FLEET PERFORMANCE AND COST EVALUATION OF A SHARED AUTONOMOUS ELECTRIC VEHICLE FLEET: A CASE STUDY FOR AUSTIN, TEXAS

Benjamin Loeb, M.S., EIT
Transportation Engineer
Delaware Valley Regional Planning Commission
190 N. Independence Mall West, Philadelphia, PA 19106
bloeb@dvrpc.org
Phone: 215-238-2944

Kara M. Kockelman*, Ph.D., P.E.
Professor, and E.P. Schoch Professor in Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu
Phone: 512-471-0210 & FAX: 512-475-8744

Presented at the Autonomous Vehicles Symposium 2017 (San Francisco) and published in *Transportation Research Part A* 121: 374-385 (2019).

ABSTRACT

Electric Vehicles (EVs) are an attractive option for shared autonomous vehicle (SAV) fleets because of their high energy efficiency and reduced emissions. Unfortunately, EVs are disadvantaged by their relatively short range and long recharge times, so it is important to understand how these factors will affect an electrified SAV (SAEV) fleet in terms of vehicle mileage, vehicle productivity, response times and cost.

This study makes in-depth estimates of the cost of this SAEV fleet based on vehicle purchasing and maintenance costs, electricity, charger construction and maintenance, insurance, registration and general administrative costs. These costs are estimated at low-, high- and mid-cost (most likely) scenarios.

This study performed a simulation of SAEVs across the Austin, Texas 6-county region under 6 different fleet scenarios highlighted by thoughtful charging strategies, dynamic ridesharing, mode choice, and a multi-step search algorithm. Results showed that for all metrics studied, a gasoline hybrid-electric (HEV) fleet performed better than EV fleets, while remaining more profitable, providing response times of 4.5 minutes. The HEV fleet is the more profitable option until the cost of gasoline exceeds $10 per gallon or the cost of a long-range EV falls below $16,000. Of all the EVs studied, the long-range fast-charging scenario not only provides the best service in terms of all metrics studied, but is by far the most profitable. Though EVs may not be financially advantageous in the near term, EVs have the potential to provide zero-carbon transportation with a renewable power grid. Gasoline vehicles have no such potential.

MOTIVATION

Shared autonomous vehicles (SAVs) are envisioned to eventually save many travelers money and time, while reducing personal-vehicle fleet sizes in use today (Fagnant and Kockelman, 2016). One way to extend such benefits is to use an electric vehicle (EV) fleet as in Chen et al. (2016) and Chen and Kockelman (2016). EVs are especially suited for the heavy use (longer daily travel distances) experienced by shared fleets due to their relatively low energy and maintenance needs (U.S. DOE, 2016). EVs are expected to reduce environmental costs in most locations, especially where renewable feedstocks are part of the power grid (Reiter and Kockelman, 2016). As the price of EV technology continues to fall (Nykvist and Nilsson, 2015) and charging facilities become more convenient, EVs may become financially advantageous over traditional, petroleum-fueled vehicles. EVs in the context of shared automated fleets have received little attention despite their rise in popularity and the challenges to implementation that they face. The viability of an electrified fleet is an important concern that needs to be addressed very soon.

Due to high fixed costs, at least in early stages of the technology's release, scenarios under which such a fleet is cost-effective, compared to a gasoline-powered fleet, should be explored before making this large capital investment, granted such scenarios even exist. Barriers for EV adoption by households in the US and elsewhere (Stephens, 2013), are steadily falling. Charge times under an hour are becoming available in more and more fast-charge locations (see, e.g., https://www.tesla.com/supercharger and Bullis, 2013) and battery ranges are rising with new vehicles such as Chevrolet Bolt (Chevrolet, 2016) and Tesla Model 3 (Tesla Motors, 2016) both expected to deliver 200 miles of range for under $40,000. The recent, dramatic, drop in battery prices will also play a big role in EV adoption, now at an estimated $190 per kilowatt-hour (kWh), roughly one fourth what they cost back in 2009 (Voelcker, 2016).

This study simulates various cost scenarios using the data found in Loeb et al. (2016) to help a fleet operator determine if an SAEV fleet is a wise and feasible option, what charge speeds and range are the most reasonable and financially advantageous, and how these results compare to simulations of an all-gasoline fleet.

LITERATURE REVIEW

There are many works that simulate SAV fleets to analyze performance in terms of response times, empty mileage, vehicle replacement rates and more. Very few works, however, make strong efforts to determine the cost of these fleets for a fleet operator and only Chen et al. (2016) studied the cost of an electrified SAV fleet.

The methods for financial analysis in this work were modeled closely after Chen et al. (2016), as was much of the charging algorithm. Their study is unique because it finds costs for an electrified SAV fleet compared to a gasoline-powered one. They also assumed the fleet operator will be responsible for costs associated with owning and maintaining chargers in addition to the vehicles. They found that an SAEV fleet can be offered at $0.66 to $0.74 per mile when accounting for vehicle costs, battery replacements, vehicle maintenance, insurance & registration, electricity (to charge vehicles), charging stations, station maintenance and general administrative costs. Their model lacked many degrees of realism and accuracy and their cost calculations missed some key assumptions. For example, costs of procuring and transforming land for charging stations were neglected; also electricity costs did not consider hefty load factor adjustments needed for fast-charging. Many of their cost assumptions are quite dated as well and sometimes not adequately supported.

Burns et al. (2013) investigated costs of an SAV fleet using agent-based simulations modeling several major US cities. They found that an SAV system could operate at costs of $0.32 to $0.39 per mile considering cost of vehicles with depreciation, financing, insurance, registration, taxes, fuel, maintenance, repair, and overhead. Their findings were somewhat unusual with average response times less than 15 seconds for vehicle replacement rates of about

6 and response times of less than 45 seconds under a replacement rate close to 9. These remarkable findings are likely thanks to the highly simplified and unrealistic model they employed, which created a significant gap in realism.

Fagnant and Kockelman (2016) and Atasoy et al. (2015) use a more basic approach to fleet cost calculations. Fagnant and Kockelman assumed a cost of $70,000 per SAV and $0.50/mile operating costs per AAA (2012). Assuming a flat fare of $2.65 plus $1.00 per mile, they used a profit maximizing function to size the SAV fleet. This provided a fleet with a vehicle replacement rate of 8.7. Atasoy et al. performed a similar optimization analysis assuming costs of $200 per day, per vehicle and an additional $0.20 per km ($0.12/mile) operating costs, though this was for a human-driven fleet.

METHODS

This financial study is carried out using a simulation of a SAEV fleet across the Austin, Texas, 6-county region. Travel demand patterns in the Austin, Texas region are not considered unusual, and the area has a very similar density and size to many other regions including Orlando, Florida, Columbus, Ohio, and Milwaukee, Wisconsin. Therefore it is expected that these results can be applied for many other regions and similar trends in model sensitivity can be expected for regions with differing density or size.

The simulator is an add-on for the MATSim program created by Bösch et al. (2016) that was modified for this study primarily to accommodate electric vehicles, but also a with series of other enhancements and modifications. MATSim is a transportation simulator that seeks a dynamic user equilibrium with a co-evolutionary process among individual agents across a network. The MATSim inputs are activity-based tour patterns for each simulated agent and a network and its output is a list of trips with arrival and departure time, path choice and mode choice. The tour patterns were produced by Liu et al. (2017) using NHTS and U.S. Census data and network data from OpenStreetMap. The model results were then validated against temporal trip distributions. The simulator created by Bösch et al. takes, as an input, this trip table created by MATSim and the same network used by MATSim. Each trip start time is registered as a request, and the simulator will search for the SAEV that can serve the trip the most quickly. If the program cannot find a nearby vehicle within 10 seconds, it simply will send the closest available one. The SAEV will pick up passengers and take them to their destinations; the duration of each trip is given in the MATSim trip file. Since *empty*-vehicle movements are not modeled in the upstream traffic assignment, empty SAV travel times are estimated using the beeline/Euclidean distance between each origin-destination pair, a trip-specific distance correction factor, and the average speed across the entire network. Since their model did not account for EVs, several improvements were written to accommodate EV behavior. First, charging stations are generated by the program before the simulation through a 30-simulation-day phase, where a station is generated when a vehicle needs to charge, but does not have the range to access a station. Vehicles will go to charging stations when they are running on less than 5% range, or their range is below 80% and they receive a request and do not have enough range to meet it. . After the station generation phase, a full simulation-day is run where vehicles are not permitted to be in a situation where they do not have enough range to access a charging station, and no new charging stations are formed. A more detailed explanation of the methods and development of this simulation can be found in Loeb et al. (2016), however, several additional modifications were included for this study. The most significant of these modifications are a mode choice model and a dynamic ridesharing model.

Mode Choice Model

Many of the trips produced in the MATSim trip file are not reasonably serviceable by the SAV fleet due to their spatial distribution, trip length, or other factors that lead to traveler wait times of tens of minutes or even hours. In former uses of this model, Bösch et al. rejected requests when they were in the system for more than 10 minutes. Loeb et al. (2016) would reject any request in excess of 75 km (46.6 miles). Unfortunately, neither of these models has any kind of stochastic behavior, not acknowledging that trips longer than 75 km may have short wait times or that many travelers are willing to wait longer than 10 minutes. This is important for cost calculations since a flexible demand model is necessary to understand how level of service affects level of usage and the resultant effect on aggregated costs. A very basic response-time-based Logit model was implemented to eliminate certain trips on the basis of wait times. The premise of the mode choice model is based on a snapshot of the near future where adoption of SAEVs has reached about 2%. Modeled travelers are assumed to have already chosen the SAEV service as their preferred mode, but do not yet know if the service's response times are adequate to meet their needs. For this reason, as response time approaches 0, probability of rejecting the service should approach 0%.

The equation for logit used in this study takes the form:

$$P(\text{reject}) = 1 - \min\left(\frac{2e^{\beta+\beta_t t}}{1+e^{\beta+\beta_t t}}, 1\right) \tag{1}$$

Where *P*(reject) is the probability that a traveler will chose to reject a ride given response time *t*, β_t is the time coefficient and β is the alternative specific constant (ASC). The multiplier of 2 in the numerator is there to scale the probability to show that simulated travelers already wish to use the SAEV service and will change their mind if and only if the response time is unreasonable to them. For example, a response time of 0 minutes, and an ASC of 0 gives a 0% probability of rejecting the trip. Without the multiplier, this probability is 50% meaning roughly half of the trips would be rejected outright which is functionally equivalent to doubling the sample size of trips while omitting the multiplier, but with much fewer computational resources needed. The provides a range of response times short enough to never be rejected. β_t, is found from Gaudry and Tran (2011) who calculated the time coefficient on waiting for a taxi to be $-0.1351\,\frac{\text{utils}}{\text{min}}$. An ASC of 1 util was chosen to give a tail of approximately 7.5 minutes wherein a user will not reject a trip. A graph for *P*(reject) can be found in Figure 1.

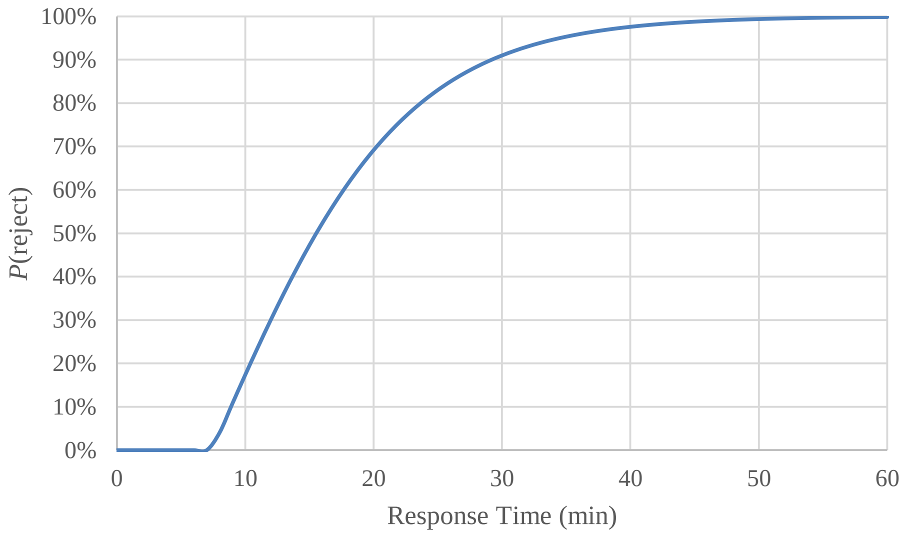

FIGURE 1 Probability of a traveler rejecting a trip given some estimated response time.

Even though travelers do not have a complete set of modes to choose from, this model is highly analogous to a traditional mode choice model in its implementation and result, so that term is used for this study.

Dynamic Ridesharing

Because traffic assignment is performed upstream of the SAEV code, dynamic ridesharing capabilities are somewhat limited. This is because, geographically, only the end points of each vehicle-trip are known, and the vehicle will "teleport" between them. Therefore, once an SAEV is headed for a destination, it may not change course before its intended arrival time. The only thing this means for ridesharing is that an SAEV may accept a ride request while carrying a passenger, but it may not change course until it arrives at its intended destination. The way this is dealt with in the code is using a first-in-last-out (FILO) pattern for pickups and drop-offs. This may appear to be unfair as a first-come, first-serve model tends is usually expected for this type of service, but the algorithm enforces the rule that no traveler may experience a delay greater than 20% to their in-vehicle travel time. Travelers will always share rides if doing so minimizes response time and no more than four travelers may share a vehicle.

RESULTS

Shown in Table 1, six scenarios were simulated for this study to learn about vehicle replacement rate, response times, vehicle occupancy, empty VMT, and more. Scenarios studied included: combinations of short range (60 miles), long range (200 miles), slow charging (4 hours) and fast charging (half hour). Additionally a gasoline powered hybrid-electric fleet (HEV) was studied as a base case and also a long range, fast charging fleet with reduced fleet size.

There were 41,242 agents in the simulation: a 2% random sample of the region’s population. The 2% sample was chosen as it was the maximum number of agents that could be simulated for all scenarios with the computational resources available. This relatively small sample size is sure to result in negligible impacts on network-wide congestion. This sample includes the agents who rejected their trips as a result of the mode choice model and a small portion of the agents whose trips were rejected due to exceeding the vehicle range (5.4% for the 60 mile range and 0% for

200+ mile ranges). Therefore, the number of agents actually using the service is reduced by the proportion shown in "% of Trips Unmet".

Vehicle replacement rate is a metric to assess the relative size of the SAEV fleet. As in Fagnant and Kockelman (2016), vehicle replacement rate is determined using NHTS data assuming the average conventional vehicle performs 3.05 trips per day on days when it is in use. Dividing an SAEV's daily trips by 3.05 yields an estimate of the number of conventional vehicles it is effectively replacing on the road.

Average vehicle occupancy (AVO) is estimated to be biased low in this study since certain types of shared trips were not simulated in the upstream MATSim traffic assignment. Examples include a parent chauffeuring a child or a family going out to dinner. Therefore, in theory AVO should be greater than one even without a DRS model.

Response time indicates the time it takes for a vehicle to arrive at a traveler's location after a request is made. The fleets studied were a gasoline-powered hybrid-electric vehicle fleet as a base case, standard SAEV, fast charging SAEV, long range SAEV, long range + fast charge SAEV and lastly long range + fast charge SAEV with reduced fleet size. A summary of the outcome of these simulations are in Table 1.

TABLE 1 Key Findings From 6 Simulation Scenarios Including a Gasoline-powered HEV Base-case for 41,242 Agents

Scenario	**Gasoline Hybrid-Electric SAV**	**Short-Range SAEV**	**Long-Range SAEV**	**Long-Range SAEV Fast Charge**	**Short-Range SAEV Fast Charge**	**Long-Range SAEV Fast Charge, Reduced Fleet**
Range (mi)	525	60	200	200	60	200
Recharge/Refuel Time (min)	2	240	240	30	30	30
# of Charging Stations/Gas Stations	19	155	155	155	155	155
% of Fleet (max) Storable at Stations	0%	65.0%	28.8%	12.0%	31.4%	12.1%
Fleet size (vehicles)	5,893	5,893	5,893	5,893	5,893	4,124
Avg. Daily miles per Vehicle	452	201	354	441	355	501
% of Trips Unmet	1.62%	60.6%	19.4%	2.67%	16.2%	15.2%
Avg. Daily Trips per Vehicle	28.5	11.4	23.4	28.2	24.3	35.1
Vehicle Trip-Based Replacement Rate	9.35	3.75	7.67	9.24	7.98	11.5
Avg. Response Time Per Trip (min)	4.45	9.82	8.76	5.49	6.16	9.55
Average Occupied Vehicle Occupancy	1.37	1.71	1.58	1.42	1.45	1.60
% Unoccupied Travel	6.05%	13.1%	7.88%	6.86%	14.2%	8.62%
% Travel for Charging/Refueling	0.65%	5.59 %	1.26%	1.05%	5.34%	1.27%
Average Station Electrical Load Factor	N/A	30%	22%	6%	9%	6%

As expected, these results indicate that the HEV fleet was able to serve travelers the best, rejecting only 1.62% of trips and meeting trips with an average response time of 4.45 minutes. Also, not surprisingly, the standard SAEV fleet served travelers the worst rejecting 55% of trips due to poor response time and another 5.4% on the basis of trip length leading to a vehicle replacement rate of only 3.75. These results can be improved significantly by either improving vehicle range or charge times. Either of these improvements brings vehicle replacement close to 8. The biggest feature of increased vehicle range is improved empty VMT at 7.88% compared to 14.2% for the fast charging (low-range) scenario. Fast charging on the other hand improves response times to 6.16 minutes on average compared to 8.76 minutes on average for the long range (slow-charging) scenario. Combining fast charging and long range further improves both of these metrics yielding 6.86% empty VMT and 5.49-minute average response times with a replacement rate over 9. Since the long-range, fast-charging scenario performs quite well, reducing the fleet size was tested to improve replacement rates. The replacement rates did rise to 11.5, but average response times exceeded 9 minutes.

The supply and demand characteristics of the system are demonstrated through the percentage of trips left unmet. When response times are poor, fewer trips are served resulting in a loss of revenue for the operator. Loeb et al. (2016) demonstrated that, when increasing range, increased *average* response time comes primarily from the addition of new, longer trips, not the worsening of performance for the trips already serviceable by the short-range fleet. Loeb et al. (2016) also found, in concurrence with literature, that response times tend to improve proportionally with fleet size.

Financial Analysis

To determine which of these scenarios is most likely to be implemented, these results must be studied from the fleet operator's perspective to understand which of these fleets is the most profitable. Costs were estimated from various sources for capital expenses, vehicle and charger maintenance, electricity and other fees. These costs were split into high, low and medium (most likely) estimates, as shown in Table 2.

TABLE 2 Low, Medium And High Price Estimates for Needed Expenses to Implement an SAEV Fleet

	Low Cost	Mid Cost	High Cost
Vehicle Capital			
SAEV (per vehicle)	$30,000	$40,000	$50,000
LR SAEV (per vehicle)	$40,000	$50,000	$60,000
Replacement battery (per kWh) + $50 install	$100	$145	$190
Vehicle Operations			
Maintenance (per mile)	$0.054	$0.061	$0.066
General Administration	$0.044	$0.11	$0.18
Insurance & Registration (per vehicle-year)	$550	$1,110	$2,220
Electricity (per kWh)	$0.08	$0.10	$0.20
Attendants (wages $/hour)	$10.00	$12.00	$15.00
Charging Infrastructure			
Level II Charging (per charger)	$8,000	$12,000	$18,000
Level II Annual Maintenance (per charger)	$25	$40	$50
Level III Charging (per charger)	$10,000	$45,000	$100,000
Level III Annual Maintenance (per charger)	$1,000	$1,500	$2,000
Land Acquisition (per vehicle space)	$1,980	$3,460	$6,900

Vehicle costs were estimated based on popular production EVs, such as the 2017 Chevrolet Volt and 2017 Mitsubishi i-MiEV, with all-electric ranges (AERs) of 53 and 59 miles, respectively. These two models presently have MSRPs of $34,095 (Chevrolet, 2017) and $20,612 (Mitsubishi Motors, 2017) respectively. As for long-range EVs, the 2017 Tesla Model S 90d has a 294-mile range and costs $87,500 (Tesla Motors, 2017). The Model S is a luxury, high-performance sedan with more range than needed. Tesla anticipates releasing the Model 3 at just $35,000 in the year 2018 with a range of 215 miles (Tesla Motors, 2016). These prices do not include government rebates, which are due to be phased out in the near future (IRS, 2016), so should not be depended upon for this study. Vehicle autonomy is reported by ENO (2013) to have an estimated marginal cost of $25,000 to $50,000 but this cost could come down to $10,000 after at least 10 years. For this analysis it is assumed that autonomy will have a marginal cost of $5,000 to $25,000, and that regular range SAEV, without autonomy will cost $25,000 and a long range SAEV will be $35,000. With the autonomy package this gives prices of $30,000 to $50,000 for short range SAEVs and $40,000 to $60,000 for long range SAEVs. The cost of HEVs is estimated as $20,000 without autonomy.

Similar to Chen et al. (2016), SAEVs are anticipated to last 215,000 miles, similar to the average lifespan of a NYC taxicab (New York City Taxi & Limousine Commission, 2014). Life cycles of such rigorously used EV fleets have not been studied and may have better or worse lifespans. A battery's usable life is estimated at roughly 100,000 miles based on standard practice by OEMs to warranty their batteries for this distance plus various reports such as Saxton (2013). Then a battery will need to be replaced at least once during a vehicle's lifetime, but it would not be a good investment to replace the battery a second time since the vehicle will be very close to (if not in excess of) the end of its service-life. Replacement batteries are expected to cost between $100 and $190 per kWh per estimates from GM and Tesla (Voelcker, 2016), substantially lower than recent estimates of $268/kWh in 2015 and $1,000/kWh in 2008 (IEA, 2016). It's assumed that a trained technician could replace a battery in about an hour billing $50 an hour. Vehicle operation and maintenance costs (including cleaning) are assumed to be similar to those for conventional, privately-owned gasoline vehicles, which AAA (2015) estimates to be 5.4 to 6.6 cents per mile for various vehicle types. Changes to insurance premiums are a big unknown pending state and federal legislation and substantial safety research. Some estimate increases to premiums by a factor of 3 or 4 (e.g. Burns et al., 2013) which may be the case in the near term as this technology is in its early stages. Currently three states (California, Nevada, and Florida) have adopted requirements for $5 million insurance policies for AVs (Technology Law and Policy Clinic, 2015), with other states looking to follow suit (PennDOT, 2016). On the other hand, a greater number of studies anticipate decreases in insurance premiums (e.g. KPMG, 2015), or even the possibility of their elimination (that is by assuming 100% manufacturer liability). AAA's 2015 estimated annual average insurance costs for privately-held cars is $1,100, so an SAV's annual insurance cost is assumed to vary between $555 and $2,200, anticipating both sides of this scenario (half and double). SAVs will be used very intensely, but are expected to operate more safely; this uncertainty is represented in the wide range of insurance cost estimates.

Electricity costs are estimated by Mickelson (2016) to be $0.08 to $0.20 per kWh. This is assuming load factors ranging from 20% to 80%. Load factor is the ratio of average usage to maximum usage, for example, if a certain station has a peak usage of 100 kW one day, but a monthly average of 20 kW, its load factor would be 20% (20kW/100kW). Unfortunately, as shown in Table 1, only two of the five EV fleets have charging stations that typically adhere to this load factor range. The data in Mickelson (2016) does not extend below load factors of 10%, so these costs are not well known. However, there are several possible strategies to increase load factor and bring electrical costs to a reasonable level so it is assumed a fleet manager would find ways to keep load factors high.

Land on which charging stations will be built is estimated using Zillow.com's classifieds of land for sale in the Austin area (http://www.zillow.com/austin-tx/land/). By compiling all listings available on November 18, 2016, the average land costs are $\$20.81/\text{ft}^2$ with a median of $\$11.84/\text{ft}^2$. The first, second (median) and third quartiles of this data can be used for a high, medium and low estimate of land costs: $6.11, $11.84 and $27.24 per square foot respectively. Some of these lots would require paving which is estimated at $1.50 per square foot for an average parking lot (Brahney, 2015). To be safe, $\$1.50/\text{ft}^2$ is added to each estimate for paving. The space occupied by each vehicle was compared to the compact EV, the Nissan Leaf, which is 175 in. long and 70 in. wide (Nissan, 2016). Adding 24 in. to each dimension for a safe spacing between vehicles yields a footprint of 130 ft^2 per vehicle. Multiplying by land and pavement prices gives $990, $1,730, and $3,540 of total pavement costs per vehicle space provided. It is assumed that each vehicle will require on average two vehicle-spaces to allow for vehicle movement within the station leading to $1,980, $3,460 and $6,900 for each vehicle at a station. It is possible that additional space will be needed to store vehicles not in use, but this space is not assumed since free parking will likely be available in most suburban areas. The HEV fleet would need even more space since it is assumed that this fleet will spend nothing on land acquisitions. Capital costs, namely acquisition of land and provision of charging infrastructure, are reduced to a per-mile basis by assuming a ten-year payback period aggregated over all mileage accrued over these years. Increases in demand for SAEV use over this 10-year period are considered accounted for in the increased revenue they provide.

Level II chargers are estimated by the U.S. DOE (2012) to cost between $8,000 and $18,000, including installation, hardware, materials, labor and administration fees, with $25 to $50 annual maintenance cost per Level II charger. The U.S. DOE (2012) and New York City Taxi & Limousine Commission (2013) estimate that Level III charger provision cost from $10,000 to $100,000, including those same fees (listed above) and $1,000 to $2,000 in annual maintenance costs per charger. The number of required chargers at each site is found here by summing the maximum number of SAEVs present at each charging station over the course of the simulation day. General administration costs were estimated by APTA (2015) Public Transportation fact book using the costs found for vanpooling data, since this was the most similar mode. They estimated $57.6 million per year for 1,319 million passenger-miles or 4.34 cents per passenger-mile. Chen et al. (2016) estimated 18.4 cents per mile for this expense (though this expense is not included in their final cost estimates), which serves as an upper estimate on this cost.

Gasoline-powered fleets are assumed to have the same associated costs, as applicable, with fuel prices ranging from $2.00 to $4.00 per US gallon, operating at 50 miles per gallon with a total range of 525 miles, similar to the Honda Civic, Toyota Prius and many other similar vehicles. The gasoline-powered vehicles will need attendants to give them fill-ups at fuel stations. The fuel stations occupied by an attendant in the simulation were the 19 charging stations generated using the long-range (200-mile) scenario. Each station is manned by one attendant whose hourly wages vary across $10, $12 and $15. If fuel stations are manned 24-hours per day, the cost will be $4,560 to $6,840 daily. It is reasonable to assume this task could be undertaken by just 19 attendants since the HEV fleet required on average approximately 2,600 fill-ups over the simulation day or 6 fill-ups per attendant per hour. Fares are assumed to be a flat $1 per mile, not far from the cost of typical TNCs today. The resulting revenue from this strategy is not the focus, but rather relative daily profits between scenarios. The costs and profits per service-mile for the three cost scenarios are shown in the Tables 3, 4 and 5.

TABLE 3 Low-cost Estimates, per Occupied-mile, for SAEV And HEV Fleets (¢/mile)

Low-cost estimates (cents per occupied mile)	**Gasoline-powered**	**Standard SAEV**	**Long-Range (LR) SAEV**	**LR, FC SAEV**	**Fast-Charge (FC) SAEV**	**LR, FC SAEV Reduced Fleet**
Electricity/fuel	4.26 ¢/mi	3.61	3.41	3.37	3.66	3.43
Vehicle Maintenance, General Administration & Attendants	10.6	11.3	10.6	10.5	11.4	10.7
Insurance/Registration	0.35	0.86	0.46	0.37	0.49	0.33
Charger Costs (Land + Infrastructure + Maintenance)	0.00	2.30	0.87	0.74	2.18	0.76
Vehicle Purchase Costs	14.0	20.7	23.6	22.6	19.0	22.8
Battery Costs	0.00	1.10	3.39	3.35	1.11	3.42
Total cost	**29.2 ¢/mi**	**39.9**	**42.3**	**41.0**	**37.8**	**41.4**
Total daily profit per vehicle ($1/mi fare)	$301	$106	$188	$243	$189	$268
Profit per revenue-mile ($1/mi fare)	70.8 ¢/mi	60.1	57.7	59.0	62.2	58.6
Avg. Response Time Per Trip	4.45 min	9.82 min	8.76 min	5.49 min	6.16 min	9.55 min
Avg. Daily Trips per Vehicle	28.5	11.4	23.4	28.2	24.3	35.1

TABLE 4 Mid-cost Estimates, per Occupied-mile, for SAEV And HEV Fleets (¢/mile)

Mid-cost estimates (cents per occupied mile)	**Gasoline-powered**	**Standard SAEV**	**Long-Range (LR) SAEV**	**LR, FC SAEV**	**Fast-Charge (FC) SAEV**	**LR, FC SAEV Reduced Fleet**
Electricity/fuel	6.39 ¢/mi	4.51	4.26	4.21	4.57	4.29
Vehicle Maintenance, General Administration & Attendants	18.4	19.7	18.6	18.4	19.9	18.7
Insurance/Registration	0.71	1.73	0.93	0.74	0.10	0.66
Charger Costs (Land + Infrastructure + Maintenance)	0.00	3.57	1.35	2.15	6.30	2.19
Vehicle Purchase Costs	19.6	27.7	29.4	28.3	25.3	28.4
Battery Costs	0.00	1.58	4.91	4.85	1.60	4.95
Total cost	**45.1 ¢/mi**	**58.7**	**59.4**	**58.6**	**58.7**	**59.2**
Total daily profit per vehicle ($1/mi fare)	$234	$72	$132	$170	$126	$187
Profit per revenue-mile ($1/mi fare)	54.9 ¢/mi	41.3	40.6	41.4	41.3	40.8
Avg. Response Time Per Trip	4.45 min	9.82 min	8.76 min	5.49 min	6.16 min	9.55 min
Avg. Daily Trips per Vehicle	28.5	11.4	23.4	28.2	24.3	35.1

TABLE 5 High-cost Estimates, per Occupied-mile, for SAEV And HEV Fleets (¢/mile)

High-cost estimates (cents per occupied mile)	**Gasoline-powered**	**Standard SAEV**	**Long-Range (LR) SAEV**	**LR, FC SAEV**	**Fast-Charge (FC) SAEV**	**LR, FC SAEV Reduced Fleet**
Electricity/fuel	8.52 ¢/mi	9.03	8.51	8.42	9.15	8.58
Vehicle Maintenance, General Administration & Attendants	26.5	28.3	26.7	26.4	28.7	26.9
Insurance/Registration	1.43	3.47	1.86	1.48	2.00	1.33
Charger Costs (Land + Infrastructure + Maintenance)	0.00	5.71	2.16	4.29	12.6	4.38
Vehicle Purchase Costs	25.2	34.6	35.3	34.0	31.6	34.1
Battery Costs	0.00	2.06	6.42	6.35	2.09	6.47
Total cost	**61.6 ¢/mi**	**83.2**	**81.0**	**80.9**	**86.1**	**81.8**
Total daily profit per vehicle ($1/mi fare)	$163	$30	$62	$79	$42	$83
Profit per revenue-mile ($1/mi fare)	38.4 ¢/mi	16.8	19.0	19.1	13.9	18.2
Avg. Response Time Per Trip	4.45 min	9.82 min	8.76 min	5.49 min	6.16 min	9.55 min
Avg. Daily Trips per Vehicle	28.5	11.4	23.4	28.2	24.3	35.1

This analysis indicates that starting an SAEV fleet from the ground up is not financially advantageous over a traditionally-fueled SAV fleet. This comes from the higher cost of EVs, extra empty VMT, replacement batteries and building and operating charging stations. However, if an SAEV fleet is implemented, it is clear that the fast-charging, long-range fleet is the most profitable, earning significantly greater profit than the other fleets. Since EVs are quickly gaining market penetration, however, there could be certain future scenarios under which an electrified fleet is the most economical option. Some possibilities to explore are increases in the price of gasoline, exceptionally inexpensive electrical generation or inexpensive EVs. These scenarios were studied for the mid-cost scenario to determine the break-even point at which fast-charging long-range SAEVs and HEV SAVs are equally profitable.

For the first scenario, a gasoline price of $10.00 (exactly) per gallon leads to daily profits of $170.19/vehicle and $170.15/vehicle for the EV and HEV fleets respectively (comparing fleets of the same size). The U.S. has never experienced these types of oil prices, but this is not far from prices seen in much of Europe in recent years. For electricity costs, even making electricity along with charging infrastructure free does not close the gap; it would increases the long-range, fast-charge fleet’s profits up to $196.33/vehicle, shy of $233.55/vehicle daily profit for the HEV fleet. For vehicles, the price of a long range EV would have to fall, possibly through subsidies, from an estimated $50,000 per vehicle to $31,300. This includes the estimated $15,000 autonomy package indicating a vehicle base price of $16,300 or an $18,700 subsidy (more than double today’s subsidies). Additionally, the batteries would need to last the entire lifetime of the vehicle to save on replacement costs. A $16,300 sticker price is not out of the question, as there are several base-model economy vehicles under $15,000 available in the U.S.

These numerical results are not intended to provide a specific forecast for any region in the world, but travel patterns and population densities in Austin, Texas are not unusual and are comparable to many other regions. Regardless, relative trade-offs between vehicle fleets are expected to remain true, and operators can extrapolate from these results using local data to better understand a particular region.

CONCLUSIONS

This study simulated a fleet of shared autonomous electric vehicles serving requests of 41,242 agents across the Austin, Texas network to determine which fleet scenarios were most advantageous to the operator and the users. It was found that in every studied metric, using a short-range and slow-charging vehicle was the worst option and that a fast-charging, long-range fleet was the best EV option. This was decided on the basis of response times, empty VMT, and replacement rates. More importantly, a long-range, fast-charging fleet is estimated to be the most profitable despite its substantial up-front costs. This is partially thanks to its ability to serve far greater demand. The long-range, fast-charging fleet, however, was not able to compete with a gasoline HEV fleet which achieved 19% better response times, 12% less empty VMT, 17% better replacement rate and 37% higher profits. The disparity in profitability is only when gasoline prices remain under $10 per gallon and long-range EVs cost over $16,300.

A fully electrified fleet is not advantageous to the operator right now, but public EV charging stations are becoming more widely available. EVs are becoming cheaper to own and operate, and the future of fossil fuels is not clear. The cost to run this EV fleet is still quite low on a per-mileage basis—less than driving a personal vehicle 10,000 miles per year (AAA, 2015) for the low- and mid-range cost estimates. It is good to know there are alternatives to fossil fuels that can be profitable for such a fleet with the uncertain future of our climate and fossil fuel prices.

ACKNOWLEDGEMENTS

The authors are thankful to the Texas Department of Transportation (TxDOT) for their financial support of this research under projects 0-6838, Bringing Smart Transport to Texans: Ensuring the Benefits of a Connected and Autonomous Transport System in Texas, 0-6847, An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs, and 0-6849, Implications of Automated Vehicles on Safety, Design and Operation of the Texas Highway System. The authors would also like to thank Patrick Bösch and Francesco Ciari for providing their SAV simulation codes, Scott Schauer-West for assistance with editing and several anonymous reviewers for their suggestions. The authors acknowledge the Texas Advanced Computing Center (TACC) at The University of Texas at Austin for providing computing and data storage resources that have contributed to the research results reported within this paper. URL: http://www.tacc.utexas.edu

REFERENCES

AAA [American Automobile Association] (2012) Your Driving Costs. Available at: http://exchange.aaa.com/wp-content/uploads/2012/04/Your-Driving-Costs-20122.pdf

AAA [American Automobile Association] (2015) Your Driving Costs. Available at: http://exchange.aaa.com/wp-content/uploads/2015/04/Your-Driving-Costs-2015.pdf

APTA [American Public Transportation Association] (2015) 2015 Public Transportation Fact Book. Available at: https://www.apta.com/resources/statistics/Documents/FactBook/2015-APTA-Fact-Book.pdf

Atasoy, Bilge; Ikeda, Takur; Ben-Akiva, Mosche E. (2015) Optimizing a Flexible Mobility on Demand System. *Transportation Research Record* 2536: 76-85.

Bösch, Patrick M., Ciari, Francesco, Axhausen, Kay W. (2016) Required Autonomous Vehicle Fleet Sizes to Serve Different Levels of Demand. Proceedings of the Proceedings of the 95th Annual Meeting of the Transportation Research Board, Washington DC

Brahney, Steven (2015) Average Cost to Pave An Asphalt Parking Lot. LinkedIn. Available at: https://www.linkedin.com/pulse/average-cost-pave-asphalt-parking-lot-steven-brahney

Bullis, Kevin (2013) Forget Battery Swapping: Tesla Aims to Charge Electric Cars in Five Minutes. *MIT Technology Review*. Available at: https://www.technologyreview.com/s/516876/forget-battery-swapping-tesla-aims-to-charge-electric-cars-in-five-minutes/

Burns, Lawrence D.; William C. Jordan; Bonnie A. Scarborough (2013) Transforming personal mobility. *The Earth Institute–Columbia University*. Available at: http://sustainablemobility.ei.columbia.edu/files/2012/12/Transforming-Personal-Mobility-Jan-27-20132.pdf

Chen, Donna, and Kara Kockelman (2016) Management of a Shared, Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. *Transportation Research Record* No. 2572: 37-46.

Chen, Donna and Kockelman, Kara and Hanna, Josiah (2016) Operations of a Shared, Autonomous, Electric Vehicle Fleet: Implications of Vehicle & Charging Infrastructure Decisions. *Transportation Research Part A* 94: 243-254.

Chevrolet (2016) 2017 Bolt EV: All-Electric Vehicle. Available at: http://www.chevrolet.com/bolt-ev-electric-vehicle.html

Chevrolet (2017) 2017 Volt: Hybrid Electric Cars. Available at: http://www.chevrolet.com/volt-electric-car.html

ENO (2013) Preparing a Nation for Autonomous Vehicles. Available at: https://www.caee.utexas.edu/prof/kockelman/public_html/ENOReport_BCAofAVs.pdf

Fagnant, Daniel J.; Kara Kockelman (2016) Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles in Austin, Texas. *Transportation* 45: 1-16. Available at: http://www.caee.utexas.edu/prof/kockelman/public_html/TRB15SAVswithDRSinAustin.pdf

Gaudry, Marc; Cong-Liem Tran (2011) Identifying all alternative-specific constants in Multinomial Logit models by Inverse Power Transformation Capture. Available at: http://www.e-ajd.net/source-pdf/AJD-141_Gaudry_&_Tran_Logit_Constants_3_September_2011.pdf

KPMG (2015) Marketplace of change: Automobile Insurance in the era of autonomous vehicles. Available at: https://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/marketplace-change.pdf

IEA [International Energy Agency] (2016) Global EV Outlook 2016. Available at: https://www.iea.org/publications/freepublications/publication/Global_EV_Outlook_2016.pdf

IRS (2016) Plug-In Electric Drive Vehicle Credit (IRC 30D). Available at: https://www.irs.gov/businesses/plug-in-electric-vehicle-credit-irc-30-and-irc-30d

Liu, Jun; Kockelman, Kara M.; Bösch, Patrick M.; Ciari, Francesco (2017) Tracking a System of Shared Autonomous Vehicles across the Austin, Texas Network using Agent-Based Simulation. Forthcoming in *Transportation Research Part C.*

Loeb, Benjamin; Kara Kockelman; Jun Liu (2016) Shared Autonomous Electric Vehicle (SAEV) Operations across the Austin, Texas Network with a Focus on Charging Infrastructure Decisions. Presented at the 96th Annual Meeting of the Transportation Research Board and under review for publication in *Transportation Research Record Part C*

Martinez, Luis (2015) Urban Mobility System Upgrade. *International Transport Forum* Available at: http://www.itf-oecd.org/urban-mobility-system-upgrade-1

Mickelson, Christopher (2016). Utility Regulatory Planner, Austin Energy. Communication by email, December 22.

Mitsubishi Motors (2017)i-MiEV 2017 Showroom Mitsubishi Canada. Available at: https://www.mitsubishi-motors.ca/en/vehicle/showroom/i-miev/2017/

New York City Taxi & Limousine Commission (2013) Take Charge: A Roadmap to Electric New York City Taxis. Available at: http://www.nyc.gov/html/tlc/downloads/pdf/electric_taxi_task_force_report_20131231.pdf

New York City Taxi & Limousine Commission (2014) 2014 Taxicab Factbook. Available at: http://www.nyc.gov/html/tlc/downloads/pdf/2014_taxicab_fact_book.pdf

Nissan (2016) 2017 Nissan LEAF® Electric Car Specs. Available at: http://www.nissanusa.com/electric-cars/leaf/versions-specs/

Nykvist, Björn, and Mans Nilsson (2015) Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change* 5: 329-332.

PennDOT [Pennsylvania Department of Transportation] (2016) Pennsylvania Takes Steps to Lead on Autonomous Vehicle Development, Testing with Newly Established Task Force, Legislation. Available at: https://www.dot.state.pa.us/penndot/districts/district5.nsf/e5da4aa0433a25af852571f400537d15/7e6acc708a6ba0fa85257fc5004cb0a7?OpenDocument

Reiter, M. S., and K. M. Kockelman. 2016. Emissions and Exposure Costs of Electric Versus Conventional Vehicles: A Case Study for Texas. In: Transportation Research Board 95th Annual Meeting. Online at: http://www.caee.utexas.edu/prof/kockelman/public_html/TRB16Emissions&Exposure.pdf

Saxton, Tom (2013) Plug In America's Tesla Roadster Battery Study. Available at: https://survey.pluginamerica.org/tesla-roadster/PIA-Roadster-Battery-Study.pdf

Stephens, Thomas. (2013) Non-Cost Barriers to Consumer Adoption of Light-Duty Vehicle Technologies. Transportation Energy Future Series Prepared for the U.S. Department of Energy by Argonne National Laboratory.

Technology Law and Policy Clinic (2015). Autonomous Vehicle Law Report and Recommendations to the ULC. University of Washington School of Law. Available at: https://www.law.washington.edu/clinics/technology/reports/autonomousvehicle.pdf

Tesla Motors (2016) Model 3. Available at: https://www.tesla.com/model3

Tesla Motors (2016a) Supercharger. Available at: https://www.tesla.com/supercharger

Tesla Motors (2017) Order a Tesla Model S. Available at: https://www.tesla.com/models/design

U.S. DOE [United States Department of Energy] (2012) Plug-In Electric Vehicle Handbook for Public Charging Station Hosts. DOE/GO-102012-3275, April. Available at: http://www.afdc.energy.gov/pdfs/51227.pdf

U.S. DOE [United States Department of Energy] (2016) Model Year 2016 Fuel Economy Guide. Available at http://www.fueleconomy.gov/feg/pdfs/guides/FEG2016.pdf.

Voelcker, John (2016) Electric-car battery costs: Tesla $190 per kwh for pack, GM $145 for cells. *Green Car Reports*. Available at: http://www.greencarreports.com/news/1103667_electric-car-battery-costs-tesla-190-per-kwh-for-pack-gm-145-for-cells