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Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach

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ABSTRACT

Although recent studies of Shared Autonomous Vehicles (SAVs) have explored the economic costs and environmental impacts of this technology, little is known about how SAVs can change urban forms, especially by reducing the demand for parking. This study estimates the potential impact of SAV system on urban parking demand under different system operation scenarios with the help of an agent-based simulation model. The simulation results indicate that we may be able to eliminate up to 90% of parking demand for clients who adopt the system, at a low market penetration rate of 2%. The results also suggest that different SAV operation strategies and client's preferences may lead to different spatial distribution of urban parking demand.

1. Introduction

There is compelling research to suggest that advances in transportation technology has a powerful and irreversible impact on urban form. The development of streetcars in the 1950s triggered the initial wave of suburbanization, which accelerated with the advent of the automobiles in the 20th century. Today, we are at the cusp of the emergence of autonomous vehicles (AVs), that is, vehicles that can drive themselves. These driverless vehicles are expected to introduce more fundamental changes to human travel behavior, which may lead to different social structures and urban forms. AVs will facilitate car-sharing and ride-sharing behavior, as the technology can overcome some key barriers, especially the limited accessibility and reliability of today's car-sharing and ride-sharing programs (Fagnant & Kockelman, 2014; Kornhauser et al., 2013; Malokin, Mokhtarian, and Circella, 2015). Given the potential capabilities of AVs, it is easy to envision the implementation of Shared Autonomous Vehicle (SAV) Systems, which will operate as a taxi service on demand. These future driverless taxis would also enable unrelated passengers to share the same ride with minimal increases in travel time and costs. It is reasonable to expect that SAVs will operate with a higher passenger load and automatically navigate to locations from where trips will originate, thereby reducing parking demand.

In this study we estimate the various levels of parking demanded under SAV systems characterized by varying fleet sizes and passenger wait times. These estimates are based on an agent-based model of a 10 mi × 10 mi hypothetical city laid out in a grid network of 0.5 mi street segments. We develop scenarios with fleet sizes between 500 and 800 vehicles, with various levels of willingness for ride-sharing, and with different empty vehicle cruising strategies. The simulation results indicate the amount of parking spaces saved when compared with conventional systems. The results also show where the most parking reductions can be expected under different assumptions in the stylized city described above.

This study adds to the growing literature on the potential impact of AVs on the built environment. While the associated technologies to enable AVs are maturing quickly, these studies also acknowledge that the social and legal infrastructure for implementing such systems are lagging. Yet, deployment of small-scale, low-speed shared autonomous vehicles will be tested in Europe (Citymobil2 Project, 2015) and possibly by Google in the near future (Markoff, 2014). In this paper we specifically address AVs as part of a sharing economy, such as car and ride sharing services that are becoming very popular. We contend that SAVs offer a number of advantages to travelers that current systems cannot match.

Compared to the conventional car-sharing program, such as Zipcar and Car2go, the SAV system offers more flexible services for clients, primarily through the elimination of the fixed rental and returning stations. For the mobile app based car-sharing program, such as Uber and Lyft, the SAV system may contribute to the

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reduction of operating costs and provide more affordable mobility services for disadvantaged groups of population. Meanwhile, by linking multiple trips and serving them using one SAV, the service holds great potential to relieve congestion on roads.

2. Earlier work

Given that the SAVs have multiple advantages over the existing car-sharing programs, several previous studies explored the feasibility of this new type of car-sharing. Ford (2012) reviewed the present social and legal barriers for the adoption of SAV systems. The study also developed a simplified model to evaluate the performance of a shared taxi system with fixed picking up and dropping off stations every half-mile to determine whether the system can support existing travel patterns. The results suggest that the system is quite feasible, even though the current legal environment will pose several barriers.

Kornhauser et al. (2013) evaluated the feasibility of a shared autonomous taxi system in various counties in New Jersey. Their results indicate that SAVs can facilitate an increase in ride-sharing travel behavior. Burns, Jordan, and Scarborough (2013) developed a more advanced agent based simulation model to evaluate the economic feasibility of a ubiquitous SAV car-sharing system. The simulation results imply that the cost per trip mile can range from \$0.32 to \$0.39, depending on the fleet size of the SAV system. This travel cost is more affordable than owning and operating a private vehicle (Burns et al., 2013).

Fagnant and Kockelman (2014) investigated whether the SAV system is environmentally sustainable. Their model assumptions are similar to that used in Burns et al.'s model, but the model pays special attention to the environmental impacts of the system. Their study results indicate that each SAV has the potential to replace approximately 11 privately owned vehicles. Additionally, some environmental benefits such as reductions in energy consumption, GHG emissions, and air pollutants emissions per vehicle life cycle can be expected once the SAV system starts to serve 5% of the population within the 10 mi × 10 mi grid-based study area. However, Fagnant and Kockelman's study suggested that the SAV system comes with associated costs of approximately 5% additional unoccupied VMT generated during the client picking up process. This side effect may be alleviated or even eliminated with the increase of ride-sharing behavior (Fagnant & Kockelman, 2014). In sum, there is evidence from multiple studies indicating this envisioned car-sharing service is economical and environmentally feasible. These and other feasibility studies show that dynamic ride-sharing service is expected to be more affordable and environmentally friendly compared to non-ridesharing systems (Chan & Shaheen, 2012; Noland, Cowart, & Fulton, 2006).

The popularity of dynamic ride-sharing can lead to reduced demand for parking. Fagnant and Kockelman (2013) estimated a saving of \$250 in parking cost for each new autonomous vehicle in the market, primarily through reallocating parking space from Central Business District (CBD) to more remote areas and from ride-sharing. Moreover, Hayes (2011) suggested that AVs can economize parking space because they can park inches from each other since there is no need to open auto doors, assuming that the passengers will be dropped off before the AVs get to the parking slots. New mobile applications can serve individuals who participate in dynamic ride-sharing service by matching the nearest vehicle with the route that matches the users' preference. Such a matching system will serve several passengers at the same time by linking trips that have origins and destinations close to each other. Once the vehicle occupancy rate is improved, more parking demand reduction can be achieved.

Past modeling efforts regarding dynamic ride-sharing focused on matching multiple clients with service vehicles so that certain objective function can be optimized. Agatz, Erera, Savelsbergh, and Wang (2011) developed a simulation of dynamic ride-sharing by linking trips and vehicles to minimize the system level VMT generation. Martinez, Correia, and Viegas (2012) proposed an agent based shared-taxi system that matched clients with taxis by minimizing the total travel time for both on-board and calling passengers. Fagnant and Kockelman (2015) developed their version of dynamic ride-sharing SAV model with more flexible objective function to maximize the possibility of ride-sharing. In their model, as long as the increased travel time for both on-board and calling clients do not exceed certain thresholds, the two clients have the potential to share rides. The SAV that can deliver both onboard and calling clients to their destinations using the shortest amount of time is assigned to the appropriate calling client.

Both the studies by Martinez et al. and Fagnant and Kockelman assume that clients' only concern is the time cost in the ride-sharing process. However, this may not be the case in reality. The primary concern for people with limited travel budgets may be the cost of travel. If so, the objective function to minimize should be the total travel cost. Thus, in this study a different objective function is used to investigate how various customer service preferences may vary the number of ride-sharing trips and urban parking demand.

Although the literature on SAVs is growing rapidly, there are limited number of papers on how SAVs can reduce the demand for parking space. It is still unclear how much the parking demand is likely to be reduced and what would be the spatial distribution of parking requirements once the system is implemented. Just as The Economist (2013) stated recently: "Town planners, property developers and builders need to start thinking about the effect of self-driving technology on demand for roads, parking, housing and so on. So far there is little sign that this is happening." This study begins to fill this gap through a simulation model, which is developed to estimate the potential impact of an SAV system on parking demand.

3. Model parameters

This simulation is conducted on a 10 × 10 mi grid based hypothetical city. The resolution of the grids, which also represents the street network, is 0.5 mi. The client agents in this model are people who are willing to use the SAV system. It is assumed that the SAV system has a low penetration rate of 2% within the region. In other words, only 2% of population within the simulated city will use the SAV system instead of private vehicles. The clients will generate vehicle trips that in general follow the same profile as estimated from the National Household Travel Survey (FHWA, 2009), in terms of trip length and trip departure time. SAVs are assigned by the vehicle–client match center to serve clients. Different vehicle assignment rules are set up in this simulation model, based on clients' willingness to share rides with others and preferences for the type of vehicle service. The Assigned SAV will then provide delivery services based on the operational rules configured within the model. These operational rules include how fast the vehicles may travel given the time of day, what kind of route the vehicles might choose to follow, whether the vehicle will continue empty cruising after dropping off the last client(s) on board, among others, described later. The parking demand will be recorded at individual grid cell level throughout the simulation process. By the end of the simulation day, total parking demand will be estimated for each grid cell in the simulation area. The time step of the model is set at 1 min, indicating that the simulated variables, such as location of vehicles, service requests from household agents, and vehicle assignments will be updated every one simulation minute.

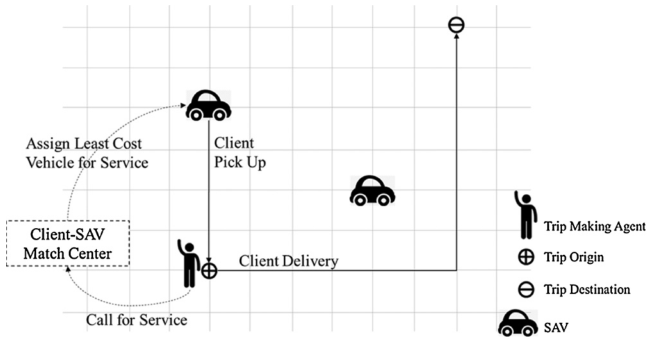

Fig. 1. Simulation model schematic graph.

4. Model specifications and implementation

The simulation model is identified and programmed in Matlab. In this model, client agents call the match center for SAV service, once they decide to make a trip. The client-SAV match center then assign the lowest cost vehicle to serve the client. After receiving command from the match center, the assigned vehicle will pick up the calling client and deliver him/her to the destination. The process is illustrated in Fig. 1. The specifics for the major components in the model are elaborated in the following sections.

4.1. Client agents and vehicle trip generation

In this model, the client agents represent people who are willing to use the SAV system. In this study, we conservatively modeled a low market penetration rate of the SAV system, assuming approximately 2% of the population within the study area will adopt the system. Each client agent generates several vehicle trips within a simulation day.

First, client agents are generated and assigned to each grid cell in the simulated area. It is assumed that the population density in the center of the hypothetical city is always higher than that in the fringe area. For a city like Atlanta, the population density is approximately 8000 per square miles in urban center and declines to around 1500 at places that are 5 mi away from the center (US Census Bureau, 2012). Thus, it is assumed that the density for client agent will be approximately 160 (8000 × 2%) per square mile in the urban center grids and 30 (1500 × 2%) per square mile in the further most grids in the simulated area. The population density within other grid cells are calculated based on their inversed Euclidean distance from the urban core. Based on the assumed population density, there will be approximately 10,000 participating clients in our study area. Meanwhile, for each client agent, the model randomly determines whether (s)he is willing to share rides with strangers, based on the aggregated level of willingness to share. The model also generates a random hourly income for each client using the cumulative density function (CDF) of 2014 U.S. national hourly salary, obtained from Bureau of Labor Statistics (2014).

Second, we estimate the trip generation rate for each grid cell based on the density of client agents, given the assumption that each person, on average, generates around 3.79 vehicle-trips per day (FHWA, 2009). As a result, daily vehicle-trip generation rate is set as 1.52 (160 × 3.79 × 0.0025) per grid cell in the very center of the simulated area and 0.28 (30 × 3.79 × 0.0025) in the four corners of the study area. The trip generation rates in all the rest of the cells are estimated using the following formula:

$$\lambda_i = \lambda_{\min} + \frac{(\lambda_{\max} - \lambda_{\min})}{\text{Dist}_{\text{corner,center}}} \times \text{Dist}_{i,\text{center}} \qquad (1)$$

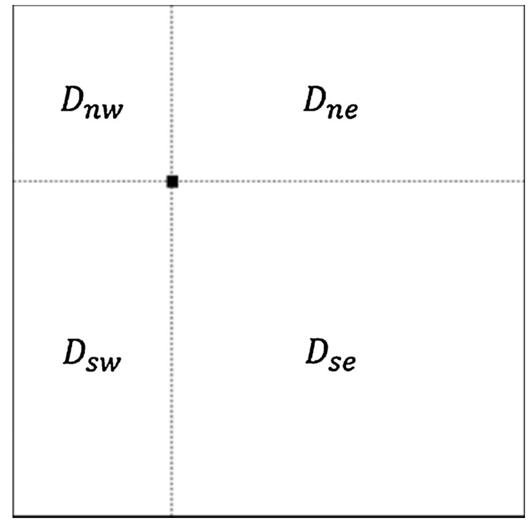

Fig. 2. Trip direction choice illustration.

where λ_i, is the trip generation rate at cell i; $\text{Dist}_{\text{corner,center}}$, is the Euclidean distance from corner to the center cell; $\text{Dist}_{i,\text{center}}$, is the Euclidean distance from cell i to the center cell.

Third, the model generates random number of vehicle trips for each grid cell given the trip generation rate λ_i for cell i, provided the assumption that the trip generation will follow Poisson distribution. Subsequently, the model determines other parameters, such as departure time, length, and destination, for the generated vehicle-trips.

4.1.1. Trip departure time and length assignment

The model assigns a random departure time and trip length for each generated vehicle-trip based on the empirical CDF obtained from 2009 NHTS weighted vehicle-trip data. First, a uniformly distributed random number between zero and one is generated. Then this random number is plugged into the corresponding inverse CDF function to generate the random departure time and trip length, as determined by functions 2 and 3 below. This process ensures that the generated vehicle-trips generally follow the trip departure time and length distributions from the 2009 national vehicle-trip profile.

$$\text{DT} = T^*(r) \qquad (2)$$

$$\text{TL} = L^*(r) \qquad (3)$$

where DT, is the simulated departure time; *TL*, is the simulated trip length; $T^*(x)$, is the inversed CDF for trip departure time; $L^*(x)$, is the inversed CDF for trip length distribution; r, is a system generated uniformly distributed random number (between 0 and 1).

4.1.2. Trip destination assignment

The model identifies the location of destination for each generated vehicle-trip, based on the origin and length of the trip. Given the trip origin and trip length, an agent has four travel direction options, which are northwest, northeast, southwest, and southeast, as shown in Fig. 2. The probability of following certain direction is estimated using Formula 4, which is analogous to the algorithm used in Fagnant and Kockelman's model (2014). An attraction factor α is used in the probability calculation formula to control the attractiveness of the urban center area. In the morning, the α is set as "1" to push the majority of trips into the CBD area. In the afternoon, the α is reduced to "0.65" to allow more trips to go outside of the CBD area. The number "0.65" is selected so that the amount of vehicle-trip arriving at CBD area will be roughly equal to that leaving the area. A uniformly distributed random number is generated and compared to the calculated probabilities to determine the general direction of the trip. Given the trip direction and trip length, the model then determines the number of valid cells within the study area. If the number of valid cells is larger than zero, the final destination cell will be randomly selected among all the possible destination cells. Otherwise, the model goes back to randomly generating another trip direction. This process ends after a valid destination is obtained.

$$Pr\,(D_i) = \alpha \times \frac{\text{Num}_{D_i}}{\text{Total Number of Cell}} + (1-\alpha) \times 0.25 \tag{4}$$

where Num_{D_i}, is the number of cell that falls in area D_i; α, is the attraction factor.

4.2. SAV fleet size and operation rules

The SAV fleet size is set as a selectable parameter, which determines the urban parking demand. Different fleet sizes from 500 up to 800 with increments of 50 are tested in the model. In the Fagnant and Kockelman (2014) model, the fleet size is determined by continuously adding more vehicles into the system once the client has been waiting for more than 10 min in the model warming up runs. In our model, the final ideal fleet size is determined by the change of average waiting time in the system. We consider the fleet size to be optimum when additional 50 vehicles in the system does not significantly reduce the average waiting time throughout the simulation day.

All the SAVs in the system are randomly distributed in the study area at the beginning of the simulation day, which is similar to Burns et al. (2013) model. To mimic traffic congestion during peak hours, the SAV travel speed is set as 30 mph during off peak hours and is reduced to 21 mph during peak hours. The SAVs are set to serve up to two overlapping vehicle trips generated by different agents. The average vehicle occupancy in the United States is 1.55 (Oak Ridge National Laboratory, 2012), thus two overlapping vehicle trips is likely to be generated by three persons. Assuming that all the SAVs are compact passenger vehicles, the SAVs may only be able to serve up to about two vehicle trips simultaneously.

Moreover, we also set up vehicle cruising rules in some scenarios to further reduce average trip delay and urban parking demand. The vehicle cruising algorithm is as follow. The study area is first divided into 16 (4×4) square subareas. For each area, the balance value is estimated using Formula 5. The SAVs that have dropped off the last client but are not assigned to any other calling trips will cruise to neighboring areas where the total balance value is higher. If the SAV is already in the area with the highest total balance value, then it will keep cruising within the area randomly to find potential clients. The SAVs will continue to cruise for several specified minutes before it eventually parks at the last cruising destination.

$$\text{Balance Value}_i = \lambda_i - \text{SAV}_i \tag{5}$$

where i, is the index for grid cell; λ_i, is the trip generation rate per minute in grid cell i; SAV_i, is the number of SAV in grid cell i.

In a grid based network, there exist multiple shortest routes between points A and B. To avoid congestion in one of the routes, the model employs several route choice algorithms under different service status of SAVs. For SAVs that are empty cruising or are assigned with an agent who is willing to share, the route with largest accumulated difference between the expected number of calling agents and the number of SAVs is selected. However, the SAV will only pick up the second passenger if the coordinate of this client falls within the blue square, determined by the existing location of the SAVs and destination of the first client as shown in Fig. 3, to minimize total costs for both clients.

For SAVs assigned with one client agent who is unwilling to share or two agents who are willing to share, the route with the least total number of SAVs will be selected to avoid traffic, as there

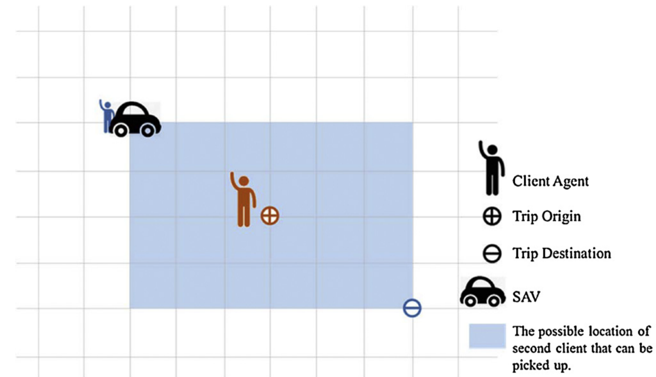

Fig. 3. Possible locations of the second client that can be picked up.

is no longer need to look for another potential sharing agent. It has to be mentioned that once an SAV is assigned to serve two different clients, the vehicle will optimize the route to deliver both agents to their destinations, i.e. the shortest route to get to both destinations, to reduce energy consumption. Thus, SAVs does not schedule route based on first come first serve principle for agents who are willing to share rides. All the scheduled routes will be updated at every time step, assuming that the SAVs are always equipped with the latest traffic conditions.

4.3. SAV–client match center

The SAV–client match center collects requests from persons requesting a trip and finds an SAV that minimize the cost of providing the service as discussed below. The match center assigns SAVs to serve agents who come first. At a certain time step, calling agents, who are not assigned with an SAV, will be put into a waiting list. Clients in the waiting list will be prioritized at the next time step to be matched with an available SAV. To avoid the situation, in which clients from certain areas will be served first, the order of the agents who called at the same time will be randomized before the SAV assignment process.

If there are multiple vehicles available in the system, the match system will select the most suitable one for the calling client. To find the "ideal" vehicle based on client's preference and tolerance, the following algorithm is implemented. First, if the calling agent is not willing to share with other people, then the closest empty SAV will be allocated to serve the client. If the calling client is willing to share with others, then the match center will first identify all the available vehicles in the system. For clients who are willing to share, SAVs that are empty and the ones, assigned to only one client who is also willing to share are all available vehicles. Then the match center will estimate costs of each available SAV for both the calling customer and the on board customer (if there is one). Ridesharing only happens when both the on board and calling client can benefit from it. In other words, if the travel cost for either one of them increases due to ride-sharing, then the sharing won't take place and the SAV with the on board client is no longer considered as an available vehicle for the calling client. After estimating all the potential travel costs, the match center will then assign the least cost SAV (with respect to the calling agent) to serve the calling clients. The potential travel costs are estimated based on client's preferences, as follows:

(1) In the scenario where clients value their time highly, the cost is estimated based on the potential detour time and waiting time cost. The time cost is estimated using the simulated client's hourly salary.

Table 1
Daily parking demand by SAV fleet size.

SAV fleet size	Daily parking demand [Std. Dev.]	Avg. parking demand (per SAV)	Avg. waiting time [Std. Dev.]	Reduction in average waiting time (s) per added SAV
500	2665 [41.6]	5.33	13.3 [2.58]	–
550	2964 [25.5]	5.39	7.2 [0.48]	7.32
600	3187 [28.5]	5.31	4.6 [0.31]	3.12
650	3363 [35.2]	5.17	3.0 [0.40]	1.92
700	3566 [32.8]	5.09	2.1 [0.30]	1.08
750	3754 [31.2]	5.01	1.8 [0.06]	0.36
800	3899 [36.5]	4.87	1.7 [0.04]	0.12

(2) In the scenario where clients have a limited budget, the cost is the actual out-of-pocket travel cost. The SAV travel cost is estimated using trip mile costs based on Burns et al.'s model. Burns et al. (2013) estimated the SAV travel cost to be from \$0.32 to a high end of \$0.40 per trip mile in their base scenarios, which have similar simulation set ups as in this study. We used the higher trip cost, i.e. \$0.40 per trip mile, as the SAV travel cost for our study. When estimating travel cost for SAVs with one client on board, the potential cost is going to be split between the two clients, using the formula as shown below.

$$\forall j \in J : \text{Split Cost}_j = \text{SAV Cost} \times \frac{\text{dist}_j}{\sum_J^{i=1} \text{dist}_i} \tag{6}$$

where j, is the jth involved vehicle-trips; J, is the set of all involved vehicle-trips; SplitCost_j, is the share of cost should be paid by jth involved vehicle-trips; SAVCost, is the cost occurred after picking up the second client; dist_j, is the distance between the second client's origin and the jth client's destination.

(3) In scenario, where client is concerned about both time and out of pocket costs, then the cost will be estimated as the sum of both costs. Similar to the above scenarios, the potential SAV travel cost will be split between the two agents who share rides.

If multiple SAVs have the lowest estimated cost, the ones with one client on board will be prioritized to promote dynamic ride-sharing behavior in the system. Otherwise, the match model randomly selects one of the lowest cost vehicles to serve the client.

5. Results

We ran the model for 50 simulation days to obtain stable results to determine how the system may influence urban parking demand. Various scenarios are developed to determine how different attributes of the SAV system may affect urban parking demand. To obtain a baseline, we first test a scenario with no-ridesharing and no-vehicle cruising to assess how different SAV fleet sizes may influence urban parking demand. We then introduce ride-sharing to check how clients' level of willingness to share influences the parking demand. In this scenario, clients' preferences for different types of SAVs are also tested. In the final scenario SAVs are allowed to cruise without passengers for specified aunt of time to determine how this strategy may further reduce urban parking demand.

5.1. Impact of SAV fleet size on urban parking demand

In this scenario, no ride-sharing service is offered by the SAV system. Different SAV fleet sizes are tested to determine how parking demand changes with the number of SAVs in the system. The result, as tabulated in Table 1, indicates that the total daily parking demand is positively correlated with SAV fleet size. The standard deviations are presented in the brackets. The results show that adding another 50 vehicles into the system is likely to increase the urban parking demand by approximately 150 and the increase is quite constant. However, the day-to-day standard deviations tend to diminish when there are more vehicles in the system, indicating that the system is more stable or reliant overall. Meanwhile, after adding more vehicles in the system, the average daily parking demand per serving SAV will decrease, as shown in Table 1.

As we might expect, the average wait times for SAVs improve significantly with more vehicles in the system but the gains become smaller as the numbers get larger (The last column in Table 1). For instance, when there are only 500 SAVs in the system, the clients, on average, have to wait approximately 14 min to be served. This waiting time is even larger than some current bus systems. In reality, if the clients have to wait longer than taking a bus, then most of them may choose to keep their own private vehicles or use the transit system instead. Additionally, the variation in results for repeated model runs for the 500-SAV scenario is quite large compared with other scenarios, indicating that the system is not stable. Therefore, it is not realistic to use 500 SAVs to serve the simulated population.

Based on the results in Table 1, the average waiting time diminishes when more SAVs are added into the system. The reduction in average waiting time per added SAV decreases from 7.32 to 0.12 s when number of vehicles in the system is increased from 550 to 800. When there are more than 700 vehicles in the system the reduction in average waiting time is smaller than one second per added SAV. This indicates that the efficiency of adding SAVs to reduce expected waiting time is very low once there are 700 vehicles in the system.

The simulation results also indicate that the parking demand is higher in the center of the simulated area, as shown in Fig. 4. Additionally, the larger the fleet size of the system, the larger the demand gap between the urban center and urban fringe area. This is attributed to the fact that we assumed the trips have a tendency to end in the central area before noon. Thus, based on this simulation result, the parking demand may concentrate in the areas where a large amount of trips are attracted to, if no operation strategy is implemented to ask vehicles to reallocate themselves.

Studies have shown that dynamic ride-sharing service is expected to be more affordable and environment friendly compared to non-ridesharing systems (Noland et al., 2006; Chan & Shaheen, 2012). Thus, we continue to explore whether introducing dynamic ride-sharing can help further reduce the fleet size and parking demand while maintaining the level of service for the SAV system. The results are elaborated in the following section.

5.2. Impact of ride-sharing and client's preference on urban parking demand

In the ride-sharing scenario, we first explore how the level of willingness to share (i.e. the percentage of population who are willing to share rides with strangers) may affect the total daily parking demand and service quality of the SAV system. Scenarios with different levels of willingness to share from 25% to 100% with increments of 25% are tested. We start with the assumption that all clients value their time the most. Each client will be assigned with an SAV with the least wasted time cost to accommodate their service preference.

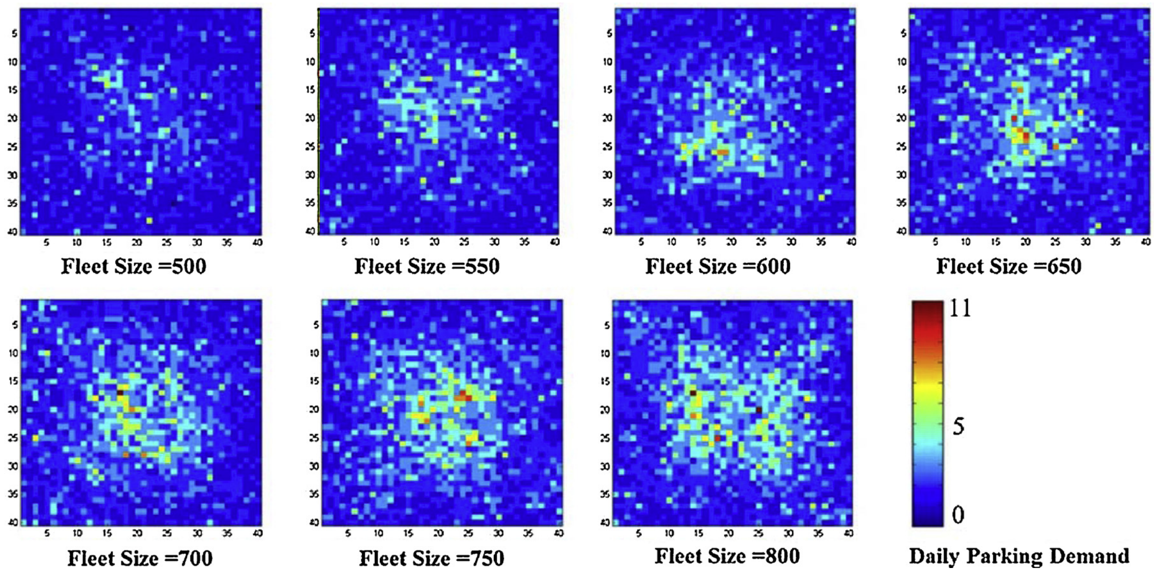

Fig. 4. Spatial distribution of parking demand by SAV fleet size.

The results of above scenarios, as illustrated in Fig. 5, indicate that the total daily parking demand is not sensitive to the level of willingness to share. The error bars in the chart represent day-to-day standard deviations. *T*-tests are conducted between results based on various levels of willingness to share and the test results indicate that the difference between various trend lines are not statistically significant. Such outcome is heavily influenced by the fact that we always assign the SAVs with the least potential time cost to each customer. In other words, the client-SAV match center may always prioritize an empty SAV for each client to avoid additional detour time costs. Therefore, even if people are willing to share, limited number of trips are linked together given the least travel time cost assignment method. Under this scenario, less than 10% of all the generated vehicle trips are actually linked trips across all level of willingness to share and SAV fleet sizes. The percentage of linked trips reduces from 9.7% to 6.3% when the fleet size increases from 500 to 800 SAVs, as there are even less motivations to share rides when there are more than sufficient number of SAVs in the system.

However, considering the needs of different clients in actual circumstances, assigning SAV with least time cost may not always be an ideal way to assign vehicles. For instance, least wasted time cost based vehicle assignment method may not be appealing for people who have a constrained budget. For this type of clients, the most desirable assignment algorithm is matching them with the least out of pocket cost SAV via maximizing the shared miles. The waiting and detour time costs are ignored in such assignment algorithm. Meanwhile, for a majority of the population the ideal SAV may be the one that can minimize the total SAV cost (i.e. the combination of time and travel cost). In this study, we also explored how the above two types of client-preferences-based vehicle assignment methods may affect the daily parking demand.

The results for the least travel cost and least total cost scenarios are plotted in Fig. 6. In the least travel cost SAV assignment scenario, the total daily parking demand is highly sensitive to the level of willingness to share. The more people who are willing to share, the less parking demand will be needed. It is also noticed that the reduction increases significantly when more than 50% of the population are willing to share. This suggests that to implement the dynamic ride-sharing SAV system, a critical mass of population is required to magnify the benefits offered by the system.

The results from least total cost scenario generally fall between the results from least travel cost and least time cost scenarios. The results indicate that the parking demand will decrease when the level of willingness to share become higher. However, the reduction is not as significant as in the least travel cost scenario. In this model,

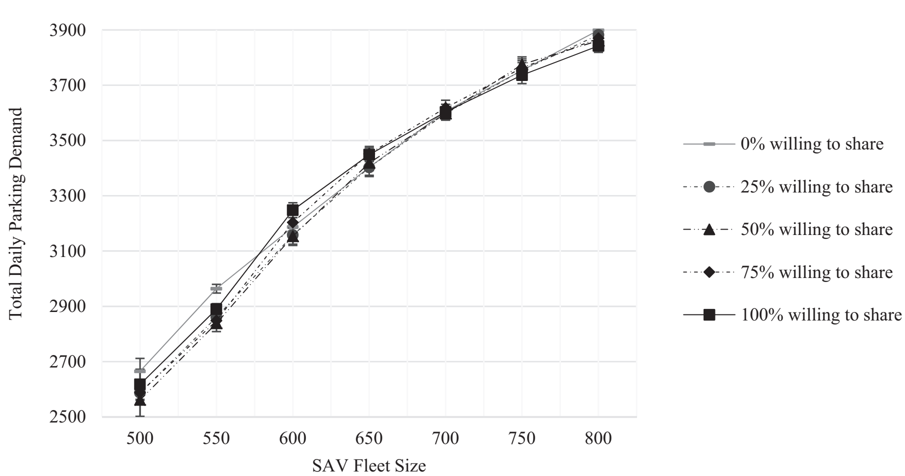

Fig. 5. Total parking demand after ridesharing (assign least time cost SAV to serve each client).

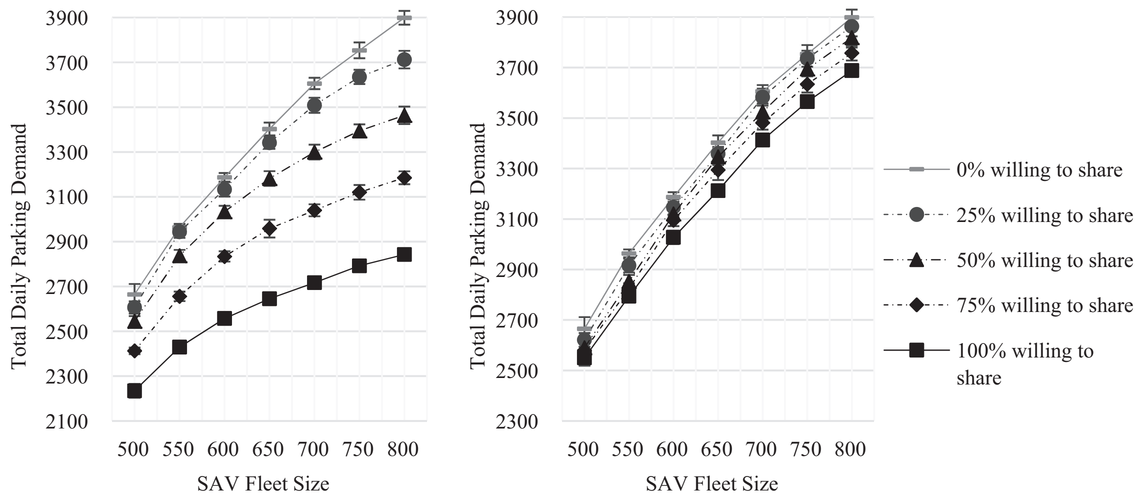

Fig. 6. Total daily parking demand by SAV fleet size for least travel cost assignment (Left) and least total cost assignment (Right) scenarios.

the reduction in parking demand is closely associated with how much people value their time. Thus, the small reduction in parking demand after ridesharing is due to the fact that people value their time based on their hourly salary. However, if the perceived time cost of travel is less than the hourly salary, then more reduction in parking demand can be expected in this scenario. However, the most reduction is not going to be larger than the least travel cost scenario.

Assuming that the least total cost assignment method is acceptable for most clients, we adopt that vehicle–client match method in the scenarios where ridesharing service is provided.

The spatial distribution of the demand for parking with 700 SAVs with various levels of willingness to share and where everybody prefers the least total cost SAV system, is shown in Fig. 7. As seen in this figure, the most significant reduction of parking demand occurs in the urban fringe area once people start to share rides with others. Also notable from the figure is that even with reduction in the overall parking demand, the parking demand in the center of the simulated area remains higher than the rest of the study area.

Finally, we compared the average waiting time of the dynamic ridesharing system with the non-ridesharing system and the results are illustrated in Fig. 8 (left). The average waiting time for all trips seems to be reduced dramatically with the increase of ridesharing, especially when there are less than 700 SAVs in the system. The results are expected, as in the no-ridesharing scenario a client has to wait for the next empty vehicle. However, in the ride-sharing scenario, the waiting time can be significantly reduced since the client is willing to avail of an SAV assigned to another agent who is also willing to share. Thus, ride sharers can expect shorter wait times during the peak hours than other riders who want the SAV to themselves.

Controlling for the number of vehicles in the system, the average detour time for shared rides decreases with increasing levels of willingness to share, as shown in Fig. 8 (right). This can be predicted since higher rates of participation in dynamic ridesharing service

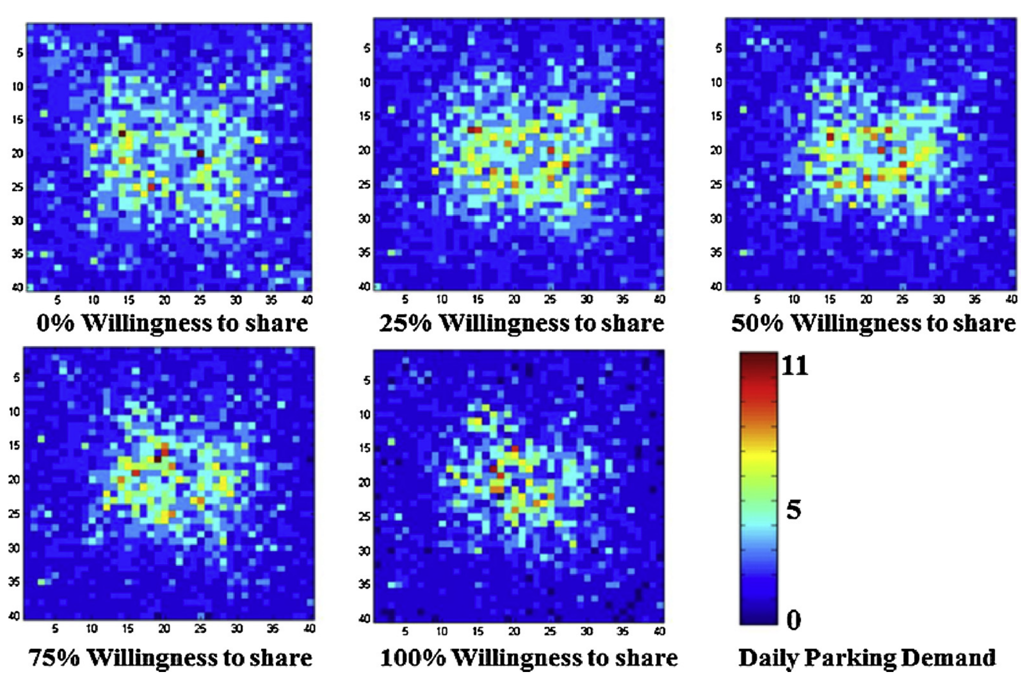

Fig. 7. Spatial distribution of parking demand by different level of willingness to share.

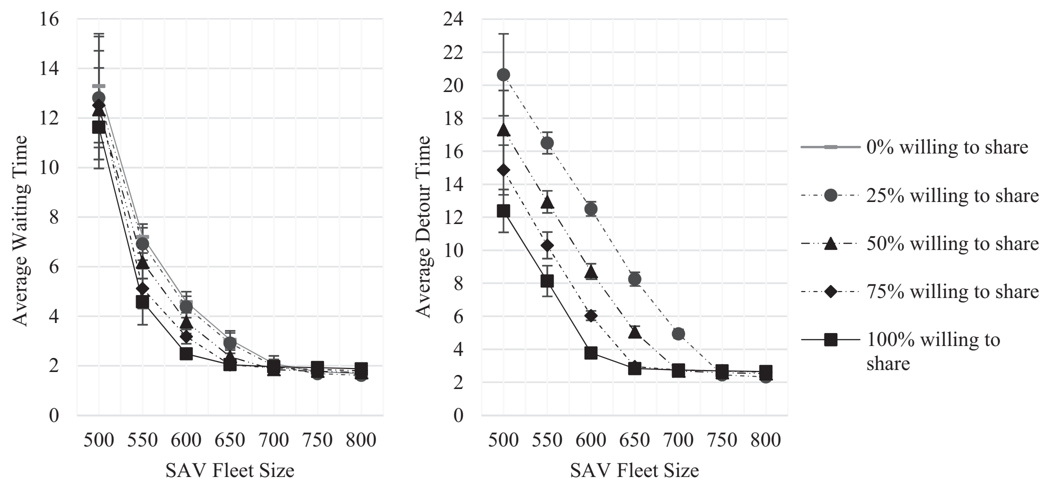

Fig. 8. Average waiting and detour time by SAV fleet size.

improves the possibility of finding a better match for shared rides. However, the average detour time declines more slowly when more people start to share rides. The most significant reduction is found between 25% willingness to share and 50% willingness to share scenarios. In addition, it is observed that when there are more than sufficient number of vehicles in the system, the benefit of ridesharing disappears. This result can be observed in the scenario when there are more than 750 SAVs in the system. In this case, both average waiting time and detour time change insignificantly for different levels of willingness to share. Thus, the fleet size should be carefully considered when designing an SAV system to encourage ride-sharing behavior.

The simulation results also suggest that less SAVs will be required to serve the participating clients if they are willing to share. For instance, if 100% of the simulated vehicle-trips are shared and we want to constrain the average waiting and detour time to approximately 2 min, then 600 SAVs will be quite sufficient to serve the population. However, this level of willingness to share will be difficult, if not impossible, to achieve in the near future. Therefore, we select 50% of population as willing to share and 650 vehicles as the default setting for further scenario development. Under this setting, the average total delay time is 2.36 min, which is only around half a minute longer than the average waiting time in the 700-SAV & No-sharing Scenario. However, the ridesharing system is able to reduce the SAV fleet size by 7% from 700 to 650.

5.3. Impact of vehicle cruising on urban parking demand

In this study, we also considered the possibility of using empty vehicle cruising strategy to further reduce the parking demand and improve the service quality. In this scenario, the SAVs will continue relocating themselves to places where the anticipated number of clients is high while the existing number of SAVs is low. Different empty cruising time threshold is set between 5 min and 30 min to determine the relationship between parking demand and empty cruising time.

The results, as shown in Table 2, suggest that longer the empty cruising time allowed in the system, lower the parking demand. It is reasonable to expect this result since the SAVs that cruise forever will not need any parking. We also notice that parking demand falls more slowly as empty cruising time increases. The parking demand is reduced by more than 10% when the initial 5-min cruising is introduced. The reduction rate falls to approximately 4% when the cruising time increases from 20 to 30 min.

It is also important to note that the parking reduction from cruising comes at a cost. The total daily VMT of the system will increase significantly as shown in Table 2. Thus, life cycle energy consumption and GHG emissions analysis should be performed to understand the full cost and benefit of the empty vehicle cruising strategy.

It is also interesting to note that the spatial distribution of parking demand changes significantly once the SAVs start to empty cruise, as illustrated in Fig. 9. The parking demand tends to be more evenly distributed throughout the study area, the longer the vehicle cruise. This can be attributed to the fact that the vehicle empty cruising process is, to some extent, similar to the vehicle reallocating process, which renders vehicles to be more evenly distributed within the region. The cruising strategy provides a means for distributing parking to lower cost areas within the city, instead of concentrating in the higher cost central areas.

5.4. Simulation results summary

The simulated results are further compared with the business as usual (BAU) parking demand scenario. We assume that without the SAV system, the 10,000 simulated clients are most likely to own their own private vehicles. The 2009 NHTS data show that the average vehicle ownership per licensed driver is 0.99. Therefore, there will be a need for 9900 private vehicles. Thus based on our model result, one SAV will be able to replace around 14 privately owned vehicles, or even more when the level of willingness

Table 2
Daily parking demand and VMT generation by empty cruising time (650 SAV, 50% willing to share).

Empty cruising time	Daily parking demand [Std. Dev.]	Avg. waiting time [Std. Dev.]	Avg. daily VMT [Std. Dev.]
No cruising	3346 [36.2]	2.36 [0.32]	210,885 [1154]
5-min cruising	2972 [32.4]	2.13 [0.31]	243,150 [1718]
10-min cruising	2676 [26.8]	1.83 [0.24]	270,523 [1437]
15-min cruising	2460 [17.2]	1.81 [0.24]	291,361 [1882]
20-min cruising	2296 [22.4]	1.76 [0.23]	313,149 [1647]
30-min cruising	2063 [20.4]	1.72 [0.22]	342,976 [2092]

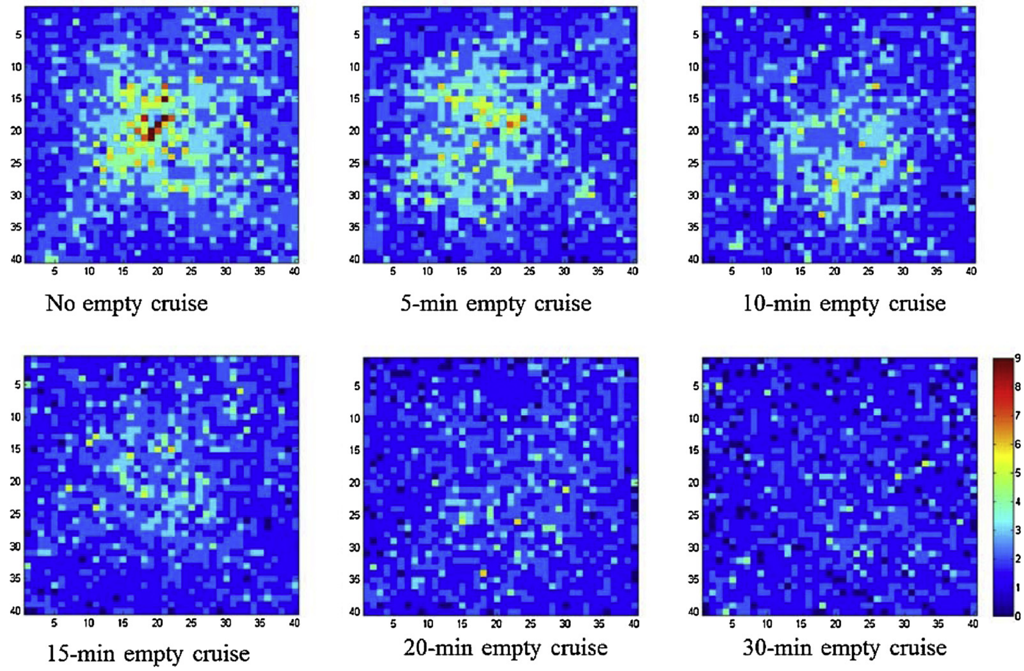

Fig. 9. Parking demand spatial distribution by vehicle empty cruising time.

to share is higher. Shoup (2005)'s study indicates that under urban context 3–4 parking lots will be needed for each private vehicle. Chester, Horvath, and Madanat (2010) estimate the ratio of parking space per private car to be around 3.3. The estimated parking spaces includes all the paid parking, commercial parking, home space, work space, and on-street parking. Chester et al. (2010) also employed a rule-of-thumb 8-1 space per car ratio, which includes both designated and non-designated parking spaces. In this study, the business as usual parking demand is estimated using space per car ratio from 3.0 to 8.0. Based on the simulation results, approximately 90% of parking demand for the participating clients can be reduced once the SAV system is implemented. Additionally, adding the ridesharing service into the system may further reduce the parking demand by one percentage point and adding 5-min cruising operation rule into the system may further reduce parking demand by another one to two percentage points. The estimation results are tabulated in Table 3.

In sum, the SAV system can help eliminate a significant amount for parking demand and the benefits of such extensive reductions in parking are significant. The parking lots are often aesthetically unpleasant and their elimination can result in improving walkability and attractiveness of the area. The decrease in parking space requirement may also contribute to alleviating the urban heat island effect if the impervious surfaces are transformed by introducing natural vegetation. In addition, a significant amount of built up space can be reclaimed for other uses in central cities where developed space is at a premium. Therefore, adoption of SAVs can offer multiple opportunities for planning aesthetically pleasing, healthy, and sustainable urban environments in the heart of the city.

6. Model verification

To verify that the simulation model is programmed without logical errors, we traced the behavior of SAVs in our model and one scenario is randomly selected to be visualized. The arrows in Fig. 10 indicate the general movement of the selected vehicles every 5 min. The behaviors of all simulated SAVs seem reasonable, indicating that the simulation model is logically consistent and correctly programmed.

We also tested the sensitivity of the model to determine whether the change of parameters in the model leads to reasonable changes in the corresponding model outputs. We have already analyzed the change of average waiting time and daily parking demand, given different SAV fleet sizes, levels of willingness to share, and empty cruising times. Here, we highlight other SAV system performance indicators, such as the number of shared trips, average travel cost (for ride-sharing scenarios), VMT generation, system delay, and vehicle utilizations.

Table 4 shows the different system performance indicators across fleet size. The results suggest that the indicators for system service quality, such the percentage of trips delayed by more than 5 min and peak hour waiting time, are improved dramatically when the fleet size becomes larger. Additionally, the wasted VMT during pick up process tends to drop when there are more SAVs in

Table 3
Simulation results vs. BAU parking demand.

Model scenarios			Avg. parking demand [Std. Dev.]	Reduction rate range (%)	Avg. waiting time [Std. Dev.]	Avg. VMT [Std. Dev.]
Fleet size	Willing to share (%)	Empty cruising (min)				
700	–	–	3566 [32.8]	87.9–95.5	2.10 [0.30]	221,855 [1678]
650	50	–	3346 [17.9]	88.7–95.8	2.36 [0.32]	210,885 [1154]
650	50	5	2972 [25.1]	90.0–96.2	2.13 [0.31]	243,150 [1718]
650	50	10	2676 [19.6]	91.0–96.6	1.83 [0.24]	270,523 [1437]

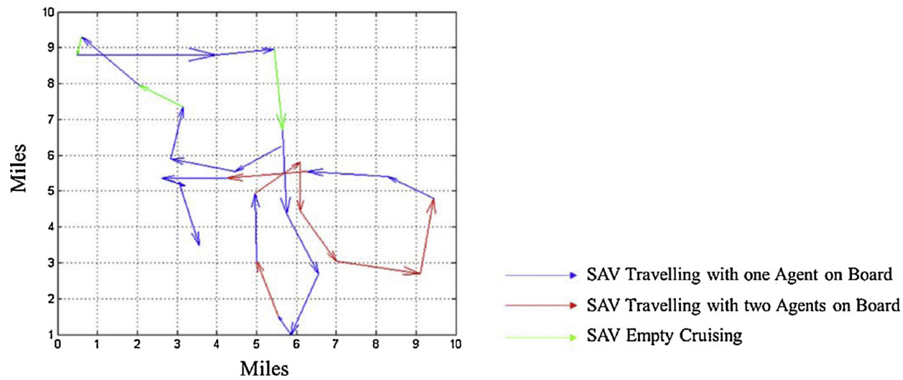

Fig. 10. SAV tracing example (from 3:00pm to 7:30pm, end of evening peak).

Table 4
SAV system performance indicators by fleet size.

Fleet size	% Trips delayed by 5+ minutes	Peak hour waiting time	Pickup VMT (in thousands)	Occupied VMT (in thousands)
500	38.6% [0.05]	34.3 [4.06]	33.3 [3.3]	141.9 [0.97]
550	27.1% [0.008]	20.7 [1.26]	24.8 [0.7]	141.9 [0.97]
600	22.7% [0.009]	15.1 [1.35]	21.0 [0.6]	141.9 [0.97]
650	18.5% [0.006]	10.2 [1.45]	18.4 [1.2]	141.9 [0.97]
700	10.2% [0.015]	4.9 [1.30]	13.6 [2.1]	141.9 [0.97]
750	3.9% [0.012]	2.6 [0.43]	9.4 [1.2]	141.9 [0.97]
800	3.0% [0.006]	2.4 [0.16]	8.4 [0.8]	141.9 [0.97]

Table 5
SAV system performance indicators by level of willingness to share (650 SAV in the system and clients prefer least total travel cost).

Level of willingness to share (%)	% Trips delayed by 5+ minutes	Peak hour waiting time	Detour time (shared trips)	Pickup VMT (in thousands)	Shared VMT (in thousands)	No. of shared rides	Cost per trip mile (shared trips)
0	18.5% [0.006]	10.2 [1.45]	–	18.4 [1.2]	–	–	–
25	15.5% [0.023]	7.4 [1.50]	8.25 [1.37]	14.8 [0.8]	2.2 [0.3]	1417 [255]	$0.27 [0.05]
50	12.2% [0.034]	5.5 [1.40]	5.05 [1.25]	13.7 [0.5]	3.5 [0.8]	2661 [209]	$0.25 [0.04]
75	7.2% [0.017]	3.3 [0.58]	2.95 [0.34]	11.2 [0.9]	4.2 [1.0]	4074 [194]	$0.23 [0.04]
100	7.1% [0.006]	3.0 [0.15]	2.83 [0.06]	10.0 [0.6]	5.5 [1.7]	6264 [119]	$0.22 [0.02]

the system as anticipated. The occupied VMT doesn't change across different scenarios, as we fixed the random number seed in each model run to control the variations in random number generation. By fixing the random seed for each run we can ensure that the variations in system performances are only associated with the changes in fleet size.

The system performance indicators for different levels of willingness to share are displayed in Table 5. As expected, the percentage of trips delayed by more than 5 min declines with the increase in people's willingness to share. The reduction is most significant during the peak hours, as the results show the rush hour average waiting time is reduced from 10.2 min to approximately 3.0 min. This is expected as the ridesharing service actually increase the service capacity of the system by improving the utilization of available seat capacity. We also observe an increase in shared VMT and number of shared rides when more people agree to share vehicles. Furthermore, we find better matches of trips when more people choose to share rides, which is reflected in the decline in detour time and trip costs. Finally, we notice that less pickup VMT is generated when ridesharing is introduced into the system. This is due to the fact that SAVs pick up the second client while serving the first client for the shared rides.

To verify the cruising scenario, we estimated the percentage of trips delayed by more than 5 min, cruising VMT, and pickup VMT, as tabulated in Table 6. The results indicate that the system service quality can be improved slightly by allowing vehicles to navigate to areas where the demand outstrips supply, as the percentage of trips delayed by more than 5 min tends to decline with the increase of empty vehicle threshold. We observe that the system

Table 6
SAV system performance indicators by empty cruising time threshold (650 SAVs, 50% willing to share).

Cruising time	% Trips delayed by 5+ minutes	VMT (in thousands)	
		Cruising	Pickup
0	12.2% [0.034]	–	13.7 [0.5]
5	9.4% [0.031]	29.5 [1.01]	13.5 [1.7]
10	7.2% [0.025]	59.3 [1.33]	12.4 [1.4]
15	6.6% [0.026]	81.2 [1.70]	11.7 [1.8]
20	6.3% [0.029]	99.3 [2.13]	11.2 [1.5]
30	5.8% [0.024]	121.5 [2.20]	11.0 [1.8]

generates more VMT during the cruising process, as we anticipated. The results show that the increase of cruising VMT is not proportional to the increase of allowed cruising time, as when longer cruising period is allowed, the probability of SAVs being reassigned to a new client becomes higher, rendering a decrease in VMT growth. The pickup VMT declines slightly, as the vehicles continue to allocate themselves to meet potential demands. However, the decline in pickup VMT is rather small compared to the growth of cruising VMT. Thus, the system generates more VMT overall.

Finally, we also compared our model outputs with Burns et al. (2013) and Fagnant and Kockelman's (2014) results to examine the reasonableness of our results. Since these studies do not involve ride-sharing, we only compared no-ridesharing model results. To make the results comparable, we selected scenarios with similar fleet size and trip generation ratios. Fig. 11 summarizes the average waiting time of different scenarios from different studies. The results indicates that the average waiting time from this study is

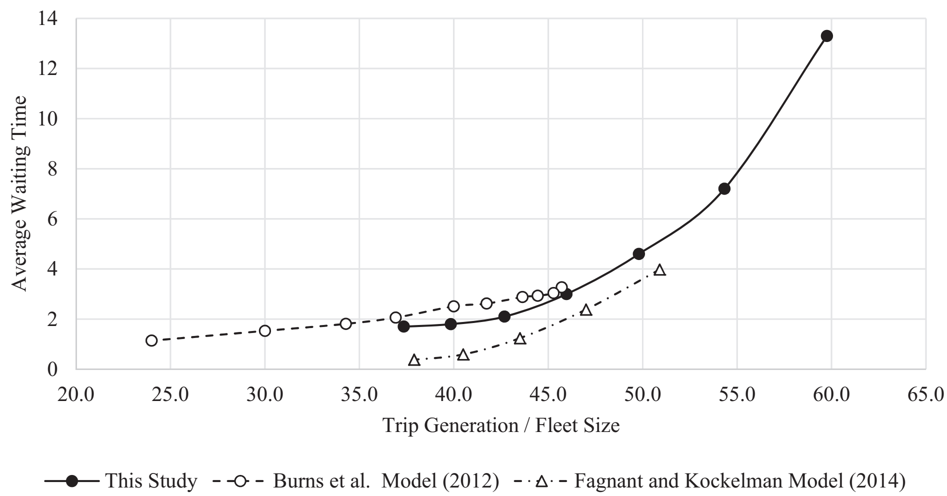

Fig. 11. Comparison of average waiting time.

quite reasonable compared with other studies. The average waiting time from Burns et al. (2013)'s study is slightly higher than ours. Such discrepancy can be attributed to the fact that their model used an average speed of 20 mph, while our simulation assumed an average speed of 30 mph during off-peak hour and 21 mph during peak hour. Fagnant and Kockelman (2014)'s model has smaller average waiting time, as their SAVs continuously reallocate themselves. Our simulation model also generates smaller average waiting time, once the vehicle empty cruising strategy is implemented in the model. In sum, our model output is quite reasonable compared with existing SAV simulation studies.

7. Model limitations

Although our simulation model adds more understanding of how SAV system may influence future urban parking demand, the proposed SAV model can still be further improved from several perspectives. First of all, parking price should be incorporated into the model framework. The SAVs doesn't necessarily need to park at the destination and can navigate to cheaper parking lots in more remote areas. The behavior will be primarily determined by the relationship between the costs of gas and pollution and the benefits of lower parking prices. Second, the model can be improved if the real world network and travel behavior patterns can be applied in the model. Currently, most of the model inputs are normalized national level data and the simulated participating clients have homogeneous socio-economic characteristics throughout the study area. Additionally, although the speed of SAV is different during peak and off peak hours, the link level speed doesn't vary within the study area. If congestion is considered in the model, then central urban residents may expect more waiting delays. Finally, the model also assumed that people with different socio-economic characteristics are equally willing to share rides with strangers, which may not be the case in real life. Thus future work should be conducted to integrate all the above important factors into the simulation model. Moreover, authors seek to make further efforts to investigate how the redundant parking spaces can be repurposed to achieve smart growth in the future.

8. Conclusions

This study developed a simulation model to evaluate the potential impact of SAVs on urban parking demand. The model incorporated three improvements over existing models described in other studies. First, it operationalized a dynamic ride-sharing system with two agents who are served by one SAV based on each agent's preferences for sharing. Second, it tested different vehicle assignment methods based on clients' preferences for both out-of-pocket and time costs to explore system performance. Third, it examined empty vehicle cruising strategies to determine their impact on parking demand and the spatial distribution of such demand.

The no-ride sharing model simulation result shows that the parking demand is sensitive to the number of SAVs in the system. To reduce the parking demand, we may reduce the number of SAVs within the system. However, the total number of serving vehicles cannot be too small, otherwise it will deteriorate the service quality of the system. For the simulated hypothetical grid-based city, at least 700 vehicles will be needed to maintain the average waiting time at approximately 2 min.

The ride-sharing model results indicate that parking demand sometimes will be sensitive to the level of willingness to share rides, depends heavily on how the system assign the SAVs to serve the calling clients. If the least time cost assignment method is used, then the parking demand will only be sensitive to the number of vehicles in the system. If the least travel cost assignment method is implemented, then higher level of willingness to share will also help to reduce the parking demand in a significant manner. The total least cost assignment method seems to be the most reasonable. Using the least cost assignment method, the SAV system can operate with 50 less SAVs in the system compared with no-ride sharing system, while maintain the average waiting and detour time to around 2 min.

The vehicle empty cruising model results suggest that we may further reduce parking demand by sacrificing VMT. However, the marginal reduction rate of sacrificing VMT diminishes when the threshold of empty cruising increase. Finally, by comparing all the above parking demand simulation results with the estimated business as usual parking demand, we noticed that up to 90% of parking demand for the simulated households can be eliminated if we put 700 SAVs in the system. Once those urban parking spaces are no longer in need, more sustainable designs, such as more green, open, and human oriented space can be introduced. Planners and local decision makers may seize this opportunity to guide the city to develop in a more sustainable way.

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