

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

Wenwen Zhang, Subhrajit Guhathakurta, and Catherine Ross  
Georgia Institute of Technology

## **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. Recently, the U.S. Department of Transportation unveiled new policy guidance that reflects the reality that widespread deployment of AVs is now feasible (DOT 02-16 Press Release). 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. In this study we specifically examine the role of shared autonomous vehicles (SAVs), a taxi system without drivers, in influencing urban parking demand.

One Previous study, based on the simulation of SAV operations in a hypothetical grid-based city, reveals that the SAV may eliminate a significant amount of parking demand for participating households (Zhang, Guhathakurta, Fang, & Zhang, 2015). The models of SAV operations tested in earlier studies are constrained by several assumptions, including highly developed grid-based transportation network, same link level travel speed all over the network, and homogeneous households over the city. This paper attempts to address these issues by simulating the operation of SAVs in the City of Atlanta, USA, using the real transportation network with calibrated link-level travel speeds, travel demand origin-destination (OD) matrix, and synthesized travel profiles. This real world data-driven discrete event simulation (DES) model will be used to determine the temporal distribution of parking demand and the spatial distribution of parking land use under charged and free parking scenarios.

Keywords: parking, autonomous vehicles, urban form, land use

## 1. 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, small-scale, low-speed, automated mobility on demand systems will soon be tested in Europe (CityMobil2 Project, n.d.) and possibly by Google and Uber shortly (Conye, 2015; Markoff, 2014). Recently, the U.S. Department of Transportation unveiled new policy guidance anticipating widespread deployment of AVs (DOT 02-16 Press Release). The vehicle automation technology combined with the sharing economy will undoubtedly lead to a new travel mode – Shared Autonomous Vehicles (SAVs), a taxi service without drivers, which will be more affordable and environmentally friendly to operate than privately owned Autonomous Vehicles (AVs) (Fagnant & Kockelman, 2015; Shen & Lopes, 2015). SAV systems have the potential to further reduce the average waiting time and improve ride-matching experiences when compared to existing ride-sharing technology (Shen & Lopes, 2015).

This promising SAV system will inevitably lead to changes in the demand for parking in cities. One Previous study, based on the simulation of SAV operations in a hypothetical grid-based city, reveals that the SAV may eliminate a significant amount of parking demand for participating households (Zhang, Guhathakurta, Fang, & Zhang, 2015a). 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 prices setting. The model output will provide insights towards the amount of parking space and the spatial distributions of the parking lots for the SAV system.

## 2. Earlier Works

Despite that the SAV system remains under development, there have been a wealth of literature exploring different aspects of the anticipated system using simulation approaches. Some early studies demonstrate that SAV systems are feasible by evaluating the existing travel demands and quantifying operation costs of the SAV system. As the concept of SAV prevails, more studies are conducted to investigate the impact of the SAV system on the urban built environment, including its indirect environmental benefits, integration of electric vehicle technology with the system, and its direct impact on urban parking demand distributions.

Several studies have validated the feasibility and affordability of the SAV system. Ford (2012) and Kornhauser (2013) evaluate the performance of a shared taxi system, *aTaxi* system, with fixed service stations distributed every half-mile in the region. Their results suggest that the system is definitely achievable. Burns et al. (2013) develop a more advanced agent-based simulation model to explore the profitability of a ubiquitous SAV car-sharing system. The simulation is set up in cities with highly developed grid-based transportation network and trip generation zones. 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. Bridges (2015) suggests that this mile based cost can even be reduced to \$0.13, if the SAVs are powered by electricity and the system can still anticipate a reasonable share of profit. In sum, all the above studies suggest that SAV system is profitable and affordable to the general public.

Fagnant and Kockelman (2014) adjust Burns et al. (2013)'s model to obtain more robust gas consumptions and air pollutant and Greenhouse Gas (GHG) emissions results. The adjustments

include introduction of different vehicle travel speeds during peak and off-peak hours and directional effect of traffic. Their study results show that each SAV can replace approximately 11 privately owned vehicles. As a result of the vehicle ownership reduction, some environmental benefits, such as reductions in energy consumptions, GHG emissions, and air pollutants emissions per vehicle life cycle, can be expected. However, the study acknowledges that the SAV system tends to generate approximately 5% more vehicle miles travelled (VMT) due to the empty vehicle navigation process. Such side effect, nevertheless, can be alleviated or even eliminated by introducing and encouraging ride-sharing behaviors in the system (Fagnant & Kockelman, 2015; Zhang, Guhathakurta, Fang, & Zhang, 2015b).

Some other SAV simulations are developed by extending Fagnant and Kockelman (2014)'s model. Zhang, Guhathakurta, Fang, & Zhang (2015a) incorporate dynamic ride-sharing service into the SAV system and explore the impact of SAVs on the urban parking demand. Their results indicate significant amount of reduction can be achieved by reducing vehicle ownership for participating households and increasing the vehicle utilization rate in the city. Chen, Kockelman, & Hanna (2016) integrate the electric vehicle charging component into the model to Fagnant and Kockelman (2014)'s model to analyze the spatial layout of charging stations for the Shared Autonomous Electric Vehicle (SAEV) system.

All of the above discussed studies develop models under the grid-based city settings 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 overcomes such limitations by simulating the operation of SAV system within a real-world context. Fagnant, Kockelman, & Bansal (2015) implements the SAV system in the context of Austin, TX to determine required fleet size and examine the system performance (Fagnant et al., 2015). International Transport Forum (2015) explores the impact of the system on urban traffic in the City of Lisbon and the results suggest there will be a vast increase in traffic flow (International Transport Forum, 2015). Spieser et al. (2014) study the feasibility of the SAV system and the level of service that the system may offer if all vehicles are automated in Singapore. Their results show that not only is the SAV system capable to serve the entire population, the service quality is also quite impressive. The expected waiting time for SAV system is even shorter than the existing transit or privately owned vehicles. Rigole (2014) simulates an SAV system that serves all the commuting trips in Stockholm and identifies the reduction in air pollutant emissions that the system can achieve. Shen & Lopes (2015) replace existing New York taxis with SAVs and monitors average waiting time given various vehicle dispatching algorithms. Their results suggest that SAV system can outperform the existing taxi system via centralized operation.

Although the literature regarding the SAV system is proliferating, only two of them attempts to quantify the influence of the system on urban parking demand (International Transport Forum, 2015; Zhang et al., 2015a). Zhang et al. (2015) include parking demand estimation module in the simulation to examine both the spatial and temporal distributions. However, the results can be constrained by the model assumptions, as the simulation is developed based on hypothetical grid-based city settings. Although the ITF study develops model using data from Lisbon City, the parking demand is not the primarily model objective of the study. In ITF's model, autonomous vehicles park directly at the client's destination if not assigned to other incoming clients. Therefore, neither parking infrastructure availability nor parking price is considered in the model. Such simplification leaves the model insufficient to evaluate spatial distribution of the

parking demand. Finally, both studies develop models based on the activity scanning simulation framework, i.e. time advances by small but constant time steps. This framework has a rather inefficient time advancement mechanism, as the model trades off between simulation time and time-related output resolutions. This paper fills the above research gaps by simulating the operation of SAVs in the City of Atlanta, USA, using the real transportation network with calibrated link-level travel speeds, travel demand origin-destination (OD) matrix, and synthesized travel profiles. This real world data-driven simulation model will be used to determine the temporal distribution of parking demand and spatial distribution of parking land use under different parking price policies. Furthermore, the Discrete Event Simulation (DES) model framework to overcome the drawbacks of activity scanning models.

### 3. Discrete Event Simulation Model Design

#### 3.1 DES Basics

The DES models the operation of a system as a sequence of events in time. The time variable, denoted 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 variable can jump from one event to the next. On the other hand, the activity-scanning or time-step based models breaks the simulation up into small 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 as defined by the simulator designer.

For this study, the DES framework is used to model the complex macro-dynamics of the SAV system in a stochastic environment, i.e., the interaction between travel demand and the SAV supply, without simulating the micro-changes rising from the movement of busy vehicles (i.e. the ones that cannot be assigned to serve other clients) in the transportation network. In our model context, the DES model presents two advantages compared with activity-scanning or time-step based models. First, there will be no need to verify and validate the selection of time step resolution in the DES model. Second, the DES model significantly reduces simulation time and coding complexity by not scanning the busy vehicles in the system. In this study, a simulator is developed based on the DES framework and the following sections will elaborate about the conceptual model and implementation algorithms for the simulator.

#### 3.2 Conceptual Model Formulation

##### 3.2.1 Model Entities

The system under investigation for this study is the SAV system. In this system, a total of  $nc$  clients generates trips or travel requests, which are modeled as the *trip entities*. The total number of trips may vary given the stochastic nature of the travel demand. It is also assumed that all involved clients will agree to share rides if a match in trip itinerary can be found. The service requests will be fulfilled by  $nv$  self-driving vehicles, modeled as *vehicle entities*. The available vehicle with the lowest travel time cost will be assigned to fulfill a specific travel request. A client will be put on a waiting list, a *queue (Q)*, if all vehicles are occupied or the closest available vehicle is too far away (i.e., more than the waiting time tolerance of the client). Once the last onboard client is dropped off, a SAV will become available again. Then if the vehicle is not assigned to serve another traveler, the vehicle will be programmed to relocate to balance SAV supply distribution in the city. After the relocation process, if the SAV remains available, it will be assigned to find a parking spot by the *parking entity*, which minimizes the parking costs,

including fuel cost and entrance cost, to park. All the modeled entities and their attributes and states variables are summarized in .

Table 1.

Table 1: Modeled entities by types

Entity Types	Modeled Entities [Descriptions]	Attributes	States
Trip Entities	<i>Trip (Travel demand)</i> [the travel demand generated by customers to travel from origins to destinations at a particular point in time ]	Origin Destination Departure time Willingness to share rides Hourly salary Client ID	Pickup timestamp Drop-off timestamp Ridesharing clients id Quit
Vehicle Entities	<i>SAVs</i> [Vehicles in the SAV system]	Vehicle ID	Waiting client ids Onboard client ids Future travel paths Current location
Parking entities	<i>Parking Lots</i> [Parking infrastructures]	Location Price Total Number of Parking	Available number of parking spaces
Queue Entities	<i>Waiting Client List</i> [A list of waiting clients]	-	-

### 3.2.2 Model Activities

All the entities in the model will get involved in a sequence of activity instances. For a client entity, once a client request for service, a *call event* will be generated, and a vehicle will then be assigned to serve the client. Once a vehicle is assigned, a *pickup event* will be scheduled for this vehicle with the estimated pickup time given network speeds. After picking up the client, a *move event* will be scheduled to move the vehicle to the next link in the transportation network given the estimated path towards the destination. A vehicle with a client who are willing to share rides may be assigned to *pick up* a second client if their itineraries match.

After a vehicle has served all the assigned customers and if the vehicle is in an area where the supply is significantly over the anticipated demand, then a *relocation event* will be arranged to find potential relocation destinations and the vehicle will *move* towards relocation destination unless it is reassigned to serve other calling clients on the way. Once the vehicle arrives at the relocation destination and is still not assigned to serve any calling clients, the system will schedule a *find parking event* to find ideal parking location for the vehicle to save energy. If the found parking lot is not where the vehicle is currently located, then the vehicle will *move* towards the parking location and *park* upon arrival. The notations of all the events are as below. The event space,  $E$ , gathers all the simulated events or activities in the system:

1.  $e_{call}$  = call event, which reserves vehicle for service;
2.  $e_{move}$  = vehicle movement event;
3.  $e_{pick}$  = vehicle pick up event;
4.  $e_{drop}$  = vehicle drop off event;

5.  $e_{relocate}$  = vehicle relocate event, which identifies relocation destination;
6.  $e_{find\ park}$  = vehicle find parking event.
7.  $e_{park}$  = vehicle park event.

The life-cycle diagram describing the sequence of events that the client and vehicle entities go through in the system is illustrated in Figure 1.

### 3.2.3 Model Inputs and Outputs

There are several inputs for the model to assign values for attributes of different entities, including transportation infrastructures, such as parking spaces and road network, local travel demand, local income distribution, SAV fleet size, among others. The transportation infrastructure inputs provide information regarding road network composition, link level capacity, number of available parking spaces, the location of the parking spaces, and their price per entrance. The local travel demand data provide information regarding the spatial and temporal distributions of trip origins, destinations (also known as the OD matrix), and the time stamp of the trip occurrences. In this study, the link level travel speed by time of the day is obtained from the local travel demand model developed and calibrated by the Atlanta Regional Commission (ARC). The primary outputs of this model include both the spatial and temporal distributions of parking demand, and other system service quality metrics, such as average waiting time, system wide VMT generation, and detour time for ride-sharing services.



### 3.2.4 Model Assumptions and Simplifications

Since the SAV system is not tested under actual conditions, several assumptions are embedded in the model. The major assumptions are listed as follows:

- 5% of the residents will give up their vehicle and use SAV system instead, which is similar to the assumption used by Fagnant and Kockelman (2014) and Burns et al. (2012);
- There will be no induced travel demand after the implementation of SAV system;
- All SAV users are willing to share rides with strangers;
- The cost of SAV is \$0.5 per minute with no startup fees (Burns et al., 2012);
- The cost of SAV is \$0.3 per minute for each onboard client when two people are sharing rides to encourage ridesharing;
- The fuel cost of SAV is \$0.04/mile (assuming the vehicles use electricity) (Chen, Kockelman, & Hanna, 2016)
- The clients will switch to other modes of transportation after waiting for more than 15 minutes.

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

- The trips always start and end at TAZ centroids;
- The vehicle travel speed is fixed given time of the day on one road segment (but will be updated hourly);
- 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 never cancel the trip once a vehicle is assigned to the client;
- The clients are first come first served during off-peak hours
- Empty vehicles will be assigned to serve the closest calling client during peak hours to optimize vehicle use;
- The system doesn't offer reservation service for the general public.

To conclude this section, Figure 2 summaries the simulation inputs, outputs, and the relationship between various modeled activities and their implementation modules. The model implementation algorithms will be elaborated in the following section.

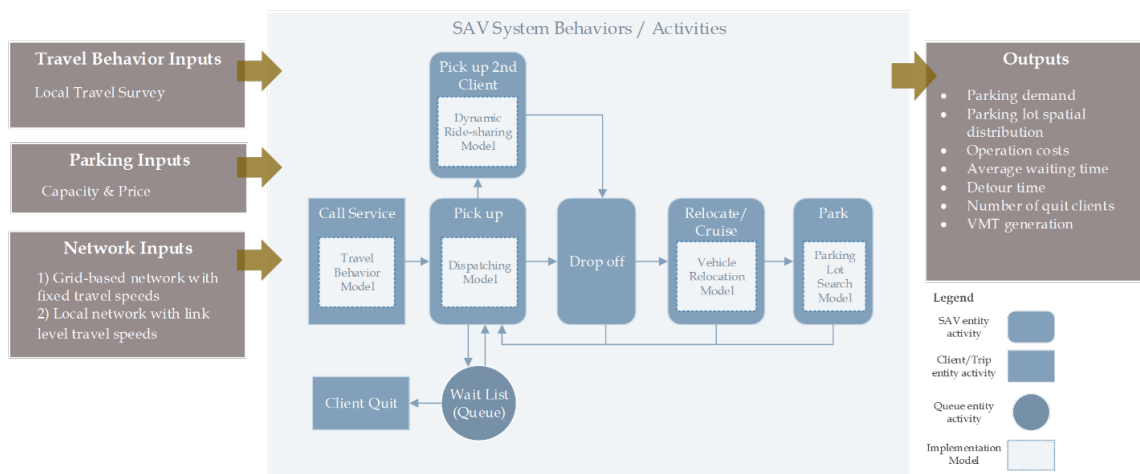


Figure 2: Framework of the Conceptual Model



### 3.3 Model Implementation Algorithms

#### 3.3.1 Travel Behavior Model

This study simulates travel demand based on the OD matrix provided by Atlanta Regional Commission. It is assumed that the trip generation follows Poisson Distribution. The total number of produced trips for each OD pair will be simulated by generating a Poisson random number given the average trip number,  $\lambda_{i,j}$ , from the 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 2009 Atlanta 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.

#### 3.3.2 Dynamic Ride-sharing Model

The dynamic ride-sharing model determines whether two trips can be pooled together to benefit both clients. In the ride-sharing process, the vehicle won't serve clients on the first come first serve basis, but will optimize the route to minimize total VMT after picking up the second client. Excessive travel time for each client is estimated based on the optimized route. If the itinerary for calling and onboard clients can satisfy the following criteria, then the trips will be served simultaneously by one vehicle.

- 1) The detour time for each client 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.

After searching for all the potential ride-sharing vehicles, if several matches are found, the one with the least total excessive travel time for both clients will be recommended as the best match for the calling client.

#### 3.3.3 Vehicle Dispatching Model

Vehicle dispatching model describes rules regarding how to assign SAVs to serve calling clients. Most of the existing models assign vehicles based on first come first serve rule. In this study, for each calling client, the system will first search for the closest empty SAV and save the time needed to pick up the client. Then the system will continue to search for the SAVs with only one onboard client to determine whether the trips can be pooled together based on the dynamic ride-sharing model described above. If no trips can be pooled together, the closest empty SAV will be assigned to pick up the client. If ride-sharing can be established, the one with the largest benefit for the calling client will then be compared with the closest empty SAV. The vehicle that offers larger benefit or smaller costs (including both time and fare costs) will be assigned to serve the client.

#### 3.3.4 Vehicle Relocation Model

The primary goal of the vehicle relocation model is to match the spatial distribution of available vehicles to the expected travel demand to reduce average waiting time. Therefore, the relocation model attempts to identify the underserved and over served areas in the city

and assigns vehicles in the over served areas to navigate to underserved areas. Fagnant & Kockelman (2014) proposes to calculate balancing value for big zones in the hypothetical city to determine the potential relocation destination for idling vehicles located in SAV supply surplus areas. The imbalance value for each zone is estimated based on the following formula.

$$BlockBalance = \frac{SAVs_{Block}}{SAVs_{Total}} - \frac{Demand_{Block}}{Demand_{Total}}$$

Based on the calculated block balance values, the model pushes vehicles in zones with 10% or more SAV surplus to zones with 10% or more SAV shortage. In this study, similar relocation strategy is used. The balance value is estimated at TAZ level to determine zones to relocate. The only difference is the selection of threshold of balance value that may trigger vehicle relocation. In Fagnant and Kockelman (2014)'s study, the balance values are estimated for 25 big zones. While, for this study, there are 208 TAZs (i.e. approximately 8 times more zones) in the study area. Therefore, the SAVs will relocate from zones with 1.25% (10%/8) excessive supply to zones with the largest shortage in SAV.

### 3.3.5 Vehicle Parking Model

After the relocation process, if the vehicle remains out of service, the vehicle will be assigned to parking at a TAZ that minimizes the summation of fuel cost and parking entrance cost and if there are available parking spaces in that TAZ. This process can be interpreted using the formula below.

$$\min_{j \in J_A} (fuel\ cost_{i,j} + entrance\ cost_j)$$

Where,

$i$ , is the TAZ index for the current location of the vehicle;

$j$ , is the index of potential parking TAZ;

$J_A$ , is a set of indices for TAZs where remain empty parking space.

## 4. Model Application and Results

### 4.1 Model Environment Settings and Initialization

This study develops the simulation model using data from the City of Atlanta, USA. Atlanta is the capital city of Georgia, with 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 (ARC, 2011). The city offers enormous parking infrastructures to meet the parking demand. The latest downtown parking survey reveals that there are about 93,000 parking spaces within Atlanta's downtown area (CAP, 2014).

The Atlanta Regional Commission (ARC) has developed an OD matrix for vehicle-trips based on the 2009 local travel survey. The OD matrix is prepared at the Traffic Analysis Zone (TAZ) level and therefore, the spatial resolution of the study is also set at the TAZ level. There are 208 TAZs located within the City of Atlanta. It is assumed that approximately 5% of the trips that both start and end in the City of Atlanta will choose the SAV system as the travel mode and the rest of the trips will be accomplished via alternative transportation modes. Under this assumption, the SAV system serves around 32,365 or 3.7% of all vehicle-trips in the 10-county Atlanta Metropolitan Area on the daily basis.

The Atlanta road network, coded with length, capacity, calibrated link level travel time (in the unit of minutes) for both peak and off peak hours, is also obtained from ARC. The centroids of TAZs are linked with adjacent nodes and the travel speeds for these links are set

as 20 and 30 mph for peak and off peak hours. The administrative boundary for the city of Atlanta is discontinuous, as the Hartsfield-Jackson airport is not connected with the rest of the city. To serve the airport area, road network located outside the city boundary but connecting the airport to the rest of Atlanta is also included in this study. There are 3,708 nodes and 8,694 edges in the final transportation network.

The City of Atlanta provides impervious surface data for all parking lots. Central Atlanta Progress (CAP) maintains downtown parking inventory, such as parking price, parking spaces, and the type of parking lots. The downtown parking data from both sources are compared to generate average area for individual parking space and then applied to the rest of Atlanta to obtain an estimation for the total available parking space given the amount of parking surface provided by the city. The parking spaces are then aggregated by TAZs. For each TAZ, only a portion of the parking lots is reserved for the SAV system. The reservation is calculated based on the following formula.

$$P_i = \frac{Attraction_i}{Total\ Attraction_i}$$

where,

$Attraction_i$ , is the attracted trips in TAZ  $i$  that will be served by SAV;

$Total\ Attraction_i$ , is all of the attracted trips in TAZ  $i$  based on the 10-county OD matrix.

The TAZ level parking price is imputed based on the average land value from tax assessor data. However, the land value in TAZs with large amount of tax exempt land is extremely low, which may not realistically reflect parking price. To alleviate such problem, the final TAZ land value is calculated as the average of all adjacent TAZs. TAZ land values are then rescaled from \$0 to \$20 as the final parking price. The distribution of allocated parking space density and parking prices are illustrated in Figure 3.

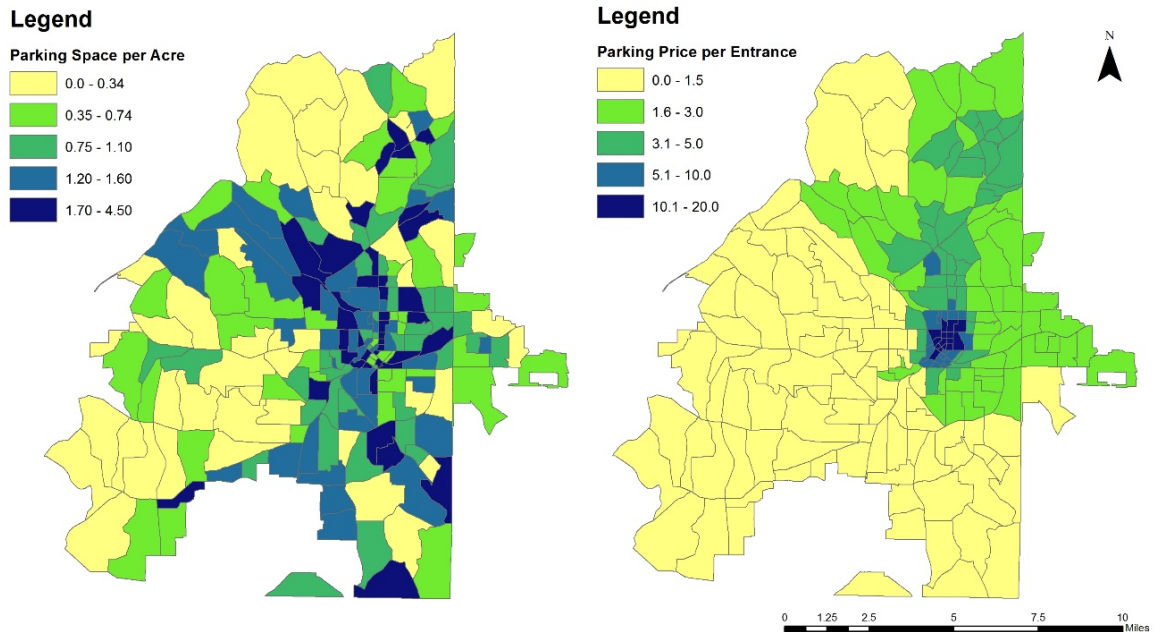


Figure 3: Parking Infrastructure Supply (left) and Parking Price Distribution (right)

At the beginning of the first simulation day, the SAVs are randomly distributed. The model is set to run 50 consecutive days to collect outputs for further analysis. The output from the first

simulation day is excluded in the final analysis, as it is a warm-up run to determine the location of SAVs at the beginning of the following simulation days.

Two scenarios, i.e., charged and free parking scenarios, are established to examine the impact of different parking price policies on SAV system parking demand and urban parking land use. The same string of random numbers is used in the simulation runs for different scenarios to ensure that the differences in outputs are not caused by noises rising from the random number generator.

#### 4.2 Spatial Distribution of Parking Land Use

At the end of the simulation, the total required parking for each TAZ is estimated based on the following formula. The total parking space is estimated as the parking lots that need to be reserved to meet the maximum parking demand throughout the simulation day. An average of all 50-day simulation runs is calculated as the final required parking space for each TAZ.

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

$$ParkingSpace_i = \sum_{d=2}^{50} ParkingSpace_{i,d} / 50$$

where,

$i$ , is the index for TAZ;

$d$ , is the index for simulation day;

$t$ , is the simulation time of the day (in the unit of minute).

Figure 4 shows the spatial distributions of the parking space for the two scenarios. In the free parking scenario, parking demand is the highest in major trip generation zones, such as Atlanta Downtown, Midtown and Buckhead areas. In the charged parking scenario, the parking spaces shifts from the highly developed TAZs to west side communities where the existing land value is significantly lower. Additionally, the results also suggest that SAVs won't be re-assigned to park in urban fringe areas, as the summation of parking and vehicle travel costs bottoms in TAZs that are adjacent to the urban cores rather than 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 raise at slower but constant speed. The distribution of total parking and travel costs are illustrated in Figure 5. Finally, in the charged parking scenario, the parking space tend to concentrate in some western communities, such as English Avenue, Bankhead, and Center Hill. Compared with other neighborhoods in Atlanta. These communities are characterized by higher poverty rates, larger percentage of African American population, and higher proportion of industrial land use. The concentration of parking space in these neighborhoods may lead to planning equity issues in these areas. However, it may also offer opportunities for new infill development as the SAV system will be more accessible to these neighborhoods and indirectly improve their mobility and accessibility.

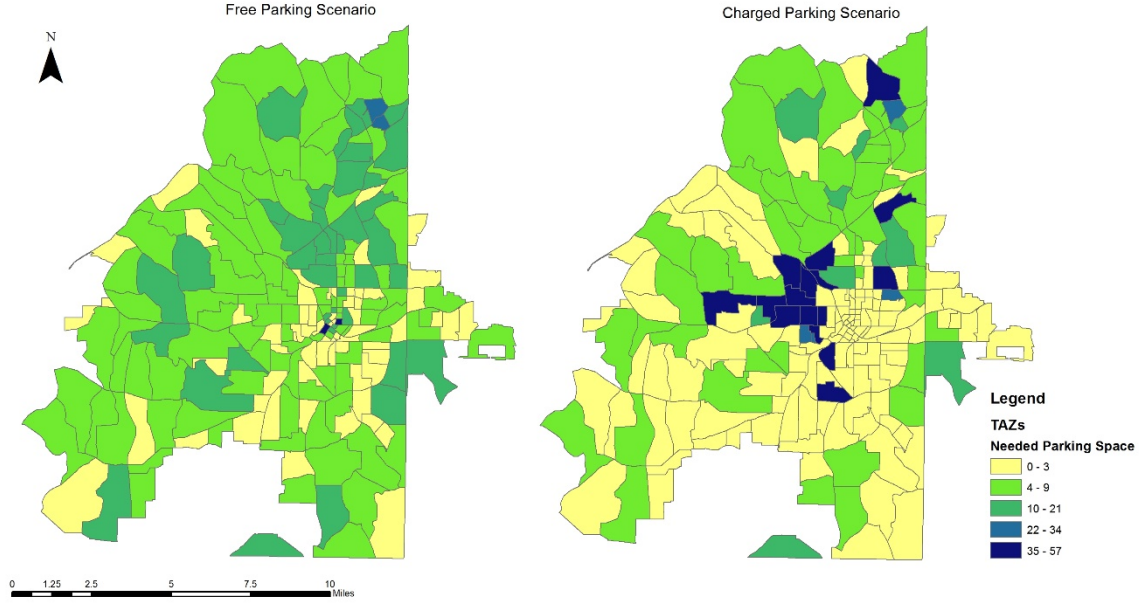


Figure 4: Spatial Distribution of Parking Spaces by Scenarios

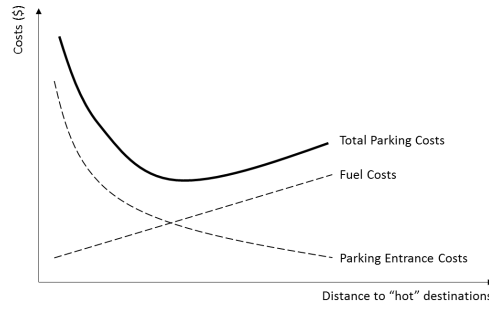


Figure 5: Total Parking Costs by Distance to Urban Cores

### 4.3 Temporal Distribution of Parking Demand

The parking demand at specific simulation time of the day is calculated by adding all parking demand at all TAZs together. An average of all 50-run results is calculated as the final output.

$$ParkingDemand_{a,t} = \sum_{i=1}^{208} ParkingDemand_{a,t,i}$$

$$ParkingDemand_t = \sum_{d=2}^{50} ParkingDemand_{a,t} / 50$$

where,

$i$ , is the index for TAZ;

$d$ , is the index for simulation day;

$t$ , is the simulation time of the day (in the unit of minute).

The total parking demand by time of the day is illustrated in Figure 6. The two scenarios do share some common patterns. For instance, the parking demand peaks during 1-3 am, when almost all the vehicles are parked somewhere in the city. The parking demand is the lowest during the evening peak hours (i.e. 5-7 pm), when virtually all the vehicles are in operation.



Additionally, the parking demand decreases and increases in similar places before the morning peaks and after the evening peaks in the two scenarios.

In contrast to the free parking scenario, the charged parking scenario suggests that the parking demand during mid-day time period is significantly higher (approximately 70% more). Such results can be counter intuitive. Nevertheless, the phenomenon can be explained by the fact that more vehicles will be in the empty cruising state during midday time period when parking lots are free. In the charged parking scenario, once completing the relocation process, the SAVs will navigate to TAZs that minimize the summation of parking cost and vehicle travel costs to park. In other words, in the charged parking scenario, the system will set certain amount of SAVs to park outside of (but close to) the densely developed TAZs and leave smaller, but sufficient amount of, fleet size inside of the expensive TAZs to serve the travel demands while minimizing parking footprint in the developed areas. Meanwhile, in the free parking scenarios, most of the vehicles will remain inside the highly developed TAZs to serve clients and go through the vehicle cruising process again after dropping off the clients. Hence, compared with the charged parking scenario, more SAVs will cruise and relocate during mid-day period in the free parking scenario, rendering a smaller parking demand for the entire system. The side effect of vehicle cruising is that the total cruising VMT generated between 10AM and 3PM in free parking scenario is 61.3% higher, when compared with charged parking scenario.

Despite the higher parking demand in the charged scenario, the parking entrance costs for the entire system during mid-day is significantly smaller. In the charged parking scenario, the system, on average, spends \$1,800 (\$1.8/SAV) to use parking lots, compared with \$14,500 (\$14.5/SAV) in the free parking scenario (if the lots were charged at similar rates as in the charged parking scenario). The parking costs reduction can be attributed to the facts that SAVs navigate to less expensive areas to park and the system tends to reduce the parking turnover rates.

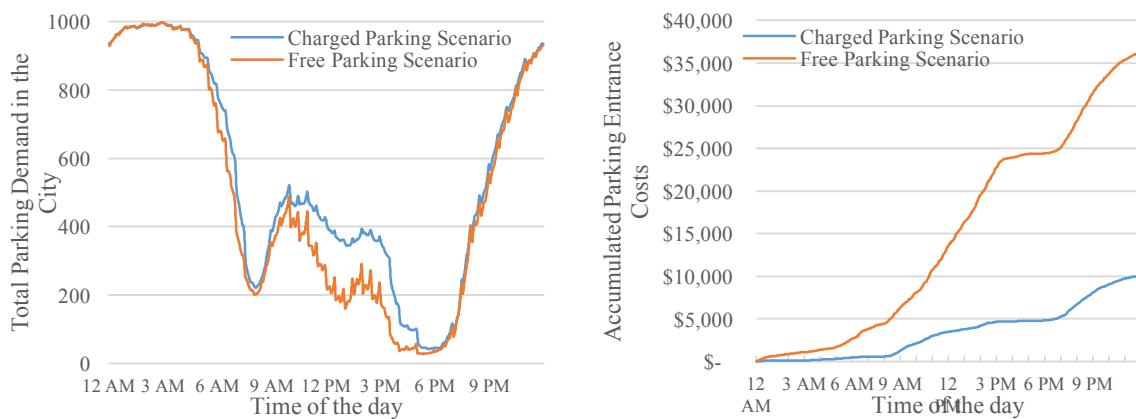


Figure 6: Temporal Distribution of Parking Demand (left) and Accumulated Parking Entrance Cost (right)

#### 4.4 Total Parking Land Use

The total required parking land use is calculated by adding TAZ level required parking space together. The number of parking lot consumed by the SAV system in free parking and charged parking scenarios is 1,371 and 1,495 correspondingly. Compared with existing parking infrastructure, the SAV system can save up to 4.9% of the parking land use at a low market penetration level of 5%. It is interesting that the SAV system has a larger parking footprint, in the charged parking scenario. Such phenomenon can be explained by the spatial mismatching in parking demand during night and midday periods. For clarification purpose,

the TAZs are classified into four types<sup>1</sup>, namely CBD, employment oriented, mixed use, and residential oriented TAZs, based on the residential household density, employment density, and recreation and service employment density. The spatial distribution of classification results are shown in Figure 7. A majority of the southeastern TAZs are residential oriented and some northern TAZs and a few southern TAZs (i.e. the ones that are close to the airport) are employment oriented.

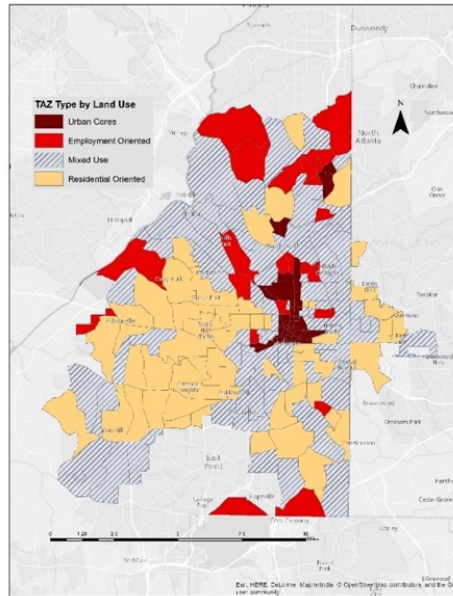


Figure 7: TAZ Types Classification Result

The TAZ level parking demand by time of the day are aggregated by the TAZ types and the results from free and charged parking scenarios are illustrated with solid and dashed lines separately in Figure 8. The parking demand in CBD areas is significantly reduced especially during night and after morning peak hours in the charged parking scenario. However, this reduced parking demand is only shifted to mixed use and residential parking areas. Moreover, the outcome also suggests that after charging for parking, the parking demand in most CBD and adjacent areas will peak during daytime after morning peak hours. This is the primary reason that the parking footprint in charged parking scenario surpasses that in the free parking scenario. A small portion of the vehicles will park in the mixed use or residential oriented TAZs during night and keep consuming parking space in CBD and adjacent areas during daytime, rendering a larger demand for parking lots. The parking demand in employment oriented TAZs remains similar in two scenarios. The employment oriented TAZs outside of CBD areas have more industrial land uses. Therefore, the parking price in these areas are acceptable for the SAV system.

<sup>1</sup> The classification criteria:

CBD TAZs: TAZs with employment density  $> 3 \times$  population density and recreation employment density  $> 9000$

Employment Oriented TAZs: TAZs with employment density  $> 3 \times$  population density and recreation

Residential Oriented TAZs: TAZs with population density  $> 2 \times$  employment density

Mixed TAZs: TAZs with employment density/population density between 0.5 to 3.

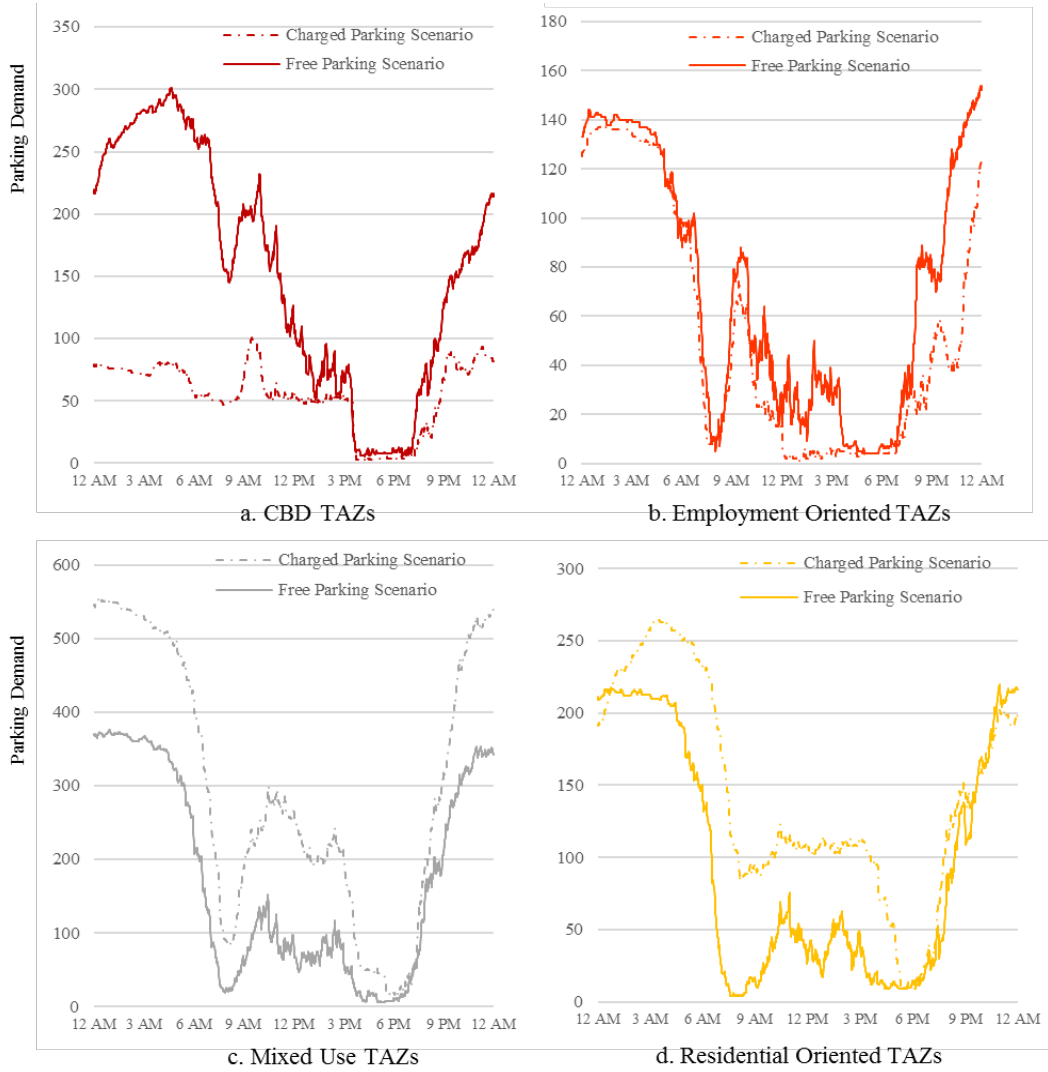


Figure 8: Parking Demand by TAZ Types and Scenarios

#### 4.5 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 VMT generation. The average waiting time for clients by time of the day is shown in Figure 9. Clients in the charged parking scenario wait longer, especially at the beginning of the peak hours, such as 7am and 4pm. In the charge parking scenario, vehicles tend to park at zones with lower land value, resulting in a spatial mismatch between vehicle and travel demand distributions. Additionally, the SAVs are less likely to cruise to balance vehicle distribution after parking in the early morning time period when the travel demand is quite low. In this simulation, the vehicles only relocate after dropping off clients and the vehicles will not relocate after parking. Therefore, the spatial mismatching between vehicles and clients is expected to be the largest in the morning when almost all the vehicles are assigned to cheaper parking lots. This mismatch causes a large discrepancy in average waiting time between the two scenarios.



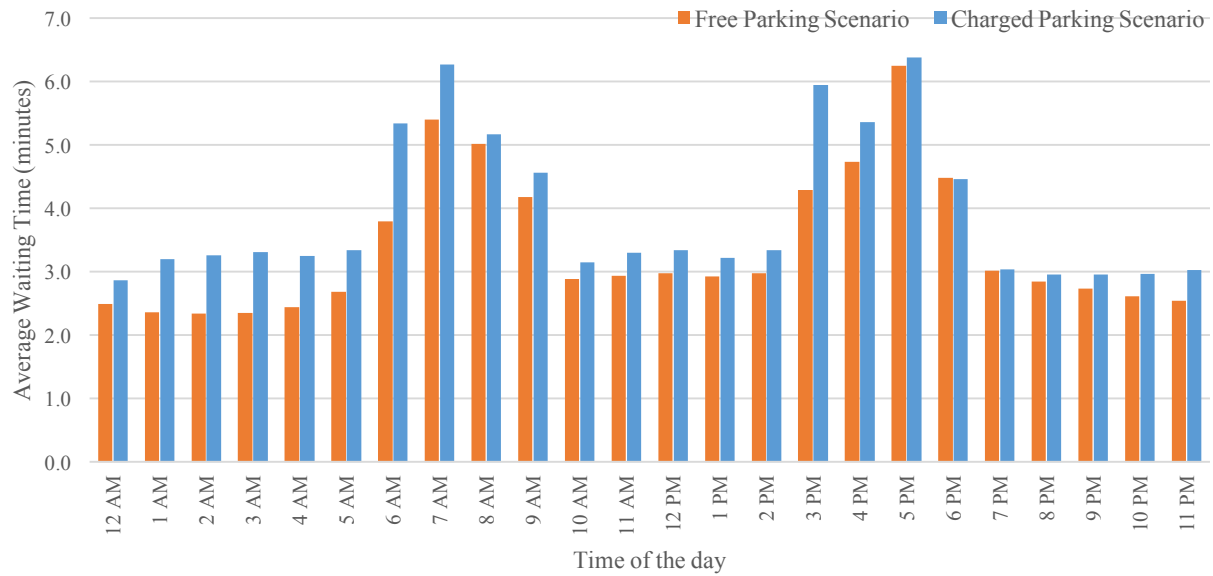


Figure 9: Waiting Time Distribution by Time of the Day and Scenarios

Finally, the SAVs tend to generate 8,131 more VMT to reduce parking entrance fees in the parking process. Additionally, the SAV system also produces 12.6% (5,006.2) more VMT in the picking up process, due to the fact vehicles concentrate at TAZs with lower parking fees.

## 5. Model Verification and Validation

The travel behavior model is verified by comparing the distributions of trip length and departure time from both simulation results and 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. Therefore, the implemented travel behavior model is considered robust in regenerating travel demand for a typical travel day.

The vehicle movements are traced to verify the activity flow implementation process. Figure 10 illustrates the travel path for a randomly selected vehicle in one simulation day from the charged parking scenario. The sequence of the nodes visited by the vehicle is marked in order. The vehicle starts to serve clients at 5:31am and ends by 7:52pm. A total of 30 trips are served by this vehicle throughout the day. Three of them ride-sharing trips, two of which involve intra-zonal trips and, therefore, are not reflected in Figure 10. The vehicle spends approximately 7.2 hours serving vehicles, and 0.9 hours relocating and navigating to parking lots. The vehicle checks into parking lot 6 times and parked for approximately 1.01 hours each time.

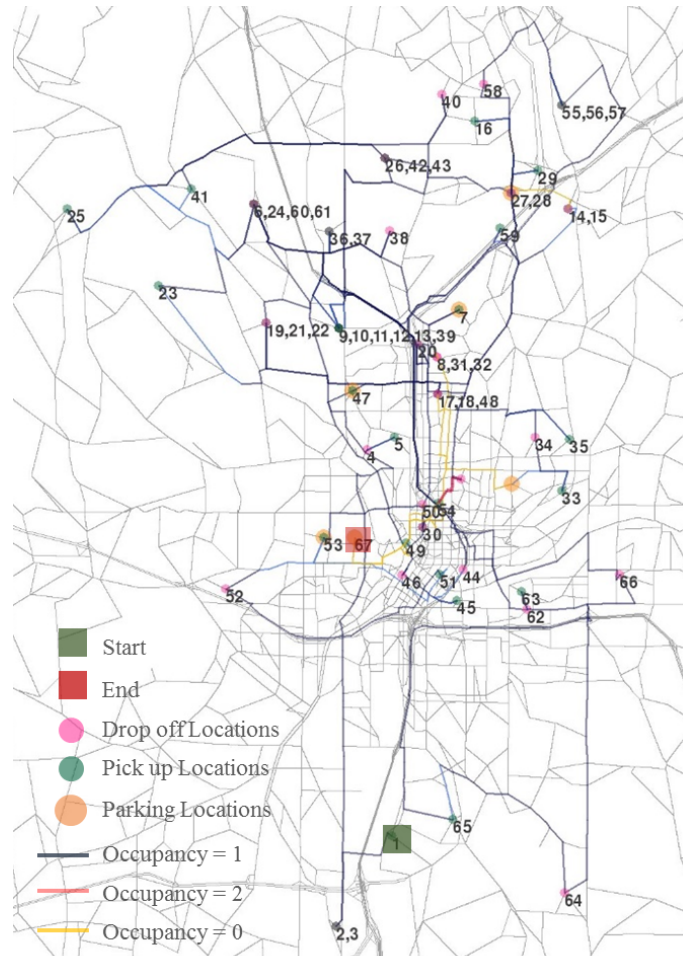


Figure 10: Vehicle Travel Path Example

## 6. Conclusions and Discussions

The simulation results show that parking land use can be reduced by approximately 4.9%, once the SAVs start to serve 5% of the trips within the City of Atlanta in both charged and free parking scenarios. The reduction is contributed 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 (Zhang et al., 2015a) and the Lisbon SAV simulation study (ITF, 2015)

The results from charged and free parking scenarios suggest that charged parking policy will effectively reduce the amount of parking in the CBD areas. The required parking lots in the CBD area is reduced by 67% from 301 to around 102 spaces. Additionally, in the charged parking scenario, the average parking lot occupancy rate in CBD area is approximately 72.1% percent throughout the day, compared with 30.5% in the free parking scenario. However, the reduced parking lots in CBD will shift to TAZs that are close to CBD areas and generates a spatial mismatching in parking lots consumption during night and daytime. In the Atlanta's case, the mismatch is large enough to even inflate the parking footprint for the SAV in charged parking scenario.

The results also suggest that the spatial distribution of parking land use in the city may change fundamentally in the two scenarios. In the free parking scenario, the parking lots will be more evenly distributed throughout the city. While, the parking infrastructures may

concentrate in the low-income neighborhoods, which may lead to equity problems if not properly regulated or planned.

This study explored the variation of parking demand and the spatial distribution of parking land use under free and charged parking policies. There remain some limitations in terms of charged parking scenario development and deserves further exploration. In this study, the parking price is entrance based, while a time sensitive parking price scheme may fundamentally change the operation strategy of SAV system and results in a change in the parking demand and parking land use. Additionally, the model doesn't offer an optimized solution for urban parking land use design, which may be achievable by a centralized operation of SAV system and can provide a more comprehensive picture for smart city development. More future studies should be devoted to examine how the SAV system can be integrated as part of sustainable urban growth policies by optimizing the parking demand and parking land use spatially via a smart parking price charging system.

## References

- ABI Research. (2013). Half of New Vehicles Shipping in North America to Have Driverless, Robotic Capabilities by 2032. Retrieved February 24, 2016, from <https://abiresearch.com/press/half-of-new-vehicles-shipping-in-north-america-to/>
- ARC. (2011). Household Travel Survey Final Report. Retrieved May 25, 2016, from <http://www.atlantaregional.com/transportation/modeling/household-travel-survey>
- Bridges, R. (2015). *Driverless Car Revolution: Buy Mobility, Not Metal*. Retrieved from Amerzon.com
- Burns, L. D., Jordan, W. C., & Scarborough, B. A. (2013). Transforming personal mobility. *Earth Island Institute, Columbia University*.
- CAP. (2014). *Parking Today: Downtown Atlanta Parking Assessment Existing Conditions*. Retrieved from [http://www.atlantadowntown.com/\\_files/docs/existing-conditions-download.pdf](http://www.atlantadowntown.com/_files/docs/existing-conditions-download.pdf)
- 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.
- CityMobil2 Project. (n.d.). CityMobil2 Project. Retrieved February 15, 2016, from <http://www.citymobil2.eu/en/About-CityMobil2/Overview/>
- 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.
- Fagnant, D. J., & Kockelman, K. M. (2015). Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In *Transportation Research Board 94th Annual Meeting*.
- 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.
- Ford, H. J. (2012). *Shared Autonomous Taxis: Implementing an Efficient Alternative to Automobile Dependency*. Princeton University.
- International Transport Forum. (2015). Urban Mobility System Upgrade: How shared self-driving cars could change city traffic.
- 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.

- Rigole, P.-J. (2014). Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.
- 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.
- Spieser, K., Treleven, 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.
- Stanley, M. (2013). Autonomous cars: self-driving the new auto industry paradigm. *Blue Paper*.
- Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015a). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, 19, 34–45.
- Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015b). 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*.