The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach

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ABSTRACT

The recently introduced concept of Shared Autonomous Vehicle (SAV) system, a taxi system without drivers or a short-term rental car-sharing program with autonomous vehicles, presents great potential to promote ridesharing travel behavior. Given the reliability and flexibility provided by the SAV system, some hurdles in the current ridesharing programs, such as lack of flexibility to handle near term travel schedule changes, can be overcome. However, the existing studies regarding SAV system are limited to non-ridesharing (NR) systems. To fulfill this research gap, this study designed and applied an agent-based model to simulate the performance and estimate the potential benefits of an SAV system with dynamic ridesharing (DR-SAV). The modeled DR-SAV system will assign SAVs to serve vehicle-trips, with similar travel profile as in 2009 National Household Travel Survey (NHTS), in a 10*10 mile grid based city, for each one-minute time step. Two vehicle-trips may voluntarily participate into the ridesharing service, if both of them are willing to share rides with strangers and the additional delay time cost triggered by ridesharing can be offset by travel cost reductions. Preliminary results show that a DR-SAV system can provide more satisfactory level of service compared with an NR-SAV system, in terms of shorter trip delays, more reliable services (especially during peak hours), less Vehicle Miles Travelled (VMT) generation, and less trip costs. Additionally, the results also indicate that a DR-SAV system can be more environment-friendly in the long run.

INTRODUCTION

Ridesharing has long been considered as a sustainable travel mode to alleviate urban problems such as congestion, air pollution, via increasing vehicle occupancy. The advancement of smartphone technology has greatly improved the feasibility of the dynamic ridesharing system (1). Some start-ups, such as Carticipate, Avego, and Piggyback, have already developed mobile based applications to create opportunities for dynamic ridesharing. However, the dynamic ridesharing industry still faces some challenges, such as lack of flexibility to handle near-term travel schedule changes. A recently introduced concept of Shared Autonomous Vehicle (SAV) system, a taxi system without drivers or a short-term rental car sharing program with autonomous vehicles, presents great potential to solve some hurdles in the existing dynamic ridesharing industry by offering more flexibility and reliability to the services (3, 5).

Most existing studies regarding SAV system has been focused on using the system to promote the car-sharing industry. Ford conducted a study to review the present social and legal barriers for an SAV car-sharing system. The study also developed a model to evaluate the performance of a shared taxi system with fixed picking up and dropping off stations every half mile away (2). Kornhauser's group evaluated the feasibility of a shared autonomous taxi system in various counties in New Jersey State. Their results indicate that there could be opportunities for an increase in ridesharing (3). Burns' team developed a more advanced agent based simulation model to evaluate the performance of a ubiquitous SAV car-sharing system. Simulation results imply that the cost per trip mile ranges from $0.32 to $0.39, depending on the fleet size of the SAV system (4). This travel cost is more affordable than owning and operating a private vehicle. Fagnant and Kockleman also investigated the performance of an SAV system with similar simulation assumptions used in Burns' model, but with a different focus on environmental impacts of the system (5). Their study results indicate that each SAV can replace approximately 11 privately owned vehicles. Additionally, some environment benefits, such as reductions in energy consumption, GHG emissions, and air pollutants emissions, can be expected once SAVs start to serve 5% of the population within the 10*10 mile grid study area. According to Fagnant and Kockleman's study, the SAV system comes with the cost of approximately 5% more extra unoccupied VMT generated during the client picking up process. This side effect, however, can be alleviated or even eliminated with the increase of ridesharing behavior.

Little study has investigated how an SAV system will perform when serving dynamic ridesharing and how much more benefits that a dynamic ridesharing SAV (DR-SAV) system can offer compared with non-ridesharing SAV (NR-SAV) system. To fulfill this research gap, in this study we generated and applied an agent based simulation model in Matlab to explore the possible performance and potential benefits of a DR-SAV system and then compare it with an NR-SAV system. The modeled DR-SAV system will assign SAVs to serve one or two vehicle-trips, with similar travel profile as in 2009 National Household Travel Survey (NHTS), in a 10*10 mile grid based city, for each one-minute time step. Two vehicle-trips may voluntarily participate into ridesharing service, if both of them are willing to share rides with strangers and the additional delay time cost triggered by ridesharing can be offset by travel cost reudctions. Preliminary results show that a DR-SAV system can offer more efficient and reliable level of service, in terms of shorter delay time, less variation in expected delays per trip, and less VMT generation. Similar to an NR-SAV system, a DR-SAV system also has the potential to reduce vehicle ownership and parking demand in urban area. Results also imply that a DR-SAV system can be more environmental-friendly in a long run.

MODEL FRAMEWORK

Our model simulates the operations and interactions of SAVs and vehicle-trips within the urban area, in an attempt to predict the performance and benefits of a DR-SAV system in the future. The modeled DR-SAV system will assign SAVs to serve vehicle-trips in a 10*10 mile grid based city, for each one-minute time step. The size of a grid cell is 0.05 mile. There are two types of agents, vehicle-trip agent and SAV agent, in the simulation model. The vehicle-trip agent generates vehicle-trips based on 2009 NHTS data (6). Vehicle-trips attributes, such as trip origin, destination, departure time, trip length, and some socio-economic attributes will be assigned to each generated vehicle-trips. SAV agents will provide information regarding the fleet size, whether a vehicle is occupied, how many vehicle-trips are already assigned to each SAV, the latest locations of SAVs, and etc. The real-time information from both vehicle-trip agents and SAV agents will be passed to vehicle-client match model, which will then manage a centralized operation assigning each SAV to one or two vehicle-trips. A detailed conceptual framework is illustrated in Figure 1.

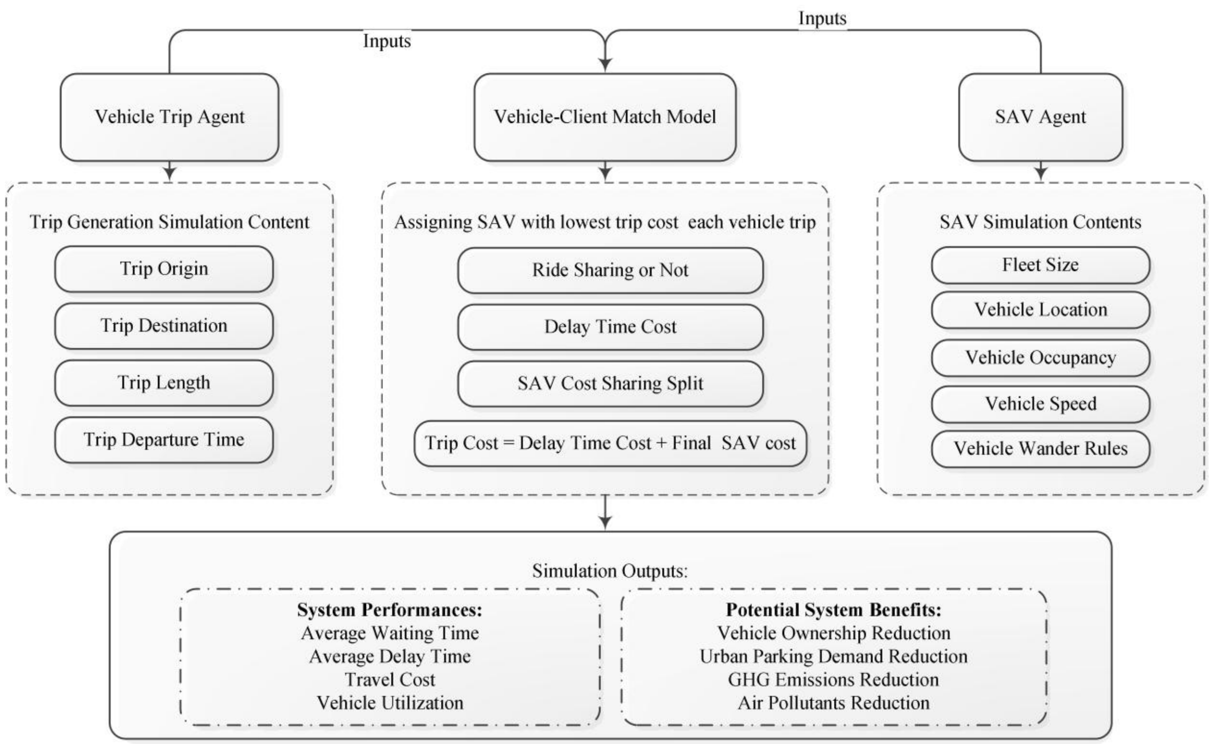

FIGURE 1: SAV simulation model conceptual framework

MODEL SPECIFICATION AND APPLICATION

The simulation model was identified and programmed in Matlab, and the model's major components are elaborated in the following sections.

Vehicle-Trip Agent

The vehicle-trip generation process includes identifying trip parameters, namely origin, departure time, trip length, destination, and socio-economic characteristics of trip makers. First, a vehicle-trip generation rate λ will be assigned to each grid cell. It is assumed that the household density in Central Business District (CBD) is always higher than that in the suburban area. The household density is approximately 4000 per square miles within CBD area and declines to around 1500 at places that are 10 miles away from the center, in city like Atlanta and each household has a vehicle-trip generation rate of approximately 5.66 (6, 7). Thus, at a low DR-SAV system penetration rate of 2%, the daily vehicle-trip generation rate is set as 1.2 (4000*5.66*0.0025*2%) per grid cell in the very center of CBD area and 0.42 in the four corners of the study area. The trip generation rates within the other cells are calculated based on the inversed Euclidean Distance from the urban core, as shown in the Formula 1. Assuming that trip generation will follow the Poisson process, the model generates a Poisson random number based on λ_i for each cell.

$$\lambda_i = \lambda_{min} + \frac{(\lambda_{max} - \lambda_{min})}{Dist_{corner,center}} * Dist_{i,center} \quad (1)$$

where,

λ_i, is the trip generation rate at cell i;
$Dist_{corner,center}$, is the Euclidean Distance from corner to the center cell;
$Dist_{i,center}$, is the Euclidean Distance from cell i to the center cell.

Second, the model will assign a random departure time and trip length for each generated vehicle-trip, using the Cumulative Density Functions (CDF) of the variables, obtained from 2009 NHTS (see formula 2-3)

$$DT = T^{-1}(r) \quad (2)$$

$$TL = L^{-1}(r) \quad (3)$$

Where,

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

Third, the model will identify the location of destination for each vehicle-trip, based on the origin and length of the trip. For each trip, the probability of going east/west and north/south is estimated using Formula 4 and 5, which is also the algorithm used in Fagnant and Kockelman's model. In the morning, the α is set as "1" to pull all the 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 random number will be generated and compared to the calculated probabilities to determine the general direction of the trip. Then the model will check the number of cells that is valid given the direction and trip length. If the number is more than zero, the final destination cell will be randomly selected among all the possible destinations. If the number of valid destination is zero, the model will go back to randomly generate another trip direction. This process will end if a valid destination is obtained.

$$Pr(E_i) = \alpha * \frac{Num_{east}}{Total\ Number\ of\ Cell} + (1-\alpha) * 0.5 \quad (4)$$

$$Pr(N_i) = \alpha * \frac{Num_{north}}{Total\ Number\ of\ Cell} + (1-\alpha) * 0.5 \quad (5)$$

Where,

Num_{east}, is the number of cell that is east of cell i;
Num_{north}, is the number of cell that is north of cell i;
α, is the attraction factor.

Finally, the model will simulate some socio-economic attributes for client(s) who generate vehicle-trips. The model will randomly determine whether the client is willing to share rides with strangers, based on the aggregated level of willingness to share. In our base scenario, it is assumed that half of the households who use the SAV system will agree to share rides. Second, the model will engenders a random hourly income for each client, based on the CDF of 2014 hourly salary, obtained from US Census Bureau.

SAV Agent

For the SAV agents, we clarified both the fleet size and operation rule for the SAVs. We first identified the fleet size that is sufficient to serve the simulated trips within the study area, by running the model with various fleet sizes starting from 500 and is incremented by 50. Similar to Burns' model, the SAVs will be randomly distributed within the study area at the beginning of the day (4). We stop to add SAVs in to the system when the reduction in average waiting time per trip is less than 0.5 minutes. The result shows that 700 vehicle is quite sufficient for the study area, as the average waiting time from scenarios with 700 and 750 SAVs are 1.70 and 1.67, which are not significantly different from each other.

The SAV operation rules are set as follows. The travel speed for SAVs is set as 30 mph during off peak hour and 21 mph during peak hour. For each grid cell, a balance value will be calculated as follow:

$$Blance\ Value_i = \lambda_i - SAV_i \quad (6)$$

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.

The SAVs will always select the serving route with the largest accumulative balance value and the route will be updated at each time step. In this way, there will be higher probability to find the second sharing client and also avoid heavy traffic. If the SAV is assigned to serve a second client, the SAV will first pick up the second calling trip, and then optimized the route to serve the both clients (i.e. select the shortest route to get to both destinations), to save energy consumption.

Moreover, we also set up vehicle cruising rules to further reduce average trip delay and urban parking demand. In this simulation, the study area is divided into 16 (4*4) square subareas. For each area, the balance values in all grid cells will be summed up. 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 lower. If the SAV is already in the area with the lowest total balance value, then it will keep cruising within the area to find potential clients. The SAVs will continue to cruise for five minutes before it eventually parks at the last cruising destination. The five-minute threshold was set up to provide SAV with sufficient amount of time to wander to the adjacent areas, as the average time needed to allocate one SAV from one area to another is approximately five minutes (given the average distance of 2.5 miles). Similar to the SAV delivery route identification process, the vehicle will always select the cruise route with the largest accumulative balance value.

SAV-Client Match Model

The SAV- Client match model is a virtual system that will assign SAVs to one or two vehicle-trips. To avoid the situation, in which clients from certain area will be served first, the order of the client (excluding the ones in the waiting list) will be randomized first before the actual SAV assignment process. Two vehicle-trips will only be able to share the ride if the following requirements are all met:

1) Both the on-board and calling clients agree to share an SAV with a stranger.
2) The cost of longer delay time caused by ride sharing will be made up by lower SAV travel cost
3) The SAV with an on-board client will not make a detour to pick up the second client.

First of all, it is assumed that only half of the population, who use SAV system, feel comfortable to share rides with others, due to safety issues and economic concerns. However, willingness to share, alone, is not enough to determine whether ride sharing will actually occur, it may also depend on the potential benefits of ridesharing. Thus, the extended delays triggered by ridesharing should also be within a reasonable range. We assumed that every clients is rational and they will only agree to share when the time cost of sharing will be offset by the reductions in SAV travel cost. The delay time cost is estimated using the simulated hourly salary rate of the client(s). The SAV travel cost is estimated using trip per mile costs from Burn and et al.'s model. Burn's research group estimated the SAV travel cost to be from 0.32 to a high end of 0.4 per trip mile in their base scenarios, which have similar simulation set ups as in this study (4). We used the highest trip cost, \$0.4 per trip mile, as the SAV travel cost for our study. The total travel cost after picking up the second client will be shared by both vehicle-trips, based on the location of the destinations, as shown in Formula 7. The second criteria will be met only when the formula 8 is satisfied.

$$\forall\, j \in J\text{: } Split\ Cost_j = SAV\ Cost * \frac{dist_j}{\sum_{i=1}^{J} dist_i} \qquad (7)$$

$$\forall\, j \in J\text{: } SAV\ Cost_{No\ Share_j} - SAV\ Cost_{Share_j} \geq Delay\ Cost_{Share_j} - Delay\ Cost_{No\ Share_j} \qquad (8)$$

Where,

j, is the j^{th} involved vehicle-trips;
J, is the set of all involved vehicle-trips.
$Split\ Cost_j$, is the share of cost should be paid by j^{th} involved vehicle-trips;
$SAV\ Cost$, is the cost occurred after picking up the second client;
$dist_j$, is the distance between the second client's origin and the j^{th} client's destination.

The third criteria is set up to simplify the trip cost split process. With this criteria, only the SAV cost occurred after picking up the second client will be split between the two clients. Finally, if several SAVs can meet the above criteria, then the one with lowest total travel cost will be selected to serve the trip(s).

SIMULATION RESULTS

We ran the model for 50 simulation days to obtain stable results to examine the performances of DR-SAV system, which serves 2% of the households within the simulated study area. The performances of a DR-SAV and an NR-SAV system are compared. The model assumptions for both simulated systems are tabulated in Table 1.

TABLE 1: Base Model and No Ridesharing SAV Model Inputs Parameters Assumptions Summary

Model Input Parameters	Assumptions	
	DR-SAV System (Base Model)	NR-SAV System
Study Area	10 mi * 10 mi	10 mi * 10 mi
Grid Cell Size	0.05 mi	0.05 mi
Time Step (Min)	1	1
Maximum Trip Generation Rate	1.2	1.2
Minimum Trip Generation Rate	0.42	0.42
Off-peak Speed	30	30
Peak Speed	21	21
Fleet Size	700	700
Vehicle Empty Cruising Time (Min)	5	5
Level of Willingness to Share Ride	50%	-
Max # Vehicle-Trips Allowed per SAV	2	1

DR-SAV System Performance

Ridesharing

The preliminary results of the simulation model shows that, on average, 2001 vehicle-trips will participate into the ridesharing service. Over 33% of the ridesharing takes place during the three traffic peak hours (7-8AM, and 5:30-7:30PM). As a matter of fact, the result shows that around 546 vehicle-trips share rides during evening peak hours, occupying 27.3% of vehicle-trips that shared rides. This result is not surprising, as the time cost to wait for an empty SAV during peak hours is significantly higher, rendering the higher frequency of the ride-sharing behavior.

We also noticed that the probability of ridesharing is larger when the vehicle-trip length is quite long. The average trip length for ridesharing trips is around 7.73 miles, which is 42.9% longer than the average simulated trip length. Ridesharing also takes places more frequently when the income of clients who generate the vehicle-trip is lower. The results indicate that the average hourly salary for ridesharing trips is around $25.3, which is 13% lower than the national average, but similar to the median hourly payment. Therefore, it implies that a majority of the family has the potential to participate into this real-time ridesharing service.

Although it's assumed that up to 50% of the simulated vehicle-trips will be willing to share rides, only 6.7% of trips participate into ridesharing service. There may be two reasons for this phenomenon. First, given certain time of the day, the probability to match trips with nearby destinations and origins is quite low, as only 2% of the trips are simulated. The number of ridesharing trips can increase, if more people start to use the SAV system. Second, the cost per mile is quite low in this simulation, providing less incentives for clients to voluntarily participate into the carpooling service. Despite the fact, that less than 10% of the trips actually shared rides, a DR-SAV system still performs significantly better than an NR-SAV system, in terms of delay time, VMT generation and costs per mile, as tabulated in Table 2.

TABLE 2: Simulation Base Model Results and Comparisons

		DR-SAV System (Base)		**NR-SAV System**		**Differences**	**Reduction Rate**
		Mean	**S.D.**	**Mean**	**S.D.**		
Delay (Min)							
Daily	Waiting Time (All Trips)	1.70	0.04 (1.27)	2.04	0.34 (2.33)	0.34	16.48%
Daily	Detour Time (Shared Trips)	0.82	0.01 (1.01)	-	-	-	-
Daily	Total Delay Time (All Trips)	1.77	0.04 (1.35)	2.04	0.34 (2.33)	0.27	13.42%
Peak	Waiting Time (All Trips)	2.54	0.12 (1.89)	4.24	1.41 (3.96)	1.70	40.05%
Peak	Detour Time (Shared Trips)	0.74	0.02 (1.05)	-	-	-	-
Peak	Total Delay Time (All Trips)	2.66	0.12 (1.97)	4.24	1.41 (3.96)	1.58	37.34%
% of Trips Delayed by 5-10 Min		4.20%	0.40%	5.60%	1.90%	0.01	25.00%
% of Trips Delayed by 10+ Min		0.20%	0.10%	2.00%	1.70%	0.02	90.00%
VMT Generation							
Total VMT		180445	1180	189416	1665	8971	4.74%
VMT per SAV		257.78	1.69	270.59	2.38	13	4.74%
Unoccupied VMT		18145	289	19385	1202	1240	6.40%
Unoccupied Pick Up VMT		5039	605	6161	2108	1122	18.21%
Unoccupied Cruising VMT		13106	760	13224	1079	118	0.89%
Shared VMT		6311	245	-	-	-	-
Vehicle Utilization							
Number of Served Trips per SAV		42.62	0.30 [6.95]	42.73	0.18 [6.00]	0.11*	0.26%*
Max. # of SAV in Service		654	20	691	16	37	5.35%
Longest Continuous Service (Mile)		46.43	1.89 [15.58]	54.93	1.35 [15.14]	8.50	15.48%
Vehicle Starts per Day		14360	498	14363	379	3*	0.02%*
Cold Starts per Day		1440	46	1348	37	-92	-6.82%
Chargeable Night Break Time (Min)		334	2.07 [73.80]	332	2.50 [71.42]	-2.09	-0.63%
# Chargeable Breaks During Day Time		1.528	0.07 [0.97]	1.383	0.05 [0.91]	-0.15	-10.48%
Chargeable Day Break Time (Min)		118	2.98 [63.73]	112	3.78 [63.78]	-5.90	-5.29%
Travel Cost							
Cost per Trip Mile (All Trips)		0.39	0.04 (0.0001)	0.40	0.00	0.01	2.50%
Cost per Trip Mile (Shared Rides)		0.25	0.040(0.001)	-	-	-	-

Note: the standard deviation (S.D.) provided is a day-to-day standard deviation, the ones shown in parentheses are average trip-to-trip standard deviation within a day, and the ones shown in brackets are average SAV-to-SAV standard deviation within a day.
* indicates differences that are not statistically significant from zero based on two-tailed unequal variance t-test result.

Delay Time

The result implies that a DR-SAV system can provide more satisfactory service than an NR-SAV system. A DR-SAV system may reduce the average delay time by 13.42%, from 2.04 to 1.77 minutes. The delay time reduction is the most significant during the peak hours. The result shows that the expected waiting time during peak hour declines by 37.34% from 4.24 to 2.66 minutes in a DR-SAV system. Additionally, the ridesharing system may provide more reliable service, as the trip-to-trip standard deviation of waiting time (the ones shown in parenthesis) in a DR-SAV system is much smaller.

For ridesharing trips, the total delay is not substantially higher than the trips without sharing. The average detour time for all ridesharing trips is approximately 0.82 minutes, which decreases slightly to 0.74 minutes during peak hours. However, due to the fact that the trip-to-trip standard deviation of the detour time is quite large, there is no significant difference between all-day and peak-hour detour time. The total delay for all ridesharing trips is about 3.44 minutes, which is only 1.67 minutes longer than the average total delay for non-ridesharing trips.

Finally, the results from the base model also indicates that the expected delays in a DR-SAV system is much shorter than the existing public transit systems, such as railway and bus. Additionally, the delay is also shorter than the average vehicle-trip terminal time, such as time spent for parking, paying parking tickets, and etc. The terminal time is usually estimated as three minutes for urban area and five minutes in the busy area of downtown for each trip end (8). The comparatively short delay time may attract more potential riders to use the DR-SAV system.

VMT Generation

A DR-SAV system also offers the benefit in VMT generation. A DR-SAV system generates 4.74% less VMT on a daily basis. Given similar fleet size, the daily VMT generation per SAV is reduced to 258, rendering a smaller vehicle turnover rate in the DR-SAV system. Most of the VMT is reduced during picking up process, as the unoccupied pick up VMT declined by 18.21%. Some VMT is also saved during ridesharing process. The base model results show that 6311 VMT is eliminated for ridesharing.

Although a DR-SAV system generates less VMT, the system still produces approximately 11% (18145) more VMT than the sum of all trip length. The average unoccupied VMT per trip is around 0.6 miles, which comes primarily from two sources: first, the SAVs have to make additional miles to the serve the next calling clients; second, the SAVs will not stop at the destination of last customer, but instead cruising to places where the supply and potential demand of SAVs are significantly unbalanced. The base model results indicate that 72.41% of the unoccupied VMT is generated during the SAV empty cruising process. This value can be further reduced if the SAV cruising strategy is optimized by eliminating SAV cruising during some off-peak hours.

Vehicle Utilization

The DR-SAV system may operates with smaller critical fleet size. The maximum number of SAVs in service are 654 and 691, in the DR-SAV and NR-SAV systems. In other words, the 5.3% less SAVs may be required in a DR-SAV system, to maintain the current level of service.

Additionally, it is easier to integrate electric vehicles (EVs) into a DR-SAV system, as the system has longer and more frequent chargeable breaks during daytime. In this study, SAV parking time longer than 1.5 hours are considered as breaks for potential charging time for EVs. In a DR-SAV system, there is likely to be two 1.97-hour chargeable breaks in every three days, which are 10.49% longer and 5.29% more frequent compared with an NR-SAV system.

However, the DR-SAV system does come with some side effects, as the share of cold starts per day increase by 6.82% compared with an NR-SAV system. This can be attributed to two facts: first, there seems to be more than sufficient amount of SAVs in the ridesharing system, rendering higher portion of cold starts. Second, in the ridesharing system, the vehicle service time can be dramatically reduced if the clients share rides, rendering longer break time, which leads to higher probability of cold starts. However, even in a DR-SAV system, the number of cold starts per vehicle per day is approximately 0.048, which is substantially less than the 3 cold starts per vehicle per day, an assumption used in MOBILE6 model.

Travel Cost

A DR-SAV system can be more affordable than an NR-SAV system. The average cost per mile can be reduced by 2.5%, in a DR-SAV system. For the ridesharing trips, the average cost per mile is approximately $0.25, which is 62.5% lower than the non-sharing trips. The average trip cost is $2.2 in a DR-SAV system, which is significantly more affordable than the existing taxi system. Additionally, the $0.4 per trip mile is also slightly cheaper than the average cost of owning and operating a typical sedan vehicle, which is $0.61 (9). The reduction in travel cost can make the system more appealing to the general public. However, it may also encourage urban sprawl. The reduction in travel cost indicates that there may be more incentives to live in suburban area, where the housing and living cost is lower.

Potential System Benefits

Vehicle Ownership Reduction

The model result shows that a DR-SAV system has the potential to reduce vehicle ownership. An average of 30,000 trips is generated in the base model. Based on the 2009 NHTS data, each household generates around 5.66 vehicle-trips per day and owns approximately 1.86 vehicles. Thus, we may expect the 700 SAVs to replace about 9858 (30,000/5.66*1.86) privately owned vehicles. In other words, the simulation result suggests that in a DR-SAV system, one SAV holds the potential to substitute around 14 household vehicles.

Parking Demand Reduction

Smaller fleet size comes with the benefit of reduced daily parking demand, which is estimated using the following formula in this study:

$$P_i = \max_{0 \le t \le 1440} P_{it}$$

where,

P_i, is the number of total parking demand within grid cell i;
P_{it}, is the number of parking demand in grid cell i at time t (in the unit of minute).

The base simulation results show that only 3,165 parking space on average is required throughout the day by the 700 SAVs. Shoup's study shows that, on average, four parking spots is allocated for each individual privately owned vehicles in the United States (10). Given the 9858 privately owned vehicles, there is a need for approximately 39,432 parking space within the urban area. Thus, the DR-SAV system will be able to eliminate around 92.5% of the parking spaces, which would, otherwise, be required by the household vehicles. Most of the parking demand is reduced due to the smaller fleet size and some is further reduced because the SAVs continue cruising after dropping off the last customer. The result shows that up to 984 daily parking demand is saved due to empty cruising process. The parking space may be further reduced by offering smaller parking lots, as there is no need to open doors after parking. If these aesthetically unpleasant parking lots are no longer in need, then more sustainable designs, such as green space expansion, work-oriented designs can be introduced.

Environmental Impact Reductions

Although the SAV systems tends to generate more VMT, the vehicle life cycle GHG and air pollutant emissions and energy consumption can still be reduced due to less cold starts and reductions in parking infrastructure requirements, compared with business as usual (BAU) circumstance. We used the vehicle life cycle inventory from Chester and Horvath's study, which included the parking infrastructures into calculation (11). It is assumed that the replaced vehicles and the SAVs are all conventional gas sedans. Additionally, the consumption and emissions during manufacturing and vehicle running phases will be similar, as all the vehicles will have similar life span mileage. The estimation results, as tabulated in Table 3, there will be a significant reduction in air pollutants such as CO, NO_X, and Volatile Organic Compounds (VOC), due to 95.3% and 95.8% reduction in the number of cold starts in the DR-SAV and NR-SAV system compared with BAU. Additionally, the energy consumption, GHG emissions, and PM_{10} will also, to some extent, be reduced, as a result of less parking demands.

TABLE 3: Environmental Benefits Comparisons

	Per Vehicle Life Cycle (Conventional Gas Sedan)					DR-SAV	NR-SAV	BAU
	Manufac.	Running	Cold Starts	Parking	Other*			
Energy (GJ)	100	890	0	15	374	1365.5	1365.5	1379.0
GHG (MT CO_2e)	8.5	69	0	1.2	34.2	111.8	111.8	112.9
SO_2 (Kg)	20	3.9	0	3.6	74.4	98.7	98.7	101.9
CO (Kg)	110	2100	1400	5.2	139.2	2415.5	2408.5	3754.4
NO_X (Kg)	20	160	32	6.4	100.3	282.4	282.3	318.7
VOC (Kg)	21	59	66	5.2	211.0	294.6	294.3	362.2
PM_{10} (Kg)	5.7	20	0	2.7	44.4	70.4	70.4	72.8

* Other includes tire, brake, repair, evaporative losses, tire production, maintenance, fixed costs, roadway construction, roadway lighting, and refining distribution. It is assumed that "other" energy consumption, GHG and air pollutant emissions will remain the same.

Although the results indicate that the NR-SAV system is the most environmental friendly, in term of vehicle life cycle emissions, the DR-SAV system can actually perform better in the long run. The SAVs need to be replaced every 1.28 and 1.21 years in the DR-SAV and NR-SAV system, with the assumption that the life span mileage is 120,000 miles (GREET 2.0 Model). In other words, 5,489 and 5,761 SAVs will be needed separately to operate DR-SAV and NR-SAV system for a decade. The DR-SAV can save an additional 4.7% of energy consumption, GHG, and air pollutants emissions, in the long run.

MODEL SENSITIVITY

In addition to the base model, 72 scenarios are simulated with different SAV fleet size, levels of willingness to share, and vehicle empty cruising time, to evaluate the model sensitivity. The results, as displayed in Figure 2, may provide additional information towards how a DR-SAV system may operate with various assumptions.

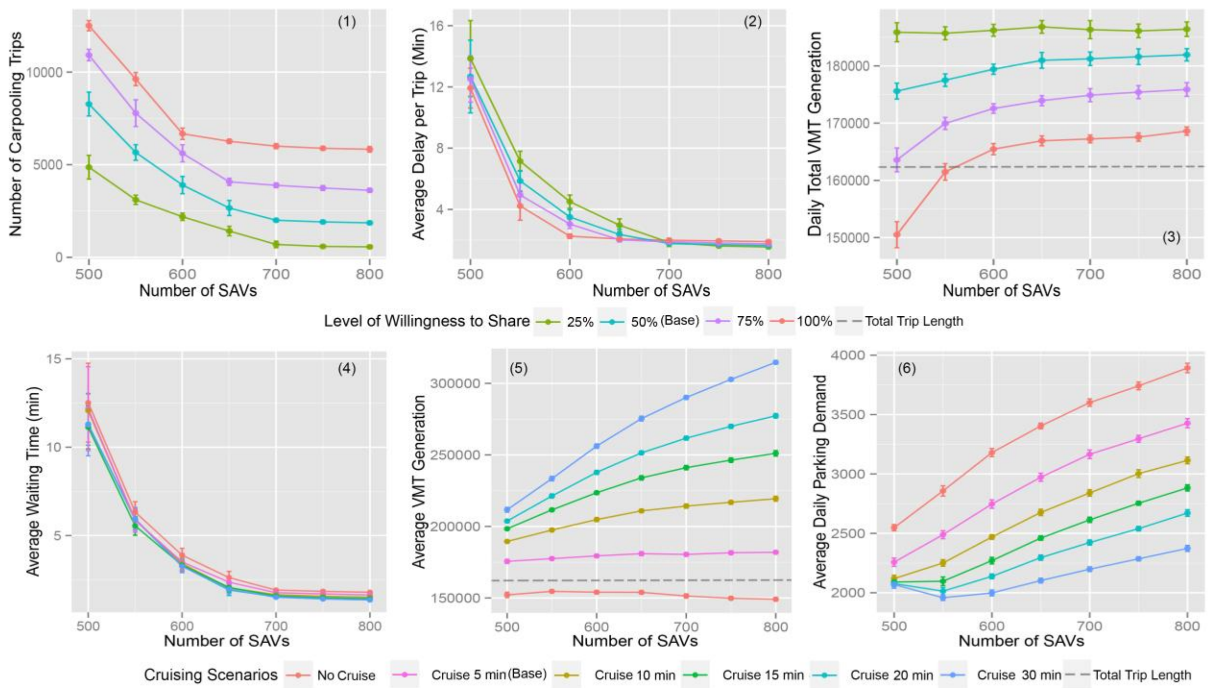

Figure 2: Model Elasticity Tests

We first ran the scenarios with different SAV fleet sizes and levels of willingness to share. The results, as illustrated in Figure 2.1, show that the number of ridesharing trips decreases, when the fleet size increases, as the potential waiting cost for an empty SAV become lower. However, the marginal reduction rate become quite small when there are more than critical amount of SAVs in the system. The number of ridesharing trips is positively associated with the general level of willingness to share.

The results, as shown in Figure 2.2, indicate that average total delay time per trip decreases when the SAV fleet size become larger. However, the marginal decrease in delay time per trip is quite small, once there are more than 700 vehicles in the system. This result is quite reasonable, as when more people are willing to share rides, the chance for ridesharing will increase, which leads to shorter waiting time during peak hour, when almost all SAVs are occupied. When the fleet size is larger than 700, the delay time tends to be slightly longer in scenarios where there are more shared rides, due to extra detour delays.

The VMT generation is positively associated with the SAV fleet size as displayed in Figure 2.3. Vehicle cruising process generates the majority of the excessive VMT in various scenarios. Fortunately, the VMT tends to decline, when the level of willingness to share is higher. In no cruising scenarios, the VMT generation is actually less than the total length of all vehicle-trips.

We also ran the model with various cruising time thresholds and the result is displayed in Figure 2.4-2.6. It seems that the expected delay time can be reduced slightly once the empty cruise time is extend, based on Figure 2.4. In scenarios with 5, 10, and 15 minutes of cruising time, the average waiting time per trip can be reduced by around 7.7% and 12.7%, and 16.6% correspondingly, compared with no cruise. However, the reductions in waiting time are no longer significantly, when the cruise time is set as more than 15 minutes.

It is interesting to notice that VMT generation shows different trajectories in different vehicle cruise scenarios, as shown in Figure 2.5. When there is no cruising, the VMT generation is highest in 550-SAV scenario. The 500-SAV scenario presents less VMT, as there are more ridesharing trips. When the fleet size become larger, the unoccupied VMT generation will be reduced, as the probability to find a close by SAV become higher. However, this phenomenon is not shown in any other cruising scenarios, as this VMT reduction effect is offset by the VMT generated during cruise process.

Longer vehicle cruising time comes with the benefit of urban parking demand reduction, as shown in Figure 2.6. Some parking demand can be eliminated if the SAVs are assigned during cruising process. Compared with no cruise scenario, approximately 12.4% of the parking demand can be eliminated in 5-minute cruise scenario, disregarding the fleet size. However, the marginal effect of sacrificing cruise VMT to reduce urban parking demand tends to decline. It's also interesting to notice that when the level of willingness to share is less than 50%, the parking demand is lowest in 550-SAV scenarios. When the fleet size is 500, the number of ridesharing trips will increase dramatically, rendering a quite low probability of being called during cruising time. As a result, despite the smaller fleet size, the parking demand is a little higher. However, when the level of willingness to share is above 50%, the dominant factor controlling parking demand become the fleet size of the system.

MODEL DISCUSSIONS

This model provides a preliminary framework to simulate and evaluate the performance and potential benefits of an SAV system. We compared our NR-SAV model results with the 1500-SAV scenario results from Fagnant and Kockleman's model, as the two scenarios share some basic settings, such as trips per SAVs (implying similar trip-SAV ratio), and study area size. The results have similar average waiting time (2.04 vs. 2.51) and number of cold start per trip (0.048 vs. 0.040). The average waiting time is 0.47 minute shorter, as in our model SAVs are continuously reallocating themselves for additional 5 minutes.

The proposed DR-SAV model can be further improved from several perspectives. Frist, the model can be more realistic, if the model simulate willingness to share based on other socio-economic characteristics of trip makers. Second, the results can be more practical, if the real world network and travel behavior patterns can be applied. Currently, most of the model inputs are normalized national level data and the households 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, to evaluate the environment benefits of the system in a more precise manner, future models may consider alternative fuel powered autonomous vehicles.

CONCLUSIONS

The model results indicate that the DR-SAV system holds the potential to facilitate ridesharing behaviors. Given the fleet size of 700 and 50% willingness to share, the system will only be able to match 2001 (6.7%) vehicle-trips to share rides, with an average of 0.82 minutes of additional delay time. Different from the current dynamic ridesharing program, the clients remain the right the change the travel schedule in the last minute, in the DR-SAV system, given the real-time characteristic of the system.

Through providing ridesharing service, a DR-SAV system can offer higher level of service, compared with an NR-SAV with similar fleet size. The base model results indicate that the average delay per trip is 13.42% shorter throughout the day in a DR-SAV system, and 37.34% shorter during peak hours. Additionally, the trip-to-trip variation in delay is substantially smaller in a DR-SAV system, indicating more reliable services. The DR-SAV system also generates 4.74% less VMT through ridesharing, rendering smaller SAV turn over rate in the long run. In scenarios with higher level of ridesharing, the DR-SAV system can even perform better than business as usual circumstance. Finally, a DR-SAV system can reduce about 62.5% trip cost for ridesharing trips, rendering the system more affordable to the general public.

Moreover, the result also implies that the DR-SAV system may offer similar benefits in aspects such as vehicle ownership and urban parking space demand reductions, compared with the NR-SAV system. Preliminary results suggest that one SAV can replace 14 private vehicles and reduce about 90% of the parking demand. Finally, the environment impact benefit estimation results indicate that the DR-SAV system can be more environmental friendly, compared with the NR-SAV system. Although air pollutants, such as CO, NO_X, and VOC, emissions are 0.3% smaller per vehicle life cycle in the NR-SAV system, the DR-SAV system may emit less GHG and air pollutants, and consume more energy in the long run, due to the 4.7% lower vehicle turnover rate.

In sum, despite the fact that DR-SAV system still faces many challenges such as psychological safety concerns and unprepared legal environment, once the barriers are overcome, the system may become a very appealing travel mode for the general public. The simulation result shows that the system can provide a more satisfactory level of service compared with an NR-SAV and the existing transit system. The system also has the potential to achieve more sustainable development via reducing vehicle ownership, parking demand and GHG emissions.

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