet size. We find out that

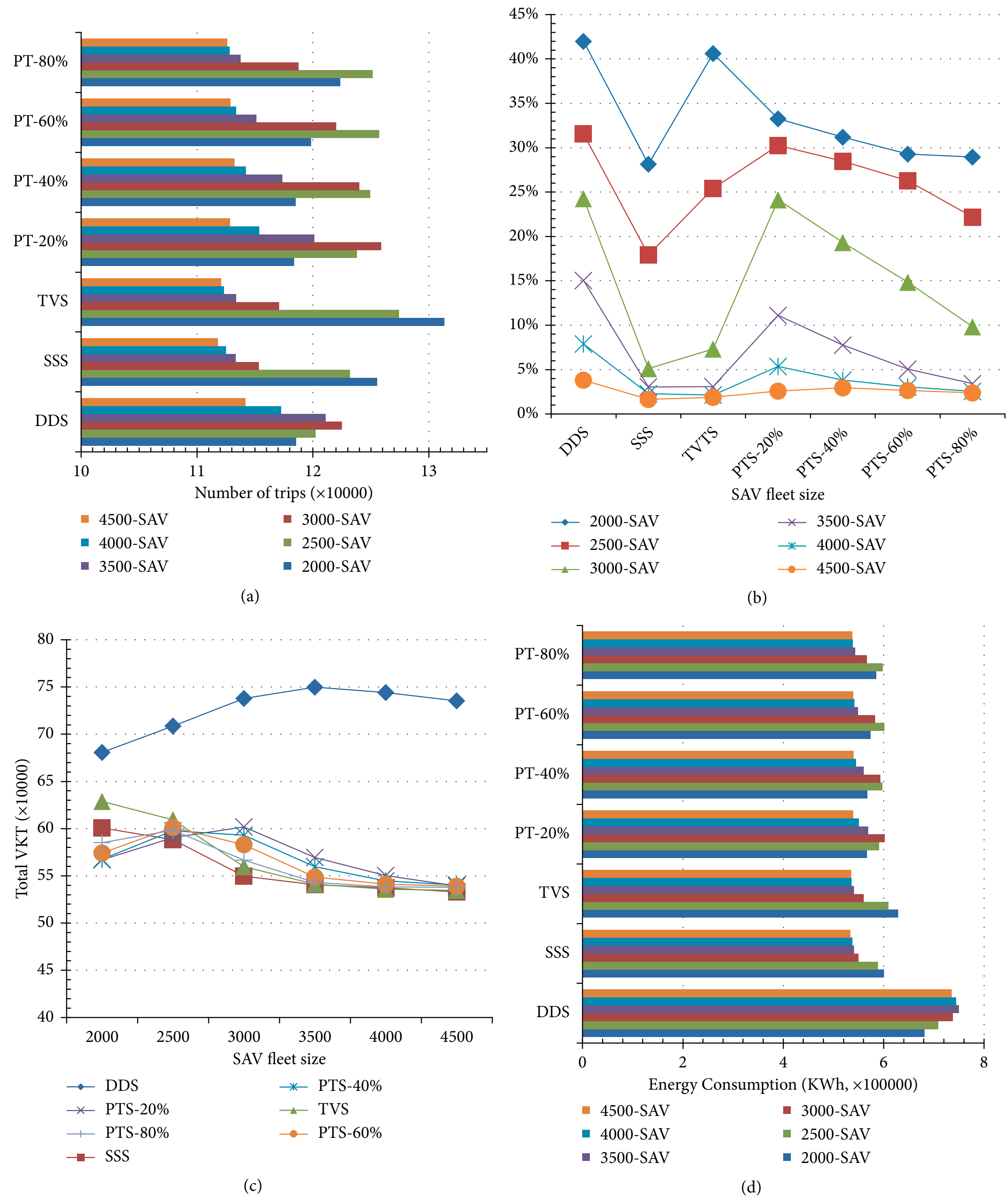


FIGURE 9: VKT, SAV trips, empty trips of SAVs and energy consumption with variations of fleet sizes for seven SAV systems. (a) Total SAV trips. (b) Percentage of extra empty trips. (c) Total VKT. (d) Energy consumption.

the PTS-60% and PTS-80% systems present about the same number of served trips as the TVTS system at about 47 trips per SAV. We compared the number of served trips per SAV with Fagnant and Kockelman (2016)'s study. Fagnant and Kockelman (2016)'s study indicates that the SAV system considering ridesharing can serve 56324 person-trips with 1715-SAV fleet size within a network in the scale of 12 miles × 24 miles. That is, each SAV can approximately serve 32.8 trips. The served trips per SAV are relatively lower than ours. One reason is that the road network in Fagnant and Kockelman's study is relatively larger than that of this study. Another reason is that a relatively large number of vehicles

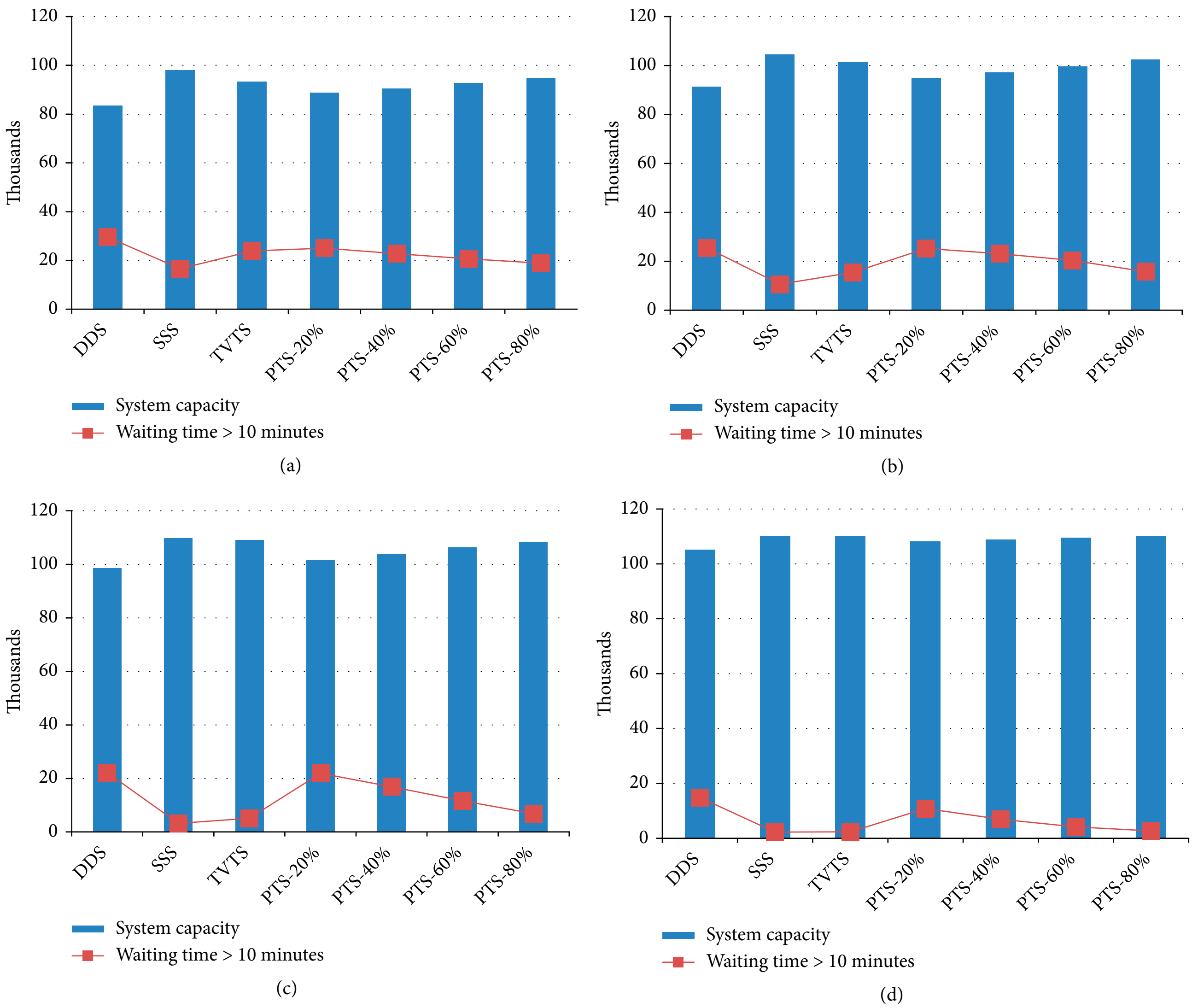


FIGURE 10: System capacity and waiting time > 10 minutes trip number. (a) 2000-SAV fleet size. (b) 2500-SAV fleet size. (c) 3000-SAV fleet size. (d) 3500-SAV fleet size.

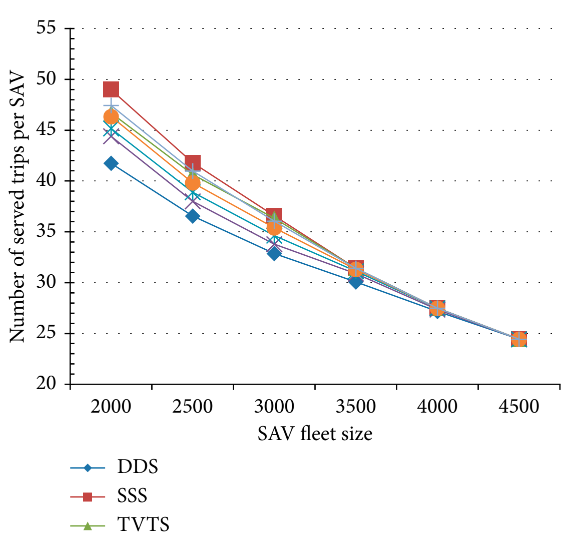


FIGURE 11: The number of served trips per SAV for different SAV systems.

are deployed in Fagnant and Kockelman study that leads to a relatively small average waiting time. The average waiting times in this paper ranges from 4.41 to 7.70 minutes with a 2000-SAV fleet size that are relatively larger than the 1.18-minute average waiting time in Fagnant and Kockelman study.

5.7. Analysis of Empty Trips. Unlike human-driven vehicles parking at the destinations, SAVs could have an unoccupied journey to pick up the next request (no pro-active rebalancing in anticipation of future demand are considered in this study). Therefore, additional empty trips will be generated to satisfy the next trip. In this study, the additional empty trips by the vehicle movement between different zone stations are calculated. These empty trips have the potential to influence traffic congestion to a great extent. Therefore, it is of importance to know the number of empty trips by SAVs. As shown in Figure 12, dynamic ridesharing can significantly reduce the generation of empty trips. PTS systems have

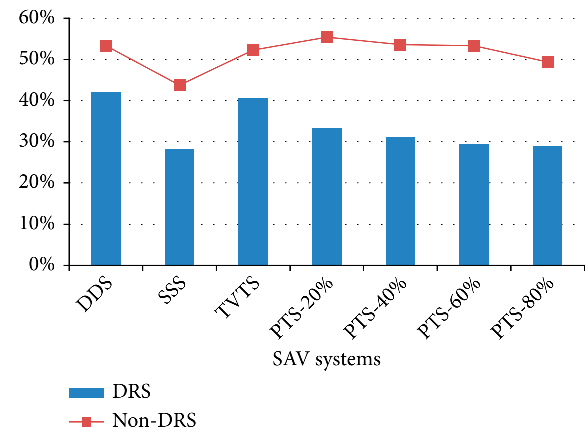


Figure 12: The percentage of empty trips with dynamic ridesharing for a 2000-SAV fleet size.

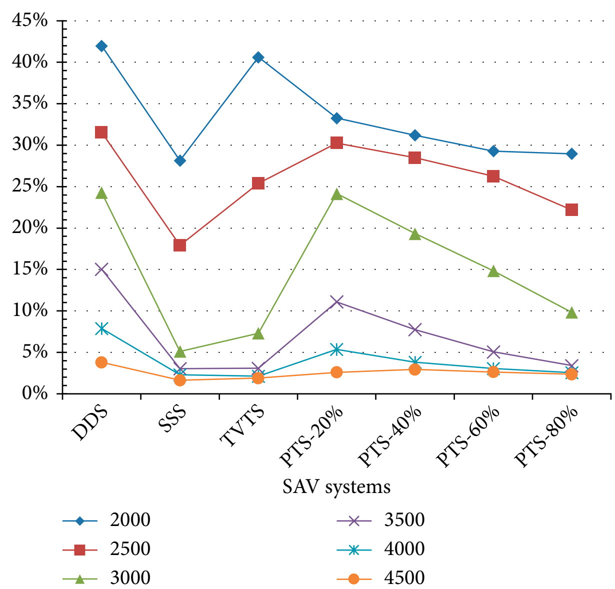


Figure 13: The percentage of empty trips with the variations of fleet size.

the greatest reduction, reaching a peak of 23% in PTS-60% system; however, there is a large number of additional empty (unoccupied) trip in all SAV systems. DDS and TVTS system with dynamic ridesharing generate many more empty trips at around 40.5% of total served trips. The PTS systems with dynamic ridesharing generate relatively fewer empty trips than that of the TVTS system.

Simulation results in Figure 13 indicate the generation of empty trips with dynamic ridesharing is sensitive to the fleet size. As the fleet size increases, the percentage of empty trips experiences a downward trend. The percentage of empty in all SAV systems drops below 5% when the fleet size is 4500. In addition, it depicts that the SSS system, TVTS system, and PTS-80% system have low numbers of empty trips by SAV, compared with other systems.

6. Conclusions

This paper developed an agent-based simulation model to assess the potential of on-demand SAV systems with various service schemes. With the help of the developed ABM, we understand what the performance of SAV systems with different service schemes is, and how the associated factors (variation of fleet size, dynamic ridesharing, different vehicle assignment methods) influence the service quality of SAV systems. Our study shows that the promotion of ridesharing can significantly improve the performance of the proposed SAV systems in terms of reducing the average waiting time, VKT and empty trips. Moreover, compared to the FCFS vehicle assignment method, the optimal assignment can reduce the generation of empty VKT for all tested systems and enable the SAV systems to transport considerably more travellers.

Although the DDS system brings great convenience of doorstep service for real-time requests; it is evident that DDS generates almost 13% of extra VKT than that of the PTS system with a fleet size of 2000 SAVs. In addition, the DDS system generates approximately 42% additional empty trips. The percentage of dropout requests takes up 22.0% of the total 110000 person-trips. That is, the DDS system cannot transport as many more travelers as the other SAV systems do. Compared to the DDS system, the TVTS system and PTS systems can reduce at least 14.6% and 14.8% of the average waiting time respectively. The empty trips in the TVTS and PTS systems with dynamic ridesharing account for 41.0% and 33.3% of total served trips respectively. The TVTS and PTS system provides a significant gain in terms of transport capacity, waiting time and additional trips by empty SAVs. In other words, the SAV systems that include two different on-demand services have the most significant improvements in system performance.

DDS system ranks the highest in total energy consumption and VKT. Compared to the VKT in the DDS system, the TVTS system and PTS system can reduce at least 7.6% and 14.0% of the VKT with 2000-SAV fleet size. On the other hand, the DDD system transports a relatively small amount of travel requests and reduces vehicle utilization that is the average number of served trips per day per vehicle. Based on the analysis of the proposed SAV systems, TVTS and PTS systems are a promising alternative to be implemented to satisfy the intracity transportation needs. In both systems, a SAV can serve many more trips per day with relatively less waiting time. The PTS systems with a relatively high percentage of choosing station-to-station service show a high level of service that could transport many more requests with less waiting time and empty trips. Although the TVTS system could generate many more VKT and consume much more energy, this system still has a relatively small waiting time and fewer dropouts with providing doorstep convenience. In the future deployment of SAV systems, the station-based service combined with the door-to-door service parallely in time and space, is of importance, since blended service could make the system operate at a relatively high degree of service quality without the inconvenient access.

7. Model Limitations and Future Work

In this model, we did not take into account realistic traffic dynamics. A traffic flow model can be implemented in the model framework to capture the traffic dynamics. Moreover, we did not design the optimal ridesharing rules for travelers and limited the maximum number of grouped travelers to two. It is acceptable to use ultra-compact vehicles with designed two seats. These low capacity vehicles could keep travelers in privacy and comfort. We will study the formation of vehicle platooning between vehicles with low seat capacity in future research. The small, ultra-compact vehicles could operate together in a platooning fashion to improve traffic capacity and eventually save energy consumption.

The fact that we use a synthetic network can introduce some limitations in the study however we also believe that by having created realistic trip requests and realistic vehicle movements the small network allows to compare well the different scenarios for the assumptions that were taken. This is a first study of exploring many different possibilities of operating the system and in the continuation of this research, we will expand the size of the network to be analysed.

Data Availability

The data of travel demand and road network used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

Acknowledgments

The first author would like to thank the China Scholarship Council (CSC) and the Delft University of Technology for the financial support towards this publication.

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