Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where?

Wenwen Zhang
Georgia Institute of Technology: School of City & Regional Planning
760 Spring Street, Atlanta, GA, 30318
404-910-5023
wzhang300@gatech.edu

Subhrajit Guhathakurta
Georgia Institute of Technology: School of City & Regional Planning
760 Spring Street, Atlanta, GA, 30318
404-385-0900
subhro.guha@coa.gatech.edu

Word Count: 5,663+ 7 Figures *250 = 7,413

Revised and resubmitted: Nov. 15th, 2016

ABSTRACT

We are on the cusp of a new era in mobility given that the enabling technologies for autonomous vehicles (AVs) are almost ready for deployment and testing. While the technological frontiers for deploying AVs are being crossed, we know far less about the potential impact of such technologies on urban form and land use patterns. This paper attempts to address these issues by simulating the operation of Shared AVs (SAVs) in the City of Atlanta, USA, using the real transportation network with calibrated link-level travel speeds, and travel demand origin-destination (OD) matrix. The model results suggest the SAV system can reduce parking land by 4.5% in Atlanta, at a 5% market penetration level. In charged parking scenarios, parking demand will move away from downtown to adjacent low-income neighborhoods. The results also reveal that policymakers may consider combining charged parking policies with additional regulations to curb excessive VMT and alleviate potential social equity problems.

Keywords: Shared Autonomous Vehicles, Parking, Land Use, Atlanta

INTRODUCTION

Autonomous vehicles, cars that drive themselves, are being tested for deployment in various locations around the globe. Multiple companies, including Google, Audi, Nissan, Tesla and BMW, have announced plans to have fully automated cars by 2020. Indeed, the deployment of small-scale, low-speed, automated mobility on demand systems will soon be tested in Europe [1] and possibly by Google and Uber shortly [2,3]. Recently, the U.S. Department of Transportation unveiled new policy guidance anticipating widespread deployment of AVs [4]. The vehicle automation technology combined with the sharing economy will undoubtedly lead to a new travel mode – Shared Autonomous Vehicles (SAVs), a centralized taxi service without drivers, which will be more affordable and environmentally friendly to operate than private AVs [5,6].

This promising SAV system will inevitably lead to changes in the urban parking land use. One Previous study, based on the simulation of SAV operations in a hypothetical grid-based city, revealed that the SAV may eliminate a significant amount of parking demand for participating households [7]. This study adds to the proliferating literature on the impact of SAVs based on real-world data-driven simulation. We developed a discrete event simulation (DES) model to examine the impact of SAVs on urban parking land use at various parking price settings. The model output provides insights about the amount and the spatial distribution of parking for the SAV system.

PREVIOUS WORK

Although SAVs are yet to be deployed, there has been a growing literature exploring different aspects of the system using simulation approaches. Several pioneering studies have validated the feasibility and affordability of the SAV system. Ford [8] and Kornhauser [9] evaluated the performance of a shared taxi system, *aTaxi* system, with fixed service stations distributed every half-mile in a region and demonstrated that the system could fulfill the travel demands. Burns et al. [5] developed a more advanced agent-based simulation model to show that the cost per trip mile can range from $0.32 to $0.39, which is more affordable than the existing private vehicles. Bridges [10] suggested electric autonomous vehicles can reduce the cost to $0.13, and the SAVs can still anticipate a 30% profit margin. At this price point the SAV system competes well with almost all existing public transit systems currently operating in the US. Recent commercial reports also suggested that the cost of SAVs can be significantly lower than conventional taxis and privately owned vehicles, ranging from 17 to 46 cents per mile [11-13].

A handful of studies has shown that the SAV system is environmental friendly. Fagnant and Kockelman's [6] study found that each SAV could replace around 11 privately owned vehicles, which can lead to 12% reductions in energy consumptions, and 5.6% decrease in GHG emissions per vehicle life cycle. However, the study pointed out that the SAV system generates 10.7% more Vehicle Miles Travelled (VMT) due to deadhead. Such side effect, nevertheless, can be alleviated via the dynamic ride-sharing techniques [14, 15]. One recent study suggested despite the excessive VMT generation, electricity powered SAVs can reduce GHG emissions by more than 85% [16].

Some other studies built on Fagnant and Kockelman's [6] model and explored the impact of SAV system on urban infrastructures. Zhang et al. [7] explored the impact of SAVs on the urban parking space and found that 90% reduction could be achieved for participating households. Chen, Kockelman, & Hanna [17] integrated the electric vehicle charging component into the model to analyze the spatial layout of charging stations for the Shared Autonomous Electric Vehicle (SAEV) system.

All of the mentioned studies developed models under the grid-based city setting and hence are constrained by several assumptions, including grid-based transportation network, constant link level travel speed across the network, and homogeneous households in the hypothetical city. More recent literature overcame these limitations by simulating the operation of SAV system in a real-world context. Fagnant et al. [14] implemented the SAV system in Austin, TX, to determine required fleet size and examine the system performance. International Transport Forum (ITF) [18] explored the impact of the system on urban traffic in Lisbon and found a 35% increase in peak traffic flow and 90% reduction in parking demand. Spieser et al. [19] studied the feasibility of a SAV system and the level of service that the system may offer in Singapore and found that the system was capable of serving the entire population. Rigole [20] simulated a SAV system that serves all the commuting trips in Stockholm and identified significant reduction in air pollutant emissions from that system. Shen & Lopes's [21] simulation indicated the SAV system could outperform the existing New York taxi system via a centralized operation.

Although the literature regarding the SAV system is flourishing, only two previous studies quantified the influence of the system on urban parking land use. Zhang et al. [7] included parking estimation module in the simulation to examine the overall reduction in parking demand. However, the model simulates a hypothetical grid-based city with undifferentiated links and nodes. Thus, the study offers limited information about parking implications for a real city. While the ITF [18] study developed a SAV model for the city of Lisbon, the primary objective was to explore traffic volume variations, not changes in parking demand. Neither parking infrastructure availability nor parking price was considered in both studies. Finally, both models used the activity scanning simulation framework, i.e. time is advanced in small but constant time steps. The framework trades off simulation time and time-related output resolutions. This paper breaks new ground by simulating the operation of SAVs in the City of Atlanta, USA, using the real parking inventory and transportation network with calibrated link-level travel speeds, travel demand origin-destination (OD) matrix, and synthesized travel profiles. The simulation results will provide the temporal and spatial patterns of parking demand under different parking price policies. Furthermore, the study implements the Discrete Event Simulation (DES) framework, which has several advantages over activity scanning based SAV models developed in prior studies.

MODEL FORMULATION

Fundamentals of DES

The DES technique models the operation of a system as a sequence of events in time. The time variable notated as t, advances when and only when an event occurs. Events are only scheduled if there will be changes in the state of the system. Therefore, in DES models, the simulation time jumps inconsistently from one event to the next. On the other hand, the activity-scanning or time-step based models breaks the simulation up into small, constant time slices and the system attempts to update the states at each time slice. Therefore, in activity-scanning models, time advances by constant time-steps defined by the simulator designer. In this study, the DES model presents two advantages compared with activity-scanning models. First, there will be no tradeoff between simulation time resolution and model runtime. Second, the DES framework significantly reduces coding complexity and model runtime by not simulating the micro-changes rising from the movement of busy vehicles. The following sections elaborate on the conceptual model and implementation algorithms for the simulator.

Model Objective and Scenarios

The goal of this study is to examine the impact of different parking price polices on the parking footprint of the SAV system and the tradeoffs between parking fees, VMT generation, and client's average waiting time. We investigated three parking price scenarios.

These are: 1) free parking, 2) entrance-based charged parking, and 3) time-based charged parking. In the free parking scenario, the SAVs can enter all the existing parking infrastructure as long as there is available space in the lot. In the entrance-based charging scenario, the SAVs need to pay an entrance fee whenever they enter the parking lot, regardless of the length of time parked. In the time-based parking scenario, the SAVs pay for parking after leaving the parking lots based on the actual parking duration. The two charged parking scenarios vary parking charges based on the variation in land values in different parts of the city.

Model Entities and Activities

In the SAV system, there are four types of entities. These include: 1) the vehicle entity, 2) the trip entity, 3) the queue entity and 4) the parking lot entity. All entities in the model will get involved in a sequence of activities. For each trip entity, the model schedules a *call event* at the trip departure time. When handling the call events, the system dispatches the vehicle with the least trip cost and schedules a *pickup event*. If the vehicle assignment process fails, the trip entity will be put on a waiting list, i.e. the queue entity. After picking up a client, the vehicle either *picks up* a second client (if ride-sharing can be established) or schedule a *drop-off event* upon arrival at the trip destination. If a busy vehicle becomes empty, the system will schedule a *relocation event* to balance vehicle distribution, if necessary. If a vehicle remains idling after relocation (or after drop-off in case relocation was not triggered), the system schedules *find park event* to identify a parking lot entity, which minimizes the total parking cost, and eventually schedules a *park event* upon arrival. The *move events* are scheduled to transfer the vehicles to another location or to a parking lot. The *move events* can be interrupted if the moving vehicle is assigned to serve incoming trips. The life-cycle diagrams in Figure 1 illustrate the sequence of events that trip and vehicle entities may go through in the simulation. The design of the events will be elaborated in the following sections.

Call Event

At the beginning of each simulation day, the model generates trip entities based on the local OD matrix and a recent travel survey. Assuming that the trip generation follows Poisson Distribution [6], we simulate the total number of produced trips for each OD pair i and j by generating a Poisson random number given the average trip number, $\lambda_{i,j}$, from the local OD matrix.

$$NumTrip_{ij} = Random.Poission(\lambda_{i,j})$$

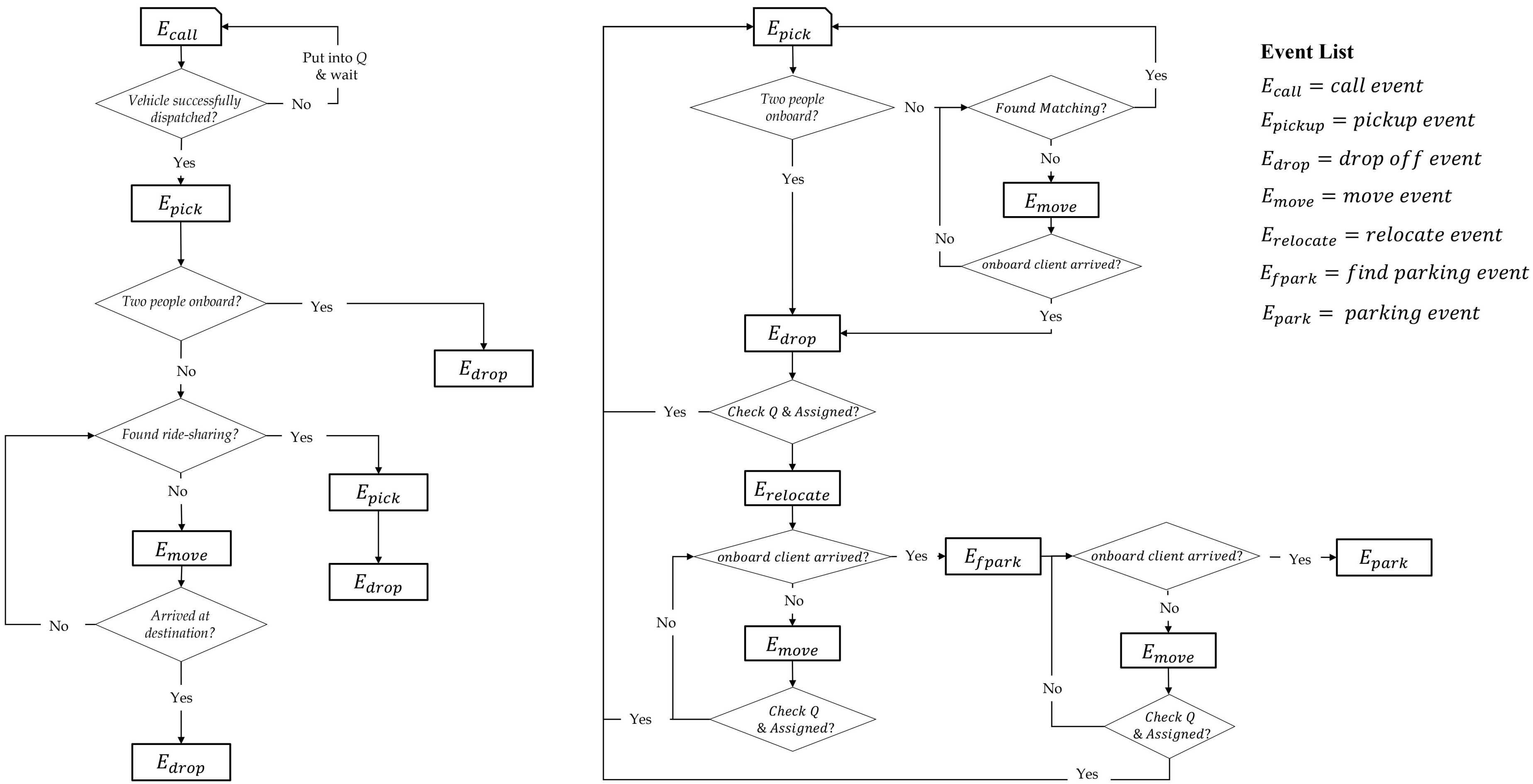
For each generated trip k, the trip departure time is assigned based on the formula below. The Cumulative Density Function (CDF) for trip departure time is estimated based on the weighted local travel survey.

$$DepartureTime_k = CDF_{dt}^{-1}(r)$$

where,

r, is uniformly distributed random number from 0 to 1.

$CDF_{dt}^{-1}(r)$, is the inversed CDF for trip departure time.



a. Life cycle of trip entities

b. Life cycle of vehicle entities

FIGURE 1 Life-cycle diagram for the client(left) and vehicle(right) entity in the SAV system

For each generated trip entity, the model schedules a call event at trip departure time *dt*. Upon the occurrence of the call event, the system dispatches SAVs to fulfill the travel demand. The system searches for SAVs whose status is not labelled as “busy” and assigns the one that offers the lowest costs, including both time and fare costs to serve.

$$Assigned\ SAV_j = \min_{j \in J_A}(time\ cost_j + fare\ cost_j)$$

Where,
j is the index for vehicle;
J_A is a set of indices for vehicles whose status is not “busy”;
$time\ cost_j$ is the potential excessive travel time cost if j^{th} vehicle was assigned;
$fare\ cost_j$ is the anticipated fare cost if j^{th} vehicle was assigned.

The time cost is calculated based on the assumption that the waiting time is valued as half of people’s hourly wage [7]. In the ride-sharing process, the vehicle does not operate on the first come first serve basis but optimize the route to minimize VMT. In return, each client can benefit from 40% reduction in SAV fare.

$$time\ cost_j = 0.5\ T_i.salary * \left(picking\ up\ waiting\ time_j + detour\ time_j\right)$$

$$fare\ cost_j = \begin{cases} \$0.5 * deliverty\ time_j, & no\ ride - sharing\ established \\ \$0.3 * deliverty\ time_j, & if\ ride - sharing\ is\ established \end{cases}$$

Ride-sharing will only be established if the following criteria are satisfied.

1) The excessive time for both trips is equal or smaller than 15% of travel time without ride-sharing;
2) For short intra-zonal trips, the acceptable maximum detour time is set as 3 minutes;
3) The ride-sharing induced detour time should be compensated by the decrease in SAV fare for both clients.

If a vehicle is assigned, then the status of the vehicle will be updated to “busy”. A pickup event will be scheduled at the estimated arrival time at the trip origin. Meanwhile, the system frees up a parking space if the vehicle was parked. The trip will be put on a waiting list if the system fails to arrange service.

Pickup Event
In the pickup event, the vehicle picks up the waiting client and then updates system states based on the vehicle occupancy. If there is only one onboard client, then the status of the vehicle becomes “one available”, the path will be updated to the shortest path to deliver the client, and a move event will be scheduled to push vehicle towards the destination. If the vehicle picks up a second ride-sharing client, then the status of the vehicle changes to “busy” and the path will be updated to the shortest path to serve both clients. A drop-off event will be scheduled for the client who should be dropped off first given the updated path.

Move Event
The system handles a move event based on the status of the vehicle. If the status of the vehicle is “one available”, the system will try to find potential ride-sharing. For the other types moves, such as relocating or parking vehicles, the system attempts to assign the vehicle to serve the closest waiting trip. Once assigned for service, the vehicle become “busy” and a

pickup event will be scheduled. If the vehicle is not assigned for service and has not arrived at its destination, the vehicle moves onto the next node in the network towards the destination. If the vehicle has arrived at the destination, the system schedules drop-off, find parking, or park event for “one available”, “relocating”, or “parking” vehicles separately.

Drop-off Event

In this event, the vehicle drops off the client who has arrived at the destination. After dropping off the client, if the vehicle becomes empty, the status of the vehicle changes to “available” and a relocation event will be scheduled. Otherwise, if there remains onboard client, the system schedules another drop-off event.

Relocate Event

The primary goal of the relocation event for j^{th} vehicle is to balance the spatial distribution of available vehicles to reduce average waiting time. This event builds on the existing SAV relocation algorithm [6] to relocate the vehicle from surplus zones to underserved areas. For each zone the imbalance value is calculated using the formula below:

$$Imbalance_i = \left(\frac{SAVs_i}{SAVs_{Total}} - \frac{Demand_i}{Demand_{Total}}\right) / \frac{Demand_i}{Demand_{Total}}$$

where,
i is the index for zones;
$SAVs_i/SAVs_{Total}$ is the share of available SAV in zone i
$Demand_i/\ Demand_{Total}$ is the share of travel demand in zone i.

If the vehicle is in a zone with imbalance value larger than 10%, then the system allocates the vehicle to zone j where the imbalance value is the smallest in the service area, updates relocating path, labels the vehicle as “relocating”, and schedules a move event. Otherwise, the system directly schedules a find parking event.

Find Parking Event

In the find parking event, the status of the vehicle will be labeled as “parking”. The zone with the lowest potential parking cost, calculated using the formula below, will be identified as the parking destination for the vehicle. In the time-based charging scenario, the potential parking cost is the product of expected parking time and the hourly parking price. The expected parking time matrix is initiated using averages from free-parking scenario and is updated every 10 minute. After determining the parking destination, the system updates the path for the vehicle, reserves one parking space at the destination and schedules a move.

$$P_{TAZ} = \min_{k \in K_A} (fuel\ cost_{i,k} + parking\ cost_k)$$

$$parking\ cost_j = \begin{cases} 0, & Free\ parking\ scenario \\ entrance\ price_k, & Entrance - based\ charging\ scenario \\ hourly\ price_k * hour_{k,t}, & Time - based\ charging\ scenario \end{cases}$$

Where,
i is the zone index for the current location of the vehicle;
k is an index from a set K_A which contain all zones where parking space remain available;
$hour_{k,t}$ is the anticipated parking time at zone k and time t.

Park Event
In the park event, the j^{th} vehicle's status will be changed to "parked". There will be no other changes to the states of the system, until the vehicle is assigned again to serve incoming calls.

Model Inputs and Outputs
There are several inputs for the model, including transportation infrastructures, local travel demand, local income distribution, and SAV fleet size, among others, to assign values for attributes of different entities. Local transportation infrastructure data provides information about road network composition, link level travel speed by time of the day, and parking inventory, including the number of spaces and prices. The local OD matrix, and travel survey offers information regarding the trip origins, destinations and departure time. The primary model outputs include the spatial and temporal patterns of parking demand, i.e., the number of times that SAVs park, and parking space, i.e., the amount of parking land needed to accommodate the parking demand, as well as other metrics for service quality. The parking demand and space available are calculated using the formula below. The first simulation day is excluded, as it is used to determine the SAV distribution at the beginning of the day [6].

$$ParkingDemand_{d,t} = \sum_{i=1}^{N} ParkingDemand_{d,t,i}$$

$$ParkingDemand_{t} = \sum_{d=2}^{D} ParkingDemand_{d,t} /(D-1)$$

$$ParkingSpace_{i,d} = \max_{0 \le t \le 1440} ParkingDemand_{i,d,t}$$

$$ParkingSpace_{i} = \sum_{d=2}^{D} ParkingSpace_{i,d} /(D-1)$$

where,
i is the index for zones and N is the total number of zones in service area;
d is the index for simulation day and D is the total number of simulation days;
t is the simulation time of the day (in the unit of minute).

Model Assumptions and Simplifications
There are several assumptions embedded in this model, listed as follows:

- 5% of the residents will give up their vehicles and use SAV system instead, which is similar to the assumption used in other studies [5-7];
- There will be no induced travel demand after the implementation of SAV system;
- These residents are willing to share rides with strangers;
- The cost of SAV is \$0.5 per minute with no startup fees [5] and reduces to \$0.3 for ride-sharing client;
- The fuel cost for electric SAV is \$0.04/mile [13];
- The clients leave the system after waiting for more than 15 minutes.

For easier model implementation, we also make the following simplifications in the model:

- The trips start and end at TAZ centroids;
- The vehicle travel speed is fixed on a certain road segment and updated for AM peak, mid-day, PM peak, and night time periods;
- The average intra-zonal travel time is modeled using the following formula:

$$intra-zonal\ travel\ time = \frac{\sqrt{area_{taz}}}{2 * travel\ speed}$$

- Both loading and unloading times are set as 1.5 minutes;
- The clients will not cancel the trip after vehicle assignment (within a 15-minute waiting time);
- The clients are first come first served during off-peak hours;
- Available vehicles will serve the closest trip on the waiting list to optimize use.

MODEL IMPLEMENTATION AND RESULTS

Model Environment Settings and Initialization

This study implements the simulation model suing empirical data from the City of Atlanta, USA. Atlanta, the capital city of Georgia, had an estimated population of 447,841 in 2013 and an area of 134 square miles. The city is highly car-dependent, with more than 92.2% of the commuting trips completed by automobiles [22]. The latest downtown parking survey reveals there are 93,000 parking spaces in Atlanta Downtown [23].

The spatial unit of the simulation is set at the Traffic Analysis Zone (TAZ) level, the same as the resolution of the OD matrix prepared by Atlanta Regional Commission (ARC). There are 208 TAZs in the City of Atlanta. At the market penetration of 5%, the system serves around 32,365 trips, which both start and end in Atlanta, on a typical weekday. The Atlanta road network with link level travel time for AM peak, midday, PM peak, and night hours is also obtained from ARC. There are 3,708 nodes and 8,694 edges in the transportation network.

The publicly accessible parking inventory is developed based on parking surface data from the City of Atlanta and the Downtown parking inventory from Central Atlanta Progress (CAP). According to CAP, the average parking area is approximately 300 square feet per space. The number of parking lots for the rest of Atlanta is approximated by dividing the total parking square feet in each TAZ with the average parking area per space. In this study, we assumed that at a low market penetration rate, only 5% of the households will give up their private vehicle and use SAVs to travel in the city. Therefore, only 5% of total parking space in each TAZ is reserved for SAV uses, which provides the system with 25,000 parking spaces throughout the city. The parking price is imputed based on the average land value from tax assessor data. TAZ land values are rescaled from \$0 to \$20 per entrance or \$0 to \$10 per hour as the final parking price. Figure 2 illustrates Atlanta parking inventory inputs for different scenarios.

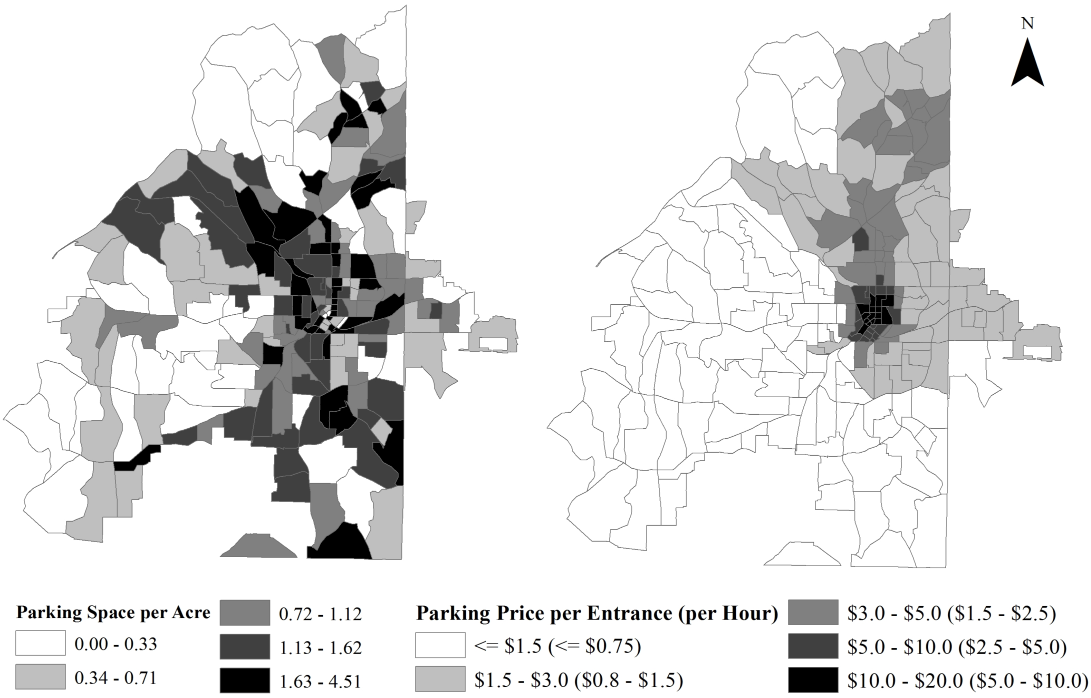


FIGURE 2 Parking Infrastructure Supply (left) and Parking Price Distribution (right)

Different fleet sizes are tested from 700 to 1200 with an increment of 100 vehicles, and it is found that 1000 vehicles are sufficient to serve the population, with no client leaving the system. The model is then set to run for 50 consecutive simulation days for each scenario. The same string of random number is used in all scenarios to ensure that the differences in outputs are not caused by noise rising from the random number generator.

Total Parking Demand and Parking Space

Simulation results from different scenarios suggest that the parking demand and parking footprint of the SAV system peaks in the free parking scenario and is the lowest in the time-based charging scenario, when parking is most expensive. An SAV, on average, parks 20.6, 16.6, and 8.6 times in free, entrance-based charging, and time-based charging scenarios, respectively. Meanwhile, the total parking space required ranges from 2,424 or 2.4 space/SAV in free scenario, to 2,144 in entrance-based charging scenario, and eventually to 1,895 in time-based charging scenario. Therefore, the occupancy rate of the 25,000 reserved parking space is 7.6% to 9.7%. In other words, around 22,575 to 23,100 public parking space will no longer be needed after the introduction of SAVs. Compared with the total parking inventory (500,000) in the city, the SAV system can emancipate around 4.5% of the public parking land at a low market penetration level of 5%. Such results indicate that one SAV can remove more than 20 parking spaces via vehicle ownership reduction and vehicle occupancy improvement. In this study, we didn’t incorporate the the potential reduction in parking space at the home end, given the lack of residential parking garage inventory. The reduction rate can be even higher if the residential parking land reduction is also included in the analysis.

Spatial Distribution of Parking Land Use

The results from different scenarios suggest that the more expensive it is to park, the more parking land will be pushed into low-income neighborhoods, as illustrated in Figure 3. In the free parking scenario (see Figure 3.a), parking demand is the highest in major trip attraction zones, such as Atlanta Downtown, Midtown and Buckhead areas. In the entrance-based parking charging scenario (see Figure 3.b), the parking spaces shift from highly developed TAZs to west side communities, such as English Avenue, Bankhead, and Center Hill, where land value is lower. In the time-based charged parking scenario (see Figure 3.c), the parking spaces concentrates in southwestern and a few northern TAZs. These communities tend to have lower median income, higher concentration of minority population, and a lower average land value, as shown in Figure 3.d. Additionally, the results from both charged scenarios also suggest that SAVs will not park in urban fringe areas, as the summation of parking and vehicle travel costs is the lowest in TAZs that are adjacent to the urban cores rather than in the urban fringe areas. Such phenomenon can be attributed to the fact that land value decreases exponentially as the distance to employment centers increases, while the fuel costs rise at a slower but constant rate. In short, the charged parking policies relocate parking space into low-income communities, which may lead to equity issues, such as inefficient use of valuable land parcels in these areas. However, it may also offer opportunities for new infill development, as the SAVs will be more accessible to these neighborhoods, which indirectly improves their mobility.

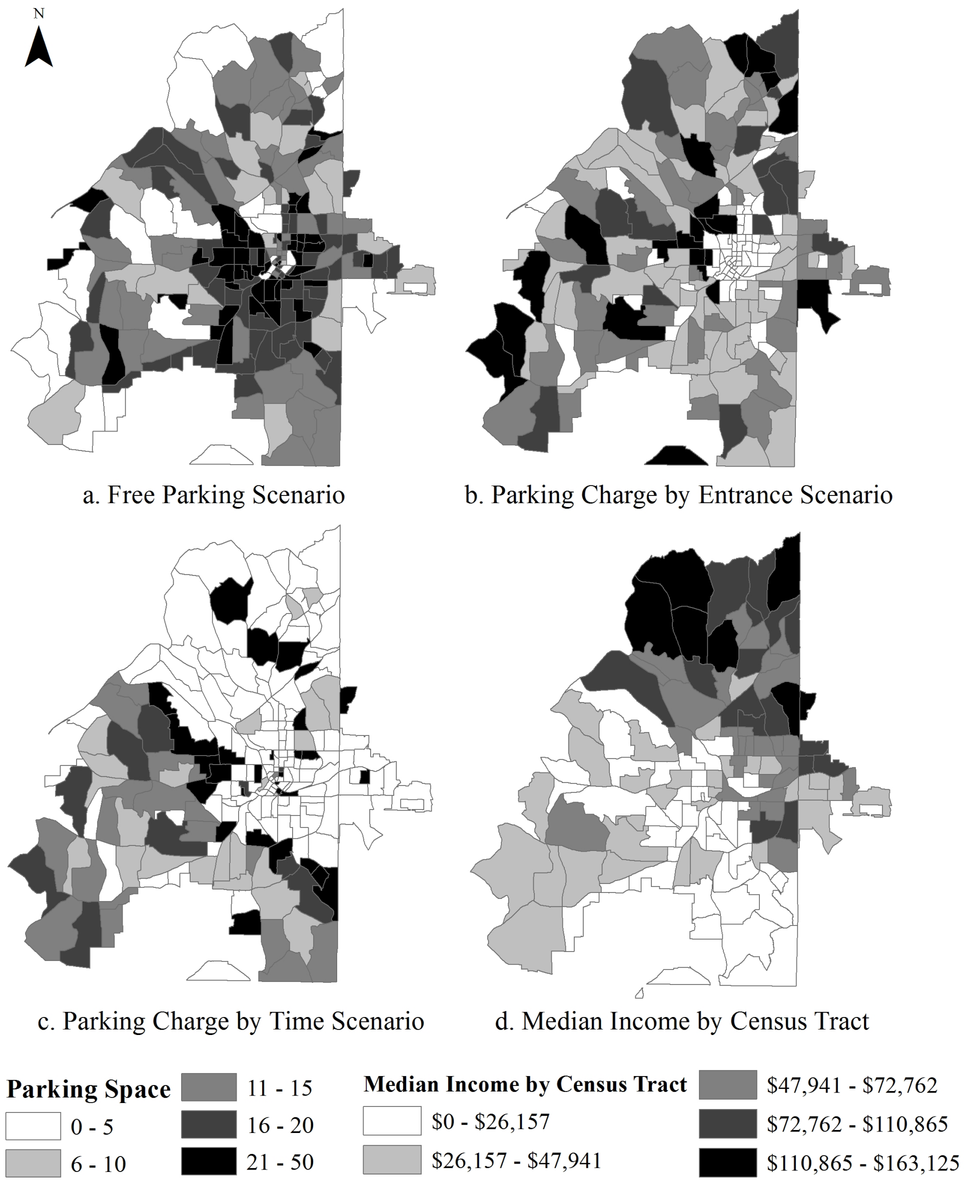


FIGURE 3 Spatial Distribution of Parking Spaces by Scenarios

Temporal Distribution of Parking Demand

Figure 4.a displays the total parking demand by time of the day from three scenarios, and the results suggest that there is no significant difference among them. The parking demand peaks during 1-3 AM when the travel demand is the lowest and bottoms during evening peak hours. However, the temporal distribution of parking demand changes significantly in TAZs with different land use types. To illustrate this phenomenon, the TAZs are coarsely reclassified into four types based on employment and household density. These four types are CBD, employment oriented, mixed use, and residential oriented TAZs (see Figure 4.b).

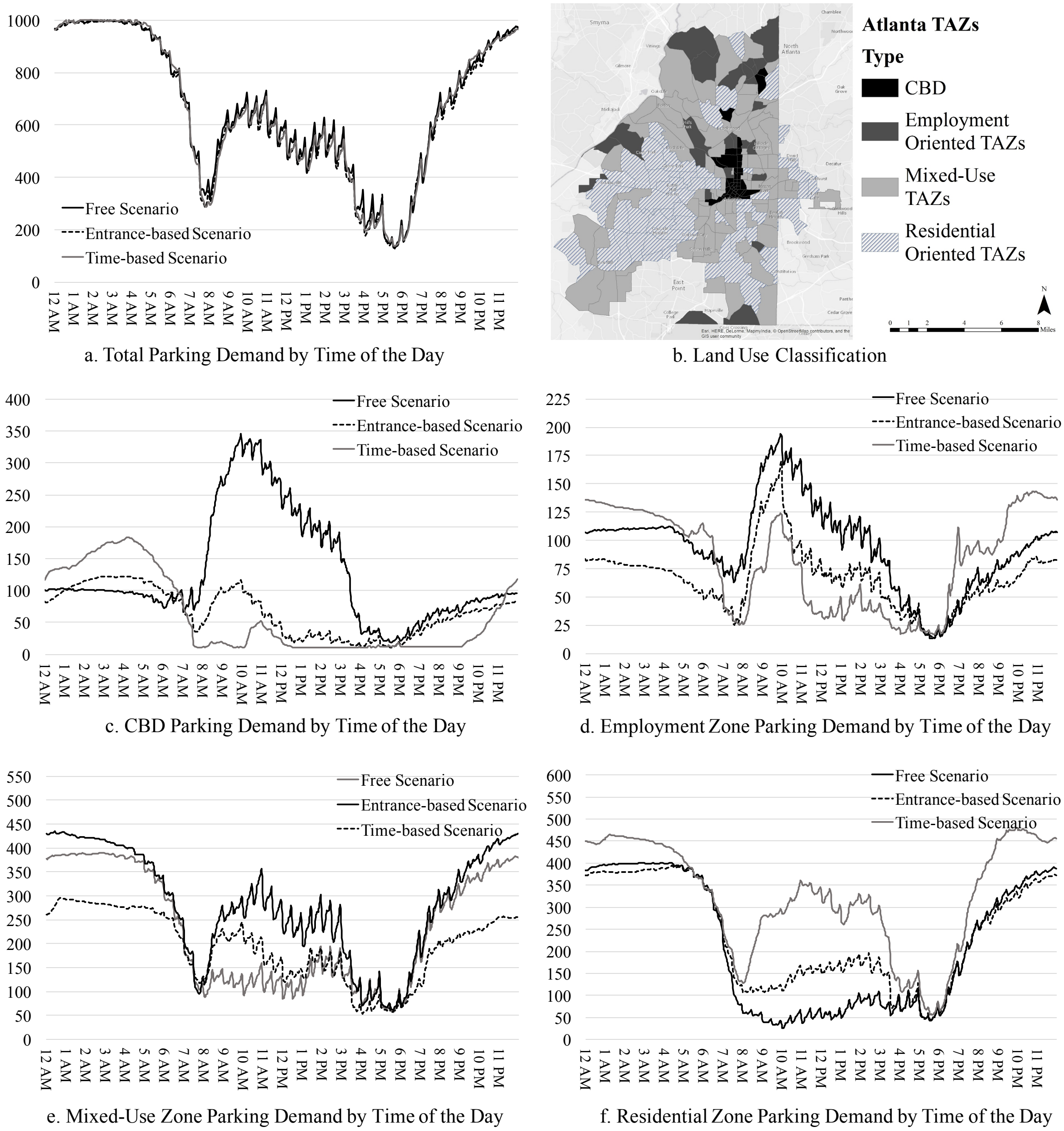


FIGURE 4 Temporal Distribution of Parking by TAZ Land Use Types

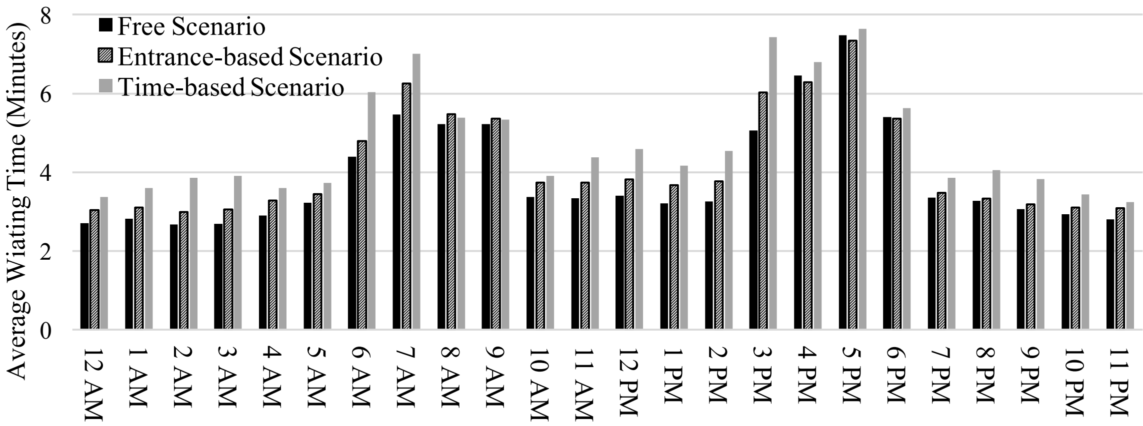
The parking demand in CBD areas declines dramatically in both charged parking scenarios compared with free parking scenario, especially after the morning peak hours, see Figure 4.c. The required parking lots in the downtown area are reduced by over 70% from

349 spaces in free parking scenario to around 102 or 51 spaces in entrance-based and time-based charging scenarios respectively. Similar parking demand variation patterns can also be found in employment oriented TAZs, as shown in Figure 4.d. However, the reduction in parking demand is not as large as the CBD areas, as the parking price is lower in the employment oriented zones.

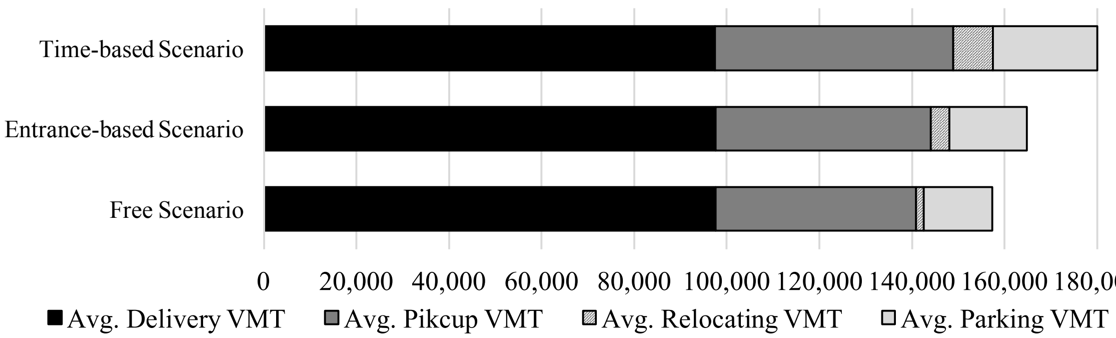
The reduced parking demand in CBD and employment oriented zones spills over into the mixed use and residential oriented neighborhoods. In the entrance based parking scenario, most of the parking demand relocates to the mix-use TAZs, see Figure 4.e. However, in the time-based parking charge scenario, even the mix-use TAZs are considered too expensive to park during midday and night time, when the average parking duration is longer. Therefore, most of the parking demand during these periods are pushed further into southern residential TAZs (see Figure 4.f).

Tradeoffs in Waiting Time and VMT

In the charged parking scenario, the SAV system trades off parking costs with client's average waiting time and system VMT generation. Clients in the charged parking scenario wait longer, particularly at the beginning of the peak hours, such as 6-7 AM and 3-4 PM, as shown in Figure 5.a. In the charged parking scenario, vehicles tend to park at zones with lower land value, resulting in a spatial mismatch between vehicle and travel demand distributions. Compared with entrance based scenario, vehicles in time-based scenario park further away from downtown, contributing to even longer average waiting time.



a. Average waiting time by time of the day in different scenarios



b. VMT generation by service types in different scenarios

FIGURE 5 Average Waiting Time (Top) and VMT Generation (Bottom) by Scenarios

The VMT generation is significantly higher in charged parking scenarios, see Figure 5.b. The SAV system generates 158,308 VMT per day in free parking scenario. The VMT generation increases by 5% and 14%, respectively, in entrance-based and time-based charging scenarios. In summary, the SAV system accounts for increases in parking costs by increasing average waiting time and generating more VMT, both of which have negative social externalities. Therefore, policy makers need to design policies that combine empty VMT charges together with parking prices to reduce the negative environmental impacts, such as energy consumption and pollutant emissions.

MODEL VERIFICATION AND VALIDATION

The trip generation process is validated by comparing the distributions of trip length and departure time from the simulation results with Atlanta travel survey. The Chi-square goodness of fit test results for trip length and departure time distributions are 0.96 and 0.98, respectively, indicating that the simulated distributions are not significantly different from the weighted Atlanta travel survey observations.

The vehicle movements are traced to verify the vehicle activities implementation process. Figure 6 illustrates the travel path for a randomly selected vehicle in one simulation day. The sequence of the visited nodes is labeled. The vehicle starts service at 5:31 AM and ends service by 7:52 PM. 30 trips are fulfilled throughout the day. There are three ride-sharing trips, two of which involve intra-zonal travel and, therefore, are not reflected in Figure 6. The vehicle spends approximately 7.2 hours serving clients, and 0.9 hours relocating and navigating to parking lots. The vehicle checks into parking lot six times and is parked for approximately 1.01 hours each time (excluding the last overnight parking).

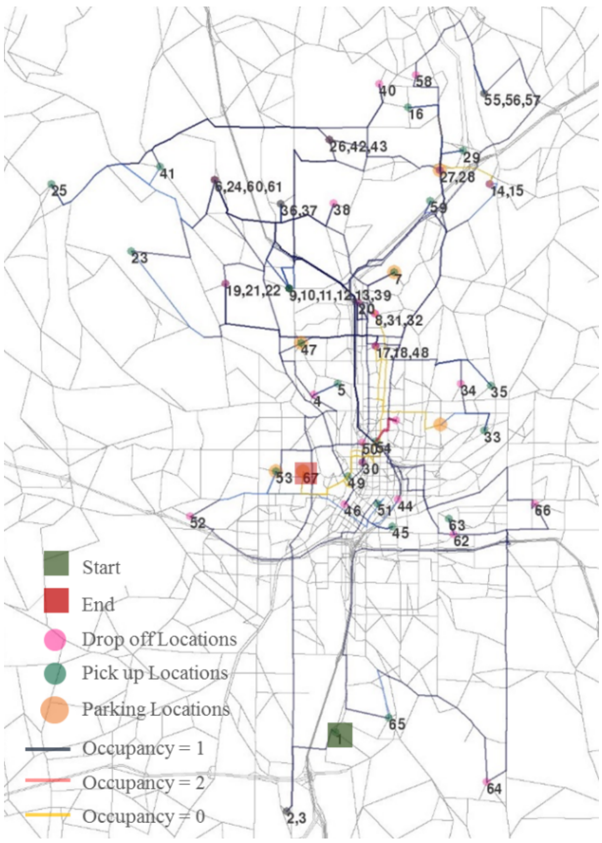
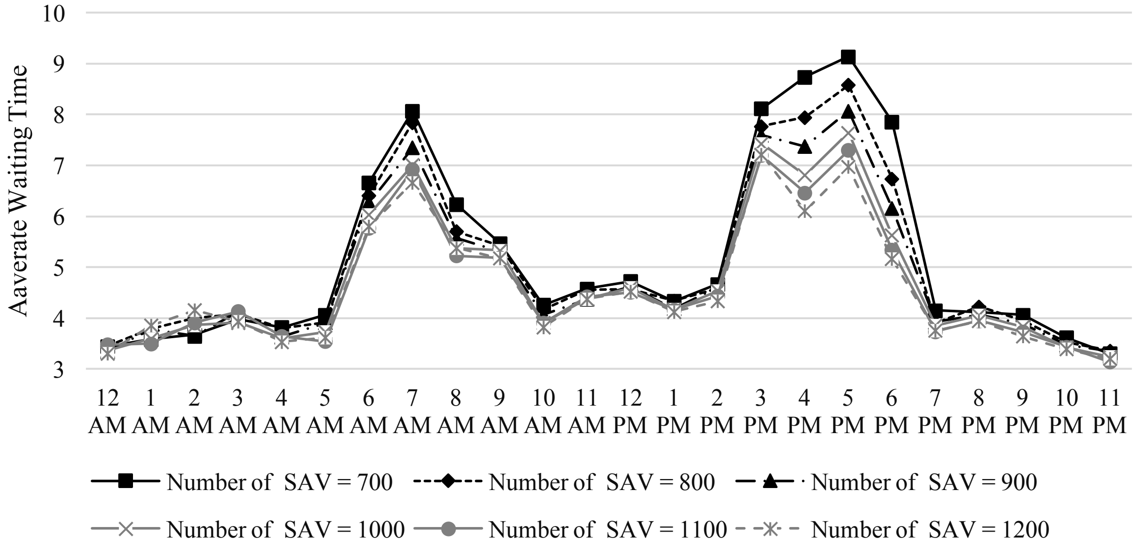
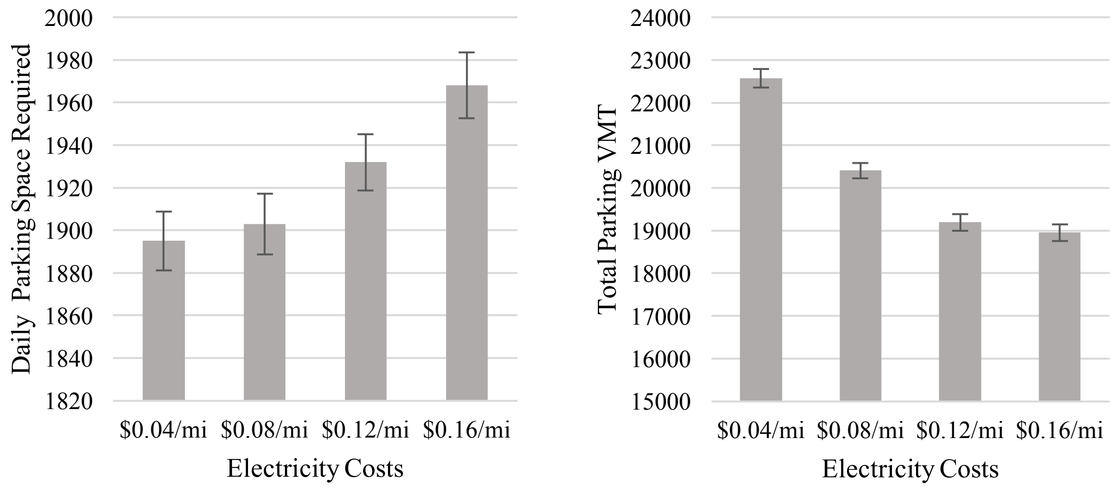


FIGURE 6 Vehicle Travel Path Example

10 alternative scenarios with different SAV fleet sizes ranging from 700 to 1200 and different SAV fuel (electricity) costs per mile base from \$0.04 to \$0.16 are tested to conduct elasticity test for the model. As shown in Figure 7.a, the average waiting time during peak hours, especially PM peaks, decreases with the increase in SAV fleet size, as expected. The decrease in average waiting time is significant at 7 AM and 4-6 PM, based on the t-test results (95% significance level, 2-tail test). The average waiting time doesn't change significantly during off-peak hours when there are adequate number of vehicles. The variation in total parking space and VMT generation for parking purpose are illustrated in Figure 7.b and c. The results indicate that when fuel becomes more expensive, the SAV system consumes more parking spaces and generates less parking related VMT, as expected.



a. Average waiting time by time of the day and SAV fleet size



b. Daily parking space required by fuel costs c. Daily Parking VMT generation by fuel costs

FIGURE 7 Elasticity Tests Results

CONCLUSIONS AND DISCUSSIONS

The simulation results show that parking land use can be reduced by approximately 4.5%, once the SAVs start to serve 5% of the trips within the City of Atlanta in both charged and free parking scenarios. The results also reveal that each SAV can emancipate more than 20 parking spaces in the city. The reduction is achieved primarily through improving vehicle utilization intensity and reducing private automobile ownership. The results are consistent with the parking demand model based on the hypothetical grid based setting [7] and the Lisbon SAV simulation study [18].

The simulation outcomes from charged and free parking scenarios suggest that charged parking policies can effectively reduce the amount of parking in the CBD areas. However, the demand for parking will be shifted to adjacent TAZs, resulting in larger VMT generation more congestion and longer average waiting time. Furthermore, results from the two charged parking scenarios suggest that when parking becomes more expensive; more parking demand is pushed into low-income neighborhoods, which may lead to social inequities. Therefore, policies to charge for parking need to be carefully considered to ensure that such adverse effects are minimized. Examples of such policies may include environmental impact fee for unoccupied VMT (i.e. relocation VMT and parking VMT) and innovative congestion fee on SAVs to restrict excessive VMT generation. Furthermore, the city may also propose smart parking policies, i.e. variable parking fee by time of day and by location of parking lots to reduce parking land use by improving the occupancy rate of the parking lots.

This study explores how the parking demand and parking land use may differ under free and charged parking policies. There remain some limitations regarding the design of the model, which deserves further explorations. To begin with, the parking destination choice is made only based on total parking price, while other factors including travel demand and vehicle distributions, are neglected. It will be ideal to design a parking lot searching algorithm that combine vehicle relocation and parking step together to minimize the operation costs of the system. Additionally, the model doesn't offer an optimized solution for urban parking land use design, which can be achieved by a centralized operation of SAV system and will provide a more comprehensive picture for smart city development. More studies should be devoted to examine how the SAV system can be integrated as part of the sustainable urban growth by optimizing urban parking land use via smart parking pricing policies. Finally, this model does not consider the environmental and social impacts of the tradeoffs between VMT generation, congestion levels, and parking space reduction, which is important for designing sustainable parking policies. Such tradeoffs can be examined with the help of models that include a trip assignment function that dynamically updates congestion at the road link level based on SAV travel patterns.

REFERENCES

1. CityMobil2 Project. (n.d.). CityMobil2 Project. Retrieved February 15, 2016, from http://www.citymobil2.eu/en/About-CityMobil2/Overview/
2. Markoff, J. (2014). Google's next phase in driverless cars: No steering wheel or brake pedals. *New York Times*.
3. Coyne, J. Here's your first look at Uber's test car. Retrieved February 15, 2016, from http://www.bizjournals.com/pittsburgh/blog/techflash/2015/05/exclusive-heres-your-first-look-at-ubers-self.html
4. U.S. Department of Transportation. (2016). DOT actions revis existing guidance and clear administrative hudles for new automotive technology. Retrieved April 17, 2016, from http://www.nhtsa.gov/About+NHTSA/Press+Releases/dot-initiatives-accelerating-vehicle-safety-innovations-01142016
5. Burns, L. D., Jordan, W. C., & Scarborough, B. A. (2013). Transforming personal mobility. *Earth Island Institute, Columbia University*.

6. Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1–13.
7. Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, *19*, 34–45.
8. Ford, H. J. (2012). *Shared Autonomous Taxis: Implementing an Efficient Alternative to Automobile Dependency*. Princeton University.
9. Kornhauser, A. (2013). Uncongested mobility for all: New Jersey's area-wide aTaxi system. Princeton University. *Operations Research and Financial Engineering. Retrieved September*, *23*, 2013.
10. Bridges, R. (2015). *Driverless Car Revolution: Buy Mobility, Not Metal*. Retrieved from Amerzon.com
11. Albright, J., Bell, A., Schneider, J., & Nyce, C. (2016). *Marketplace of change: Automobile insurance in the era of autonomous vehicles*. KPMG.
12. Barclays. (2016). *Disruptive Mobility: A Scenario for 2040*. Barclays Research.
13. Corwin, S., Vitale, J., Kelly, E., & Cathles, E. (2016). *The Future of Mobility*. Deloitte University Press.
14. Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market. *Transportation Research Record: Journal of the Transportation Research Board*, (2536), 98–106.
15. Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach. In *Transportation Research Board 94th Annual Meeting*.
16. Greenblatt, J. B., & Saxena, S. (2015). Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change*.
17. Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of Shared Autonomous, Electric Vehicle Fleet: Two Implications of Vehicle and Charging Infrastructure Decisions.
18. International Transport Forum. (2015). Urban Mobility System Upgrade: How shared self-driving cars could change city traffic.
19. Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., & Pavone, M. (2014). Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore. In *Road Vehicle Automation* (pp. 229–245). Springer.
20. Rigole, P.-J. (2014). Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.
21. Shen, W., & Lopes, C. (2015). Managing Autonomous Mobility on Demand Systems for Better Passenger Experience. In *PRIMA 2015: Principles and Practice of Multi-Agent Systems* (pp. 20–35). Springer.
22. ARC. (2011). Household Travel Survey Final Report. Retrieved May 25, 2016, from http://www.atlantaregional.com/transportation/modeling/household-travel-survey
23. CAP. (2014). *Parking Today: Downtown Atlanta Parking Assessment Existing Conditions*. Retrieved from http://www.atlantadowntown.com/_files/docs/existing-conditions-download.pdf