Transportation Research Part C 89 (2018) 222–233

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions☆

Benjamin Loeb[a], Kara M. Kockelman[b,*], Jun Liu[c]

[a] Delaware Valley Regional Planning Commission, Philadelphia, PA 19106, United States
[b] Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall, Austin, TX 78712-1076, United States
[c] Virginia Department of Transportation, Richmond, VA 23219, United States

ARTICLE INFO

Keywords:
Charging station placement
Electric vehicle charging
Shared autonomous vehicles
Taxi fleet simulations

ABSTRACT

Shared autonomous vehicles, or SAVs, have attracted significant public and private interest because of their opportunity to simplify vehicle access, avoid parking costs, reduce fleet size, and, ultimately, save many travelers time and money. One way to extend these benefits is through an electric vehicle (EV) fleet. EVs are especially suited for this heavy usage due to their lower energy costs and reduced maintenance needs. As the price of EV batteries continues to fall, charging facilities become more convenient, and renewable energy sources grow in market share, EVs will become more economically and environmentally competitive with conventionally fueled vehicles. EVs are limited by their distance range and charge times, so these are important factors when considering operations of a large, electric SAV (SAEV) fleet.

This study simulated performance characteristics of SAEV fleets serving travelers across the Austin, Texas 6-county region. The simulation works in sync with the agent-based simulator MATSim, with SAEV modeling as a new mode. Charging stations are placed, as needed, to serve all trips requested (under 75 km or 47 miles in length) over 30 days of initial model runs. Simulation of distinctive fleet sizes requiring different charge times and exhibiting different ranges, suggests that the number of station locations depends almost wholly on vehicle range. Reducing charge times does lower fleet response times (to trip requests), but increasing fleet size improves response times the most. Increasing range above 175 km (109 miles) does not appear to improve response times for this region and trips originating in the urban core are served the quickest. Unoccupied travel accounted for 19.6% of SAEV mileage on average, with driving to charging stations accounting for 31.5% of this empty-vehicle mileage. This study found that there appears to be a limit on how much response time can be improved through decreasing charge times or increasing vehicle range.

1. Motivation

An exciting application of self-driving automated-vehicle technology is one-way car sharing, similar to services like Car2Go and transportation network companies such as Lyft – but without a driver. Shared autonomous vehicles (SAVs) are envisioned to eventually save many travelers money and time, while reducing personal-vehicle fleet sizes in use today (Fagnant et al., 2015). One way to extend such benefits is to use an electric vehicle (EV) fleet (as in Chen et al., 2016; Chen and Kockelman, 2016). EVs are

☆ This article belongs to the Virtual Special Issue on "Operations & automation".

* Corresponding author.
E-mail addresses: benloeb1@utexas.edu (B. Loeb), kkockelm@mail.utexas.edu (K.M. Kockelman), jun.liu@utexas.edu (J. Liu).

https://doi.org/10.1016/j.trc.2018.01.019
Received 9 May 2017; Received in revised form 18 January 2018; Accepted 19 January 2018
Available online 21 February 2018
0968-090X/

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, 2017). A system of shared autonomous electric vehicles (SAEVs) can carry a relatively high fixed cost due to the cost of large batteries, which provide greater range before charging is required and additional charging infrastructure, but may reduce overall costs via lower energy and maintenance needs. EVs are also expected to reduce environmental costs in most locations, especially where renewables 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 will become increasingly financially advantageous over traditional, petroleum-fueled vehicles.

With heavy use of a shared fleet (e.g., over 100 miles per day per vehicle, rather than 20 miles as in Fagnant et al., 2015), vehicle turnover will be faster, leading to quicker adoption of new EV technologies (ITF, 2015). However, all-electric (non-hybrid) EVs are limited by their range (the distance an EV is able to drive on a single charge) and battery charge times, which tend to require two to forty times (or longer) as long as gas station refueling, depending on the electricity delivery rate. Anticipating the number, placement and size of charging stations is also an important prerequisite for an SAEV fleet, since charging stations are rare, while gas stations are quite common. Any self-driving fleet will incur high fixed costs, at least in early stages of the technology's release, so scenarios under which such a fleet is cost effective over a gasoline-powered fleet should be explored before making this large capital investment, if such scenarios even exist. Slow charging times and poor battery-range have been major barriers for EV adoption by households in the US and elsewhere (Stephens, 2013), but these barriers are steadily falling as charging times under an hour are becoming more widely available in many fast-charge locations [see, e.g., Tesla Motors, 2017a] (Bullis, 2013). Battery ranges are rising with the Chevrolet Bolt (Chevrolet, 2017) and Tesla Model 3 (Tesla Motors, 2017b) both delivering 200 miles of range for under $40,000.

The benefits of fleet automation are reflected in the simulation in a number of ways. First, vehicles are able to operate continuously 24 h a day, unlike drivers for TNCs or taxis who will only drive for a portion of the day. Second, autonomy allows for very specific and optimizable charging strategies; there are no drivers required to keep track of their vehicle range and to charge at their own discretion. Third, vehicles respond to all ride requests immediately upon receiving them. Human drivers, on the other hand, may reject requests that are not convenient, or may easily miss a request while not paying attention.

Until now, electrified fleets have not been modeled with adequate detail, leaving major questions about the usefulness of those past results. This new study's aim is to re-evaluate the techniques of past SAEV models using state-of-the-art modeling practices, including activity-based travel patterns, a true-to-life network (via OpenStreetMap), sensitivity analyses (for fleet attributes, highly variable population densities and land use patterns across the region), and detailed traffic assignment outputs for time-of-day and link-dependent traffic conditions — practices not found in previous SAEV work. The sensitivity analysis is especially important as it uncovers a better understanding of SAEV operations as a result of fleet technology decisions.

This study simulates robust locations around the region for charging station placement, as well as the effects of battery range, charging times, and fleet size on SAEV system performance for the 5301 square-mile, 6-county Capital Area Metropolitan Planning Organization (CAMPO) region surrounding Austin, Texas. The simulation framework improves upon agent-based simulations by both Chen et al. (2016) and Bösch et al. (2016) by using more realistic vehicle speeds, allowing still-charging/not-yet-fully-charged vehicles to respond to requests, using more robust charging strategies, and requiring that all demand for trips under 75 km (47 miles) be met. The framework also helps in conducting much more in-depth sensitively analyses, along with other improvements. All improvements deliver greater realism and many improve the fleet's performance, via flexible-charging and passenger-pickup strategies. All of these improvements seek to provide much more reliable and practical estimates of SAEV fleet operations.

2. Literature review

While several studies have recently simulated the operations of SAV fleets in urban environments (Fagnant et al., 2015; ITF, 2015; Spieser et al., 2014; Zhang et al., 2015), only Chen et al. (2016) and Chen and Kockelman (2016) have allowed for electric vehicles or for rural and low-density trip-making locations at this time. They modeled SAEV services over a 100 × 100-mile homogenous grid with quarter-mile spacing. They concluded that an SAEV system could serve nearly all passenger demand with competitive response times as low as 2.9 min with 240-min charge times, 80-mile vehicle range, and costs comparable to that of a gasoline-powered fleet with just 6.6% more vehicles. Their systems were estimated to be cost-effective with gas prices as low as $2.50 per gallon assuming a $45,000 purchase price for a long-range SAEV, $405 per kWh for replacement batteries (with batteries replaced once per vehicle, at 115,000 miles), $0.061 per mile in vehicle maintenance costs, $1600 in annual insurance and registration costs (per vehicle), and $0.13 per kWh (for battery charging). Their simulations begin by generating SAEVs wherever trips are generated and cannot be quickly served by existing vehicles, while adding charging stations as needed, across the gridded network, to ensure SAEVs will be within range of a charging station after meeting any request. After stations are located, fleet size is created in the same manner as the charging station generation phase to ensure that travelers in the initial runs do not wait longer than 10 min. After the initial runs, fleet size and charging stations are fixed and these simulations are performed several times, for a range of scenarios; scenarios include short-range (80-mile) and long-range (200-mile) EVs, as well as fast charging versus regular charging (30 min vs. 4 h, respectively).

Given their specific setup, Chen and Kockelman's (2016) and Chen et al.'s (2016) simulation results suggest that fleet size is highly sensitive to charge times, as well as vehicle range, and that long-range (200-mile) SAEVs are able to reduce fleet size by 20 percent (relative to short-range, 80-mile, settings) while fast chargers reduce fleet size by 30% (comparing 4-h charges to 30-min charges.) Combining long ranges and fast charges reduces fleet 44% over the base case. Their simulation setup suggests that the number of charging stations will not vary much, but the number of chargers needed at each station can be cut by 45.2% and 85.6%, network-wide, for short-range and long-range SAEVs respectively, using fast chargers. After analyzing all costs involved, they concluded that SAEV travel could be priced at $0.66 to $0.74 per person-trip-mile while allowing for 10% profit margins. This level of pricing would make SAEVs economically competitive with conventional cars, even with gasoline costing just $2.50/gallon; however, automated chargers are important (rather than having human attendants connecting charging cords to SAEVs), if SAEVs are to be competitive with gasoline-fueled SAVs (requiring attendants).

While this current paper borrows much of its inspiration from the Chen et al. (2016) and Chen and Kockelman (2016) papers, these older works are extremely limited in their realism as no network is considered and no network loading or traffic assignment takes place. Instead, vehicles are allowed to travel freely throughout a large, nearly-homogenous square. Trip generation and distribution were also highly simplified in those papers, and remained uniform across a simulation day. Here, this new work seeks, in part, to determine the validity of their past results by relying on a much more realistic network with 234,444 directed (one-way) links, an activity-based model representing travelers' unique tours which vary throughout the day, and actual network loading with time-dependent shortest paths. Additionally, more complex charging strategies are implemented here, to see if fleet performance can be improved further with the addition of some new ideas. Finally, many more scenarios are studied here, with a vigorous sensitivity analysis that is lacking in past work.

In order to simulate SAV operations in Zurich, Bösch et al. (2016) created a special program to work with MATSim (Horni et al., 2016), which is an agent-based and activity-based model of travel demand that allows for dynamic traffic assignment on large-scale networks with reasonable computing times. Like most MATSim users, Bösch et al. simulated 10% of total personal travel demands. But they focused on SAV operations and SAV fleet size, concluding that one SAV could serve 10 trip-makers per day with wait times of 3.11 min after rejecting 3.8% of trips due to response times over 10 min. For most times of the day, a third or more of the SAVs were not needed/not in use; however, privately owned cars in Switzerland are used productively just 3.2% of the day (according to survey data). Bösch et al.'s program is a major contribution to this paper's work, along with Horni et al.'s (2016) MATSim code. Bösch et al.'s study, while thorough, modeled a very small region (two orders of magnitude smaller than the Austin region), relied only on conventionally fueled vehicles, and ignored energy use and refueling times. To adapt this code for this new study, the code was modified substantially to monitor real-time energy consumption, generate charging stations across the network and then to utilize those charging stations when needed.

Loeb and Kockelman (2017) offer further enhancements to the work by Chen et al. (2016), Chen and Kockelman (2016) and Bösch et al. (2016), by including a more efficient vehicle search algorithm, a mode choice model, dynamic ridesharing capabilities, and, most importantly, a detailed cost evaluation. It was found that an SAEV fleet could be offered at a cost of 59 cents per occupied mile providing response times of 5.49 min for a fleet with 30-min charge time and 200-mile range. A fleet with lower range and/or charge time did not affect the per-mile cost, but the fleet was not able to service as many trips each day, so it was less profitable. Unfortunately, only six different range and charge-time scenarios were studied, so trends and parameters sensitivities could not be studied in depth.

Some studies were much more optimistic in their predictions of response times and replacement rates (the average number of conventional vehicles that can be replaced by each SAV). In a small (10 mi × 10 mi) region, with a tightly gridded network, Fagnant and Kockelman (2014, 2015) estimated that a single SAV could replace the trip-making of 9 conventional vehicles while providing minimal wait times and reductions in several emissions species (thanks to smaller-than-average-US fleet vehicles and reductions in engine cold starts). Fagnant and Kockelman's (2016) dynamic ride-sharing (DRS) evaluations of Austin's 12 × 24 mile core region yielded similar results. However, higher replacement rates appear feasible when trip distances are shorter, as in the case of smaller-region simulations, which neglect longer-distance trip-making. Their results also show vehicle replacement rates rise, wait times fall, and empty vehicle-miles-travelled (empty VMT) falls with greater spatial intensity of trip-making (thanks to more efficient use of SAVs and more opportunities for DRS). This study provides a more realistic network; however, it does not accommodate electric vehicles, or a large network with mixed land use, which are both modeled here.

Yi and Shirk (2018) developed an energy-minimizing charging model for privately owned autonomous EVs. Their simulation model looks at travel itineraries and allows for vehicles to perform charging trips while the owners are busy at their own destinations. They simulated the greater Chicago network using regional surveys and included true locations of the region's public fast charging stations. Each traveler used an autonomous EV starting the day with 20 kWh (60–70 mile range). They found that 94.3% were able to complete their itineraries without charging, and 1 to 2% were unable to find adequate charging stations in time and so were stranded. While it is promising that several of the regions longer tours could be completed with existing stations, the failure rates are probably too high for most households to ignore charging decisions, especially on days involving long-distance tours. Yi and Shirk's (2018) model underscores the importance of a *shared* fleet and framework for low-range EVs, since 1% to 2% of Chicago vehicles' daily itineraries probably will not accommodate the charging trips needed to complete all activities using existing charging infrastructure and low-AER vehicles.

Even though EV technology is quickly gaining market share, literature typically avoids this technology when modeling SAVs. Also, large networks with suburban and exurban zones included are rare, since SAVs tend to yield more enticing results in city-centers. The following is the only methodology to date to combine all these factors including an activity based model on a highly detailed network.

3. Methodology

3.1. Tour generation

This study uses three major steps to simulate SAV operations across Austin, Texas: tour generation, traffic assignment, and SAV simulation. The travel data come from Austin's 2010 Capital Area Metropolitan Planning Organization (CAMPO) trip-making predictions, in addition to U.S. National Household Travel Survey (NHTS) data for the year 2009 (U.S. Department of Transportation, 2009). Liu et al. (2017) used CAMPO's trip tables by trip purpose to generate reasonable activity plans (a key input to MATSim) for every resident of the 6-county region (Burnet, Bastrop, Caldwell, Hays, Williamson and Travis counties). As described in Liu et al. (2017), a 5% sample of the region's roughly 8.8 million daily trips were re-constructed, to provide far more spatial resolution (mapping to specific homes and then to the ends of every block or road segment in Open Street Maps) than an MPO's TAZs allow. Since just 5% of trips are simulated, the capacity of network links is reduced proportionally, to deliver realistic congestion effects. This technique is very common in agent-based models to balance out the very heavy computational needs of modeling millions of person-trips in real time. A 24-h 100% model-run on a region of this size would take many days, even running on supercomputers. These trips were chained for individual travelers, creating daily tours for performing planned/desired activities. MATSim model outputs (described below) were used to validate the tour patterns by comparing the temporal and spatial distribution of trip departures against NHTS data for the state of Texas. The data and model runs were calibrated until the data matched closely. Data showed that 15.7% of persons make no trips on the given travel day, while 22.6% of persons make two trips. The travel patterns and road network of the Austin region are not unusual, and can be compared across many cities of similar size around the world. It is anticipated that modeling a similar urban area would provide similar results.

These activity plans are important for building a tour-based or activity-based model. Tour-based models are believed to offer a more realistic simulation of network use by connecting trip ends, and bringing most travelers back to their homes at the end of a travel day, rather than allowing trips to form and end rather independently in conventional (aggregate) models. This type of travel demand modeling is very uncommon for SAV simulations due the additional effort required.

3.2. Traffic assignment to obtain travel times

Dynamic traffic assignment (DTA) was performed using the agent-based MATSim model (Horni et al., 2016), which also seeks to optimize individuals' trip patterns through a co-evolutionary process of scoring competing travel plans, for each traveler, across desired activity sets, in order to approach a network-wide user equilibrium. MATSim iteratively seeks to improve each traveler's routes, modes – when flexible, and departure time selections, as feasible, through individualized scoring, and resulting vehicle demands are dynamically loaded onto the provided network, delivering real-time travel time estimates and congestion. Agents improve their scores (that is their utility) via faster travel times and on-time arrivals at activity sites, but are penalized for slow travel times and late or early arrivals at their desired destinations. The MATSim simulation is run several times consecutively, as subsets of agents modify their behaviors slightly, in order to improve their own utility scores. This is simulating real life travelers' behavior as they find their optimal travel choices. The agent data for the traffic assignment framework comes from the tours generated in the previous section, and the network comes from OpenStreetMap, which contains highly detailed network information for the Austin region, at a much higher resolution than former SAV simulations in the region. MATSim's time-step is just one second, so trip departures are scheduled nearly continuously over a 24-h day. After the 1-day simulation is complete, MATSim creates an event-file containing a list of trips for each agent that is then used for calls on the SAEV simulation, as described below.

3.3. SAV simulation code

The underlying code for much of the SAEV simulator was developed by Bösch et al. (2016) to model a conventionally-fueled SAV fleet serving the Zurich region. For this study, their SAV simulator was modified to enable range-constrained SAEVs, with relatively long battery-charging times and spatially constrained recharging locations. The revised code includes more accurate speed data, and requiring trips to be met regardless of wait times. The following explains Bösch et al.'s (2016) original code, and the many enhancements and modifications pursued for this paper's new analysis and fleet type.

For Bösch et al.'s Zurich simulation, a random sample of travelers/agents was assumed to use SAVs throughout their day (rather than rely on their original modes) and request their SAVs 5 min before their desired departure times. This 5-min pre-planning (by travelers) is chosen to mimic travelers' tendency to anticipate vehicle response times. Modifying that assumption, from 0 to 10 min, delivered little change on average response times in the Austin scenarios simulated here; so 5 min is the standard case.

Once the traveler's request is registered, Bösch et al.'s program searches for a vehicle that can reach the traveler within 5 min after the scheduled departure time (within 10 min after the trip request). The vehicle search is repeated every timestep (i.e., every second) until an available vehicle is found; the first available vehicle found that can reach the traveler in time is then given the request. If more than one suitable vehicle is found during a certain timestep, the closest vehicle is assigned. If no suitable vehicle is found within 5 min of the requested departure time, the original search algorithm (applied to Zurich) cancels the trip (and this strict assumption was loosened for this Austin study). Once an SAV receives an assignment, it drives to the trip-maker. If the vehicle arrives before the scheduled departure time, it waits for the traveler; otherwise, the traveler boards immediately and heads to his/her destination.

Travel time transporting SAV users to their destinations is given in the MATSim event-file, from the MATSim run results described above. Since *empty*-vehicle movements are not modeled in the upstream traffic assignment, 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. The correction factor comes from a separate program that finds the ratio of every trip's true network distance (using the MATSim assignment) to its Euclidean distance. The average of these ratios is the overall distance correction factor. Average speed was taken from data collected in the Zurich region and was assumed constant throughout the day, but for the Austin SAEV-fleet simulations, average speed is updated every timestep. After an SAV drops off its user, in the Bösch et al. (2016) code, it remains at that location until it receives a new assignment. In reality, SAVs must refuel every so often, and range-limited SAEVs deserve special re-charging consideration, as described below.

3.4. Code modifications to simulate SAEVs

Bösch et al.'s SAV code effectively assumes all SAVs are gasoline-powered vehicles, and ignores refueling times and locations, as well as energy use. In SAEV applications, recharge times are likely to vary from 20 min to 8 h, depending on charging station power and battery capacity, so vehicle range can have important impacts on an SAEV's ability to serve trips throughout the day. The code was modified to track each vehicle's range, every second, to increase the range (if the vehicle is charging), lower it (if the vehicle is moving) or leave the range the same (when idle and turned off). Every 1-second timestep, the program checks if the vehicle should go to charge or cease charging, in addition to its typical tasks of serving travelers.

The locations and number of charging stations also affect the amount of time SAEVs will spend driving to and from them, so a method to place these stations was added to the code. In addition, vehicles can now search the list of available charging stations to determine which station is closest. This includes checking the location of charging stations relative to travelers to determine if the vehicle has enough range to reach both the traveler and a charging location. This study examines how station locations, vehicle range, and recharge speeds are likely to affect SAEV fleet performance. Several assumptions used here come from Chen et al.'s (2016) charging station generation and SAEV charging algorithms (which had been applied to a homogenous/highly idealized 100-mile region) and were added to Bösch et al.'s (2016) SAV codes.

3.4.1. Charging station generation

Here, the first part of the SAEV simulation generates a base set of charging stations. This is done by first assuming a large/oversized (1 vehicle per traveler) SAEV fleet, randomly distributed over space, running to meet trip demands. Whenever a vehicle receives a travel request, it checks to see if it has enough remaining range/battery charge to pick up the passenger and then take the passenger to the desired destination. If not, it will check to see if it has enough range to travel to an existing charging station. If it again does not, a charging station is generated at the vehicle's location, and the vehicle is immediately assigned to charge at that station. That vehicle is then removed from consideration for that particular request, and the simulator searches again to find a suitable vehicle. This process is run for 30 simulation days, and the vehicle fleet is reset to random origins at the beginning of each day, while the list of charging stations is carried over into each subsequent day. For days 21 through 30, the daily number of visits for each station is recorded and at the end of the 30-day simulation, the stations with less than one visit per hour on average are removed. The vehicle fleet is then randomized again and the simulation is given a final run where no new stations can be formed. This algorithm provides no guarantees of optimality for station locations; however, it does serve to minimize the number of stations given vehicle parameters, as shown in Fig. 1. This is because vehicles with lower range will generally have less range remaining when it is time to charge. Thus, stations must be placed more often (at higher spatial density) so that shorter-range SAEVs can reduce total travel spent accessing charging stations. The station generation algorithm is also not intended to predict long-term or highly specific siting decisions for charging stations across the region, as a fleet expands. Instead, it seeks to help simulate travel to and from charging stations for a fixed fleet size, by estimating the general number and locations of charging stations needed to ensure that range-constrained vehicles can reasonably meet demand without becoming stranded. If station capacities were restricted by parcel sizes and/or charging cord counts at peak times of day, more, smaller stations would be created by the algorithm, enabling shorter-distance trips (less empty VMT) for recharging for many SAEVs. Even if few stations are needed, thanks to use of long-range SAEVs, fleet manager will probably prefer having more stations, located throughout the region, to provide more system flexibility (e.g., shorter distances to a recharging site and more station options if the closest site's chargers are all in use). Such decisions are not a focus of this paper, which simply ensures that SAEVs will not run out of charge during their operations.

3.4.2. SAEV charging rules

After the charging-station generation process, Bösch et al.'s (2016) upgraded SAV simulation code is run normally. Similar to the earlier model runs for station generation, vehicles have to check that they have adequate range before accepting a request – but they also now must be able to reach a charging station after delivering the passenger(s). If the vehicle cannot meet these conditions, it will reject the request and the program will search for a different suitable vehicle. With this technique, an SAEV will always have a charging station in range, so it cannot be stranded.

There are several conditions under which a vehicle may be assigned to a charging station. For example, in every 1-second simulator timestep, SAEVs with a range below 5% of their battery's capacity will be sent to charge. Those that have been sitting idle/without trip assignment for 30 min are also sent to charge so as to utilize its time more effectively and not to waste public parking space. Lastly, a vehicle will charge when it receives a request that it has too little range to fulfill and has less than 80% charge remaining as is shown to work well by Chen et al. (2016).

To start the charging procedure, the vehicle travels to the nearest charging station and immediately begins charging upon arrival. Charging occurs in two stages, when remaining range is above or below 80%. To achieve full charge, the battery first charges to 80% during the first half of the total assumed charge time, and the remaining 20% charges in the latter half which closely approximates many state of charge graphs, a good example of which can be found at Buchmann (2017). This implies two different charging rates:

$$\text{For remaining range under } 80\%\text{:}\quad Rate_{fast} = \frac{0.8Range}{0.5T_{full}} \tag{1}$$

$$\text{For remaining range above 80\%:} \quad Rate_{slow} = \frac{0.2Range}{0.5T_{full}} \tag{2}$$

where T_{full} is the time needed to achieve full charge if starting from zero charge, *Range* is the vehicle's range when it has full change, and $Rate_{slow}$ and $Rate_{fast}$ correspond to the charging rates when remaining range lies above or below 80% of battery capacity, respectively. Charging rate is expressed in units of distance per time (or miles per hour of charge time). Each one-second timestep, the vehicle's range is incremented proportionally to the appropriate charging rate. Unlike Chen et al.'s (2016) SAEV simulations, charging vehicles may be undocked to fulfill a service request after all other eligible SAEVs are first evaluated for their availability during that timestep. If a charging vehicle is assigned, it will always be the vehicle with the greatest range at its respective station. A charging vehicle will cease charging when it has reached a full charge, but will not leave unless assigned to a request. In theory, charging stations should be able to operate without attendants, if the SAEVs are equipped with robotic or inductive charging interfaces, though bigger/more active stations can have attendants to fill tires, clean windows, and more.

Besides EV adaptations, Bösch et al.'s code was given some other modifications to improve realism. Instead of cancelling trips after 5 min without finding a vehicle in a 5-min radius, the program will simply assign the closest vehicle to the request. If no vehicles are available anywhere on the network (this is rare), the next available vehicle is assigned. Also, average network speeds (for determining unoccupied vehicle travel time) are updated every timestep, based on the speeds of all SAEVs driving on the network at that time.

3.5. Simulated scenarios

The charging station assignment and SAEV simulations were run for several fleet-size plus range plus charging-rate scenarios to appreciate system performance metrics, like average response times, empty VKT, and number and size of stations generated. Scenarios were chosen to be comparable with Chen et al.'s work (2016) to help validate, and add to, their results. Many more scenarios where chosen to fill the gaps between Chen et al.'s scenarios, enabling a much stronger sensitivity analysis. Fleet size is predetermined here in terms average ridership per vehicle, or the average number of travelers served per SAEV. These average ridership rates were varied from 3:1 to 9:1 in increments of 1. In some cases, a ratio of 10:1 was tested, but with poor performance, due to longer wait times.

The share of travelers assumed to use an SAEV is fixed at 2% of the 5% trip sample simulated. In other words, 0.1% of the region's travelers or total person-trip-making is simulated in each scenario, in order to avoid exceeding memory space on a personal computer. Since this is a relatively small number of vehicles, this fleet is not expected to have an important effect on congestion. Charging time requirements were varied from 30 min through 240 min, in 30-min increments, across scenarios simulated. Battery ranges varied from 100 km to 325 km, in 25 km increments. Unless otherwise noted in the discussion of results (below), the standard or base scenario's range is assumed to be 150 km (93 miles), with a complete charging time of 240 min, and average ridership of 5 travelers or 5 trip-makers per SAEV. (Note: Since 15%of the population does not travel on any given day, this 5:1 ratio means about 6 persons in the local population per SAEV.) Table 1 provides a summary of all tested parameters. Of the 800 possible combinations of these parameters, 102 were actually tested here, plus another 25 scenarios where station count and locations were fixed, resulting in a total of 127 distinct one-day scenarios. In order to keep response times reasonable, trip length is capped at 75 km and trips over this limit (approximately 8% of all trips) are rejected outright. Via trial and error, this number was found to give reasonable response times while rejecting a reasonable share of trips. Allowing all trips resulted in computation times of days and average response times of hours, especially with the low-range SAEV scenarios. Further reducing the limit on trip length does not provide much marginal improvement to fleet performance. Supercomputers allow for much more comprehensive runs with much larger sample sizes (as in Loeb and Kockelman (2017)).

4. Results

First, various vehicle ranges were simulated and the number and location of stations generated for these scenarios were found (as shown in Fig. 1).

As seen in Fig. 1's 4-h (240-min) charge time scenario, the density of stations generated to meet demand depends greatly on vehicle range: it goes from 222 stations (23.9 mi^2/station) at 100 km (62-mile) range to just 5 stations (1060 mi^2/station) when assuming SAEVs have 325 km (201-mile) range.

Response times for these scenarios were also computed, to illuminate how they may be affected by the sparse stations present at higher ranges. As shown in Fig. 2a, for the 4-h charge scenario, as range increases, average response times fall: from 35.9 min for 100-km range vehicles to 7.39 min with 175-km range. After this point, response times show very little change, reaching a minimum at of

Table 1
Summary of all vehicle parameters simulated. Base case parameters are shown in bold.

Vehicle Range (km)	100	125	**150**	175	200	225	250	275	300	325
Charge Time (min)	0	30	45	60	90	120	150	180	210	**240**
Fleet Size (travelers/vehicle)	3	4	**5**	6	7	8	9	10		

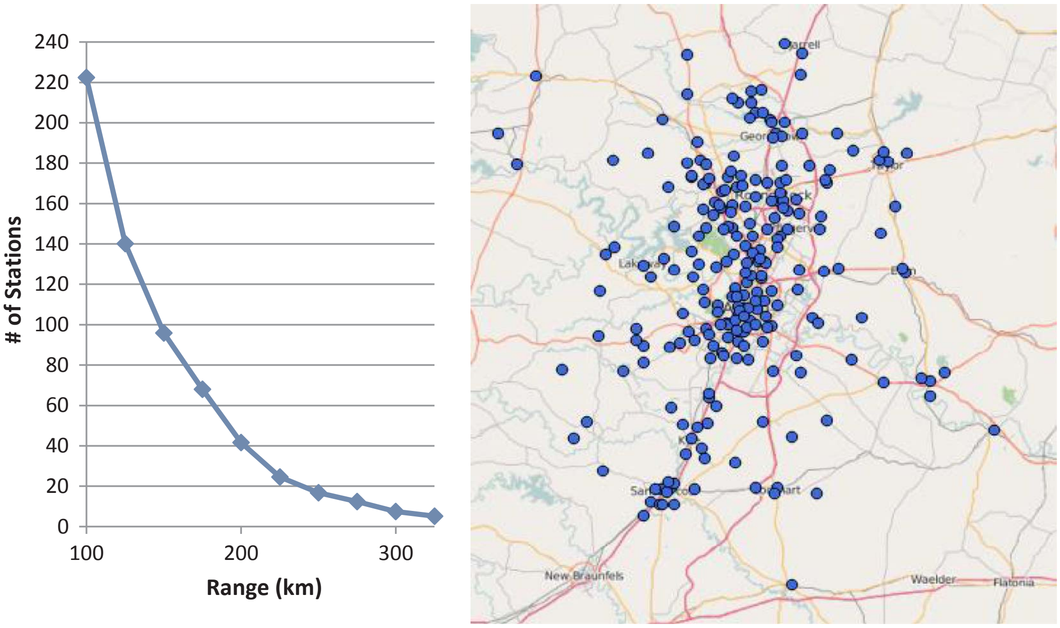

Fig. 1. Number of stations relative to vehicle range (left) and map of stations for the 100 km-range, 4-h charge time scenario across the CAMPO region (right).

7.18 min at 300 km and climbing back up to 8.76 min at 325 km (as station count falls further, so SAEVs are spending more time getting to and from charging locations). However, for shorter charge times (120 min, 60 min and 30 min), there appears to be no such correlation. At all other ranges and charge times, response times fall between a minimum of 3.85 min and a maximum of 6.30 min.

A gasoline-powered fleet was also approximated by giving each vehicle an infinite range and ignoring refuel times (effectively presuming that they can be handled each night, without compromising service levels). This fleet yielded the best response times, at 3.70 min. The gasoline-powered vehicles still rejected trips over 75 km and averaged 5 travelers per fleet vehicle in order to ensure comparability across test scenarios.

Fig. 2b shows distributions of wait times, where a trip met "on time" indicates an SAEV arrived before the agent's scheduled departure time, met in "0–5 min" indicates the SAEV was 0 to 5 min late, and so on. This chart shows that trips met within 5 to 10 min late are very rare. This is because the search algorithm maintains a 5-min search radius until the request is 5 min old; thus, it is fairly unlikely that a nearby vehicle will suddenly become available that was not available prior. Improvements in response times come primarily from shrinking the relatively small proportion of trips met in over 30 min: decreasing from 8.97% at 100-km range to 3.36% at 175-km range. The distribution of response times appears to become more polarized as range increases, with the percentage of responses more than 30 min late reaching a minimum of 3.27% at a 300-km range and trips met on time reaching its minimum of 51.3% at 275-km range. Since trips greater than 30 min carry a lot of weight when averaging, shrinking this term improves response times quite a bit even if the proportion of "met on time" trips decreases slightly.

Response times were then modeled with respect to charge time (Fig. 3) assuming 150-km range, demonstrating that response times are mostly unaffected by charge time until charge times exceed about 90 min increasing from 4.25 min at 90-min charge times to 9.40 min at 240-min charge times (Fig. 3a). This increase in response times is again heavily weighted by trips more than 30 min late (as shown in Fig. 3b), which increased from 0.95% to 4.11% for the same scenarios.

Various fleet sizes were modeled to determine their effect on response times in Fig. 4. It is clear that for each charge time, the response time "breaks" at a certain point and increases rapidly for higher replacement rates. It is important to see that for larger fleet sizes, improving charge times may not help with response times. A similar study was repeated with four different range scenarios shown in Fig. 5a. Results for the base case of a 240-min (4-h) charge time are not presented here because it results in unreasonable response times for most fleet sizes. (Fig. 4 illustrates how response times for the 240-min charging scenarios quickly exceed 30 min for all fleets serving more than 5 travelers per vehicle). The 30-min charge time provided very reasonable response-time results, enabling practical applications, so it is as the base case for that figure.

The results in Fig. 5 appear similar to Fig. 4, where there is a clear linear relationship up until a "break point" at a ridership rate of 7 travelers (and almost 27 person-trips per day) per vehicle. Most notably there are negligible differences between the 100-km and 175-km range scenarios. The poorer response times correlated with higher range is likely caused by the substantial decrease in the number of charging stations generated during the station generation phase. To account for this, the station locations for one of the 100-km range runs was kept fixed for all subsequent runs, and those results are shown in Fig. 5b. Somewhat surprisingly, when stations are fixed, vehicle range does not seem to have an effect on response times (at least with 30-min charge times), except at very high ridership rates. Only at a ridership rate of 9 travelers per vehicle is there a strong correlation between range and response times yielding response times of 23.3 min, 18.3 min, 17.7 min and 17.1 min for the 100-km, 175-km, 250-km, and 325-km ranges, respectively.

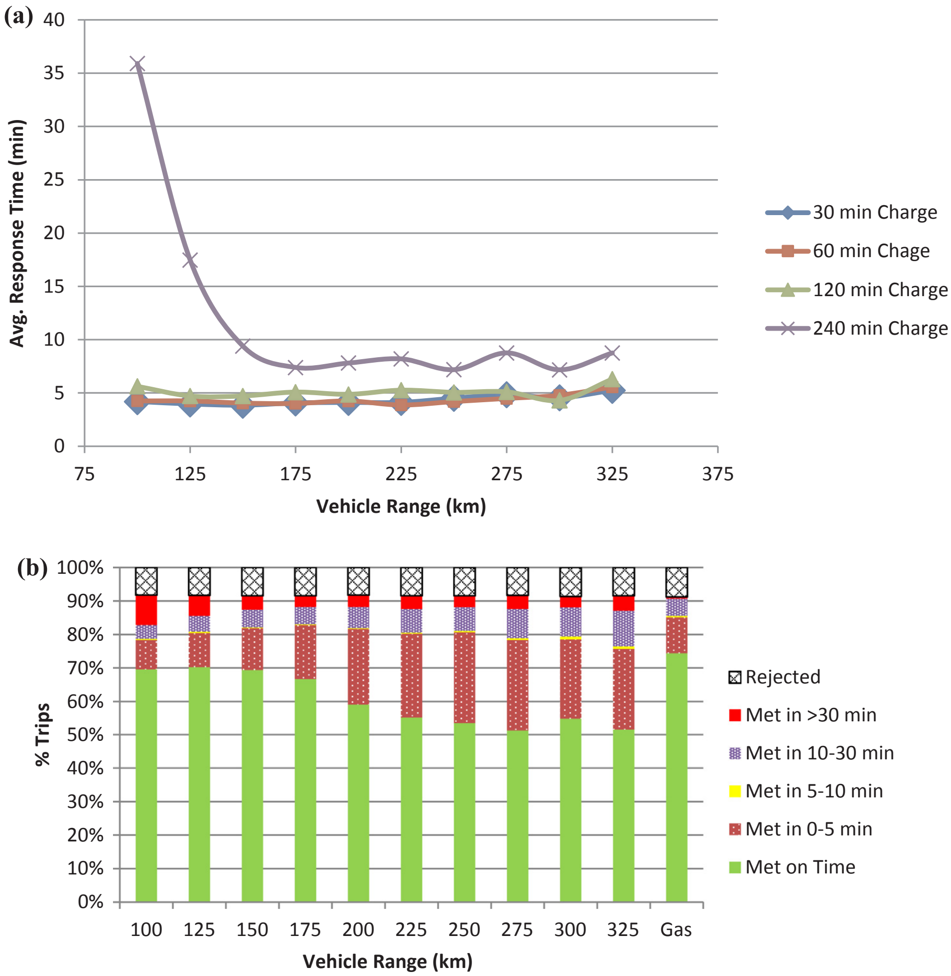

Fig. 2. Response times relative to vehicle range (assuming 5:1 average vehicle ridership and 240-min charge times, unless otherwise noted). (Stacked values follow the legend's order.)

Table 2 provides a summary of key results for five major scenarios that demonstrate the extreme ends of charge times and range. Chen et al. (2016) found similar results where number of charging stations appears to be wholly dependent on vehicle range. They did however find, in general, lower response times and lower empty unoccupied travel. The primary reason for this is likely their highly aggregate and unrealistic network which could not account for the nuances of a true network with directed links. Another way Chen et al. (2016) reduced average wait times was by rejecting trips after a passenger waits for 30 min to be picked up.

5. Discussion

Many scenarios were simulated across various charge times, fleet sizes, vehicle range and number of charging stations. 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, one can expect that these results apply for many other regions and that similar behavioral relationships exist for regions of different density and size.

Fig. 1 shows that the density of charging stations generated tends to be proportional to the population density in those areas. This is analogous to gas station locations, which follow a similar trend. It is less intuitive that higher-range scenarios result in fewer stations being generated. This occurs because longer-range vehicles tend to have more range remaining when receiving a charging assignment. Since there are no vehicle-occupancy restrictions on stations, few stations will be needed when vehicles are able to travel further. The number and spatial distribution of stations remains similar when randomizing the location of trip requests and starting positions of vehicles. If certain capacity constraints on stations were to be enforced, the relationship between vehicle range and number of stations generated may differ. Correlations may emerge between the number of stations and other factors, like charge times. However, one can think of these as regions where charging stations are present rather than the number of individual stations themselves. When there is a small number of stations generated (e.g., 12 stations are needed for the 275-km range scenario), there should not be a significant difference between one large station and a cluster of stations within a small neighborhood (as is often seen

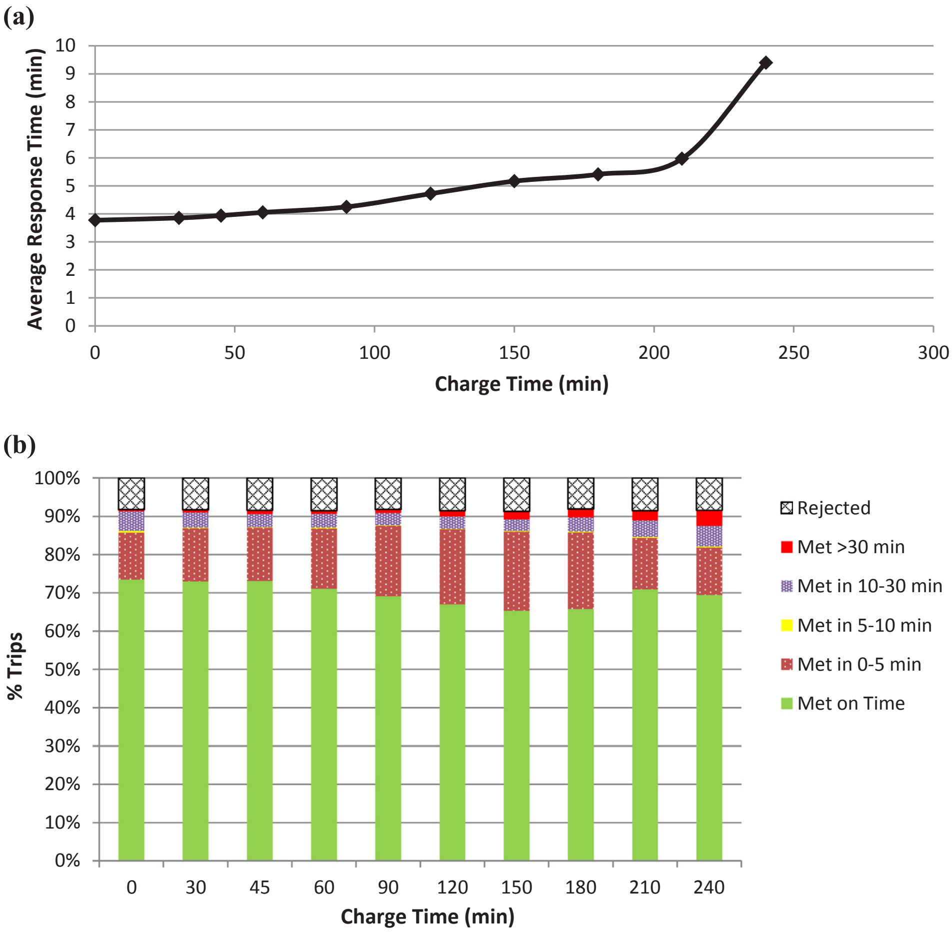

Fig. 3. Response times with respect to charge times (150-km scenario).) (Stacked values follow the legend's order.)

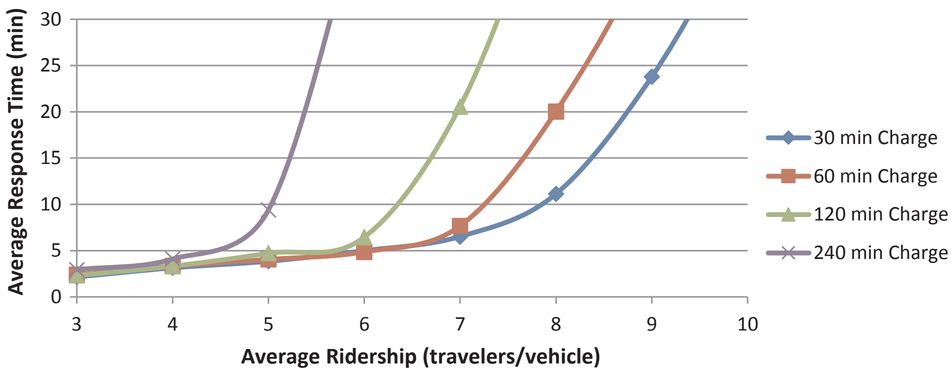

Fig. 4. Response times with respect to vehicle ridership rates for four charge scenarios (150-km scenario).

with gas stations). Therefore, this tool remains very useful for understanding the required density of stations across a region; the number of parking spots and inductive charging pads or robotic charging arms at a station (and battery charge on site or power generation availability) can easily vary across sites.

When studying vehicle ranges, a longer range does help reduce the number of needed charging stations but does little in terms of improving response times (Fig. 2). This is not the case when charge times are very long (4 h for example), likely because charging will take up a significant portion of a working day for these vehicles if they have to charge frequently. When a charge time is quicker, vehicles do not need to spend very long at charging stations, even if they have to visit a bit more often.

Fig. 3 explores the important gap in response times between the 120-min and 240-min charge times. Consistent with Fig. 2, charge times play a small role in response times when charging times are under 90 min. But response times increase at what appears to be an

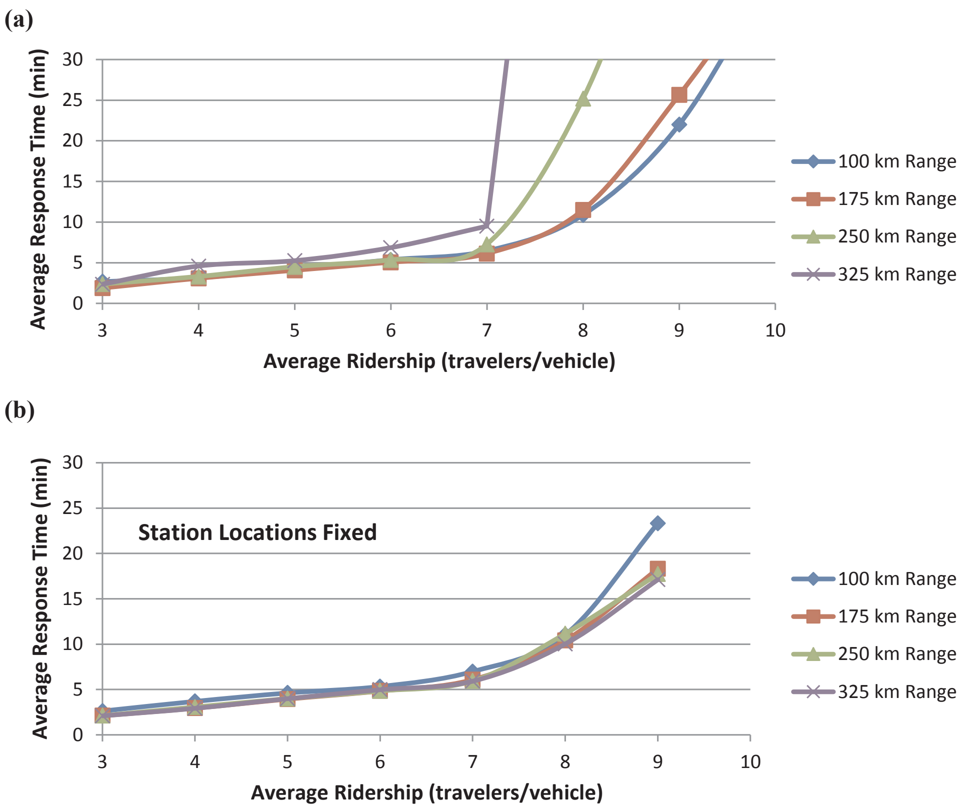

Fig. 5. Response times relative to vehicle ridership rates for four range scenarios (assuming 30-min charge times) with station locations varied (a) and fixed (b).

Table 2
Key findings from 5 simulation scenarios including a gasoline-powered base-case.

Scenario	Gas SAV	Short-Range SAEV	Short-Range SAEV Fast Charge	Long-Range SAEV	Long-Range SAEV Fast Charge	Long-Range SAEV Fast Charge, Reduced Fleet
Range (km)	Infinite	100	100	325	325	325
Recharge Time (min)	N/A	240	30	240	30	30
# of Charging Stations	N/A	222	219	5	5	7
Avg. Travelers Served (per vehicle)	5	5	5	5	5	7
Avg. Daily Trips per Vehicle	18.8	19.2	19.0	18.9	19.0	26.8
Avg. Daily Miles per Vehicle	297	328	318	355	331	489
Avg. Wait Time Per Trip (minutes)	3.69	35.9	4.20	8.76	5.25	9.50
% Unoccupied Travel	11.2	18.7	15.3	24.0	17.6	22.3
% Travel for Charging	N/A	7.25	4.16	7.75	5.21	6.45
Max % Concurrently Charging Vehicles	N/A	82.8	46.4	53.9	13.0	23.1

approximately exponential rate for longer charging times. It is difficult to tell why this occurs without much more microscopic analysis. One possibility is that, during peak hours, trip request counts are quite high. If response times are high enough, trips could be entering the system faster than they are being served. This may deliver an over-sized queue of trip requests that would not stabilize even after the peak period. This is of course not sustainable and will cause wait times to rise extremely quickly. Once excessive charge times prevent vehicle supply from keeping up with demand, response times will spike. This means charge times are an important factor when looking at response times, but it is recommended a fleet operator determine if there is a threshold under which response times will no longer improve before investing in very fast charge times.

Fig. 4 shows that this charge-time threshold continues to appear in other scenarios but changes under varying fleet sizes. When the fleet size is large (fewer than 5 travelers per vehicle), charge times seem to make little difference. At 5 travelers/vehicle, the same results from Fig. 2 are apparent. At seven travelers per vehicle, the 120-min charge time is no longer close to competing with quicker charge times and by 8 travelers per vehicle, only half-hour charge times can provide reasonable service. This means that not only is it important for operators to determine the threshold for acceptable charging speed, but this number may need to be re-evaluated with different fleet sizing strategies.

Fig. 5a shows that vehicle range does not affect response times significantly unless the fleet size is smaller (more than 5 travelers/vehicle). Somewhat counter-intuitive is that longer ranges tend to perform more poorly here. This is because scenarios with longer ranges are provided fewer stations during the station generation process (see Fig. 1). This is confirmed in Fig. 5b that shows how little vehicle range affects response times when the number and location of charging stations are held constant, even though longer ranges tend to perform a little better. Table 2 demonstrates that increasing vehicle range sometimes improves response times - but at the expense of VKT. This is because increasing range also increases the distance a vehicle is able to travel to pick up passengers. For some requests, a vehicle may be far away while still able to respond faster than other SAEVs in the network. When range is shorter, a vehicle must be fairly close to a request in order to serve it, using fewer VKT. In some cases, extra range increases response times slightly, but this is due to the higher-range scenarios having far fewer charging stations available.

These analyses are based mostly on the methodology presented in Chen et al. (2016), but expose several shortcomings in their model. First we see that studying just five scenarios leaves out a lot of important information that can be found in this discussion. The thorough sensitivity analysis revealed useful trends that could assist future studies in this field. Next, their highly-simplified model appears to have predicted results that may be too optimistic. Namely that unoccupied travel and response times are in some cases much higher in this more realistic model. In application, this would lead to a service with lower-than-expected performance and higher costs, a major problem for the fleet operator. Bösch et al. were able to accomplish higher realism but did not attempt to model electrified vehicles. Furthermore, the network they used was too small and urbanized to determine if their findings are applicable to a larger, more diverse metropolitan region.

6. Conclusions

The rising popularity of car sharing, electric vehicle technology, and vehicle automation is leading to new research on the operations of SAV fleets. This study sought to find more cost-effective and more environmentally sustainable solutions for long-term mobility needs and demands by all types of travelers. These simulations of SAEV fleet activities across the greater Austin, Texas region provide promising results. Operations of various SAEV fleet scenarios were simulated to appreciate the need for different charging station locations and charge times. After excluding trips over 75 km, a fleet size serving 7 travelers per SAEV was able to serve 84% of travelers' requests within 10 min, with an average response time of 6.1 min, assuming 175-km range vehicles and 30-min charge times. Under this same scenario, unoccupied travel accounted for 19.8% of VKT, with driving to charging stations accounting for 23.0% of this empty-vehicle mileage. This percentage of empty VKT is higher than found in other papers, as somewhat expected, thanks to a very large and realistic network along with frequent travel to and from charging stations. Moreover, charging stations become scarce as vehicle range rises, increasing those distances. If operators wish to offer more charging locations (with fewer charging cords, for example), this excess VKT statistic can be brought down. Economies of scale and density in sizing and siting the stations will probably determine the optimal result.

A sensitivity analysis was conducted next, using different charge times, vehicle ranges, and average vehicle occupancies or travel party sizes, to see how these factors impact vehicle response times and the number of charging stations simulated. Those results suggest that the number of stations is highly dependent on vehicle range, calling for 222 stations for a 409-vehicle fleet with 100-km ranges, but just 5 to 6 stations needed for the same size fleet with 325-km ranges. The other two factors considered (fleet size and charge times) do not appear to correlate/vary with the number of stations generated. Average response times tend not to depend on vehicle range, except when charge times are very long (i.e., 4 h). However, in all cases, ranges above 175 km do not appear to improve response times, even when the number of stations is fixed. These results suggest that a fleet operator should determine the minimum range needed to achieve optimal service for their network and demand before investing in very long ranges.

Importantly, increasing fleet size (or SAVs per traveler) is found to have a profound effect on response times. With 150-km range vehicles and 30-min charge times, a fleet averaging 10 travelers per vehicle resulted in average response times of 41.6 min, whereas a fleet with 7 travelers per vehicle delivered average response times of just 6.52 min. At 3 travelers per vehicle, average response times fell to 2.16 min. Results will vary in other regions, but the correlation between fleet size and response times is so strong it is expected to manifest in any real region. Reducing charge times also improves response times. For the fleet with 150-km range and 5 travelers per vehicle, a charge time of 4 h resulted in an average response time of 9.40 min, which falls to 4.25 min with 90-min charge times. However, these improvements diminish quickly, since 30-min charge times deliver an average response time of 3.85 min. Therefore, it is not recommended that a fleet manager assume in all cases that faster charge times will improve customer service. Lastly, results suggest that trips originating in the urban center are served best, since every trip within city limits was served in less than 30 min. These findings suggest that a fully electric SAEV fleet is reasonable for a region similar to Austin, Texas, with the support of policymakers and fleet managers.

Understanding financial tradeoffs between vehicle range and station construction is another important prerequisite for delivering such services which we investigate in Loeb and Kockelman (2017). Also important will be analyzing the balance of charge times and fleet size with desired response times. Since improved realism showed dramatic changes in results over a highly-simplified model, further improvements to model validation could reveal slightly more accurate results still. Beginning the simulation with a destination choice model is an important next step to understand long-term adoption.

Acknowledgements

The authors are thankful to the Texas Department of Transportation (TxDOT) for its 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.

References

Bösch, Patrick M., Ciari, Francesco, Axhausen, Kay W., 2016. Required autonomous vehicle fleet sizes to serve different levels of demand. Transp. Res. Rec. 2542 (4), 111–119.

Buchmann, Isidor, 2017. Charging Lithium-Ion Batteries. Available at: http://batteryuniversity.com/learn/article/charging_lithium_ion_batteries.

Bullis, Kevin, 2013. Forget battery swapping: tesla aims to charge electric cars in five minutes. MIT Technol. Rev. Available at: https://www.technologyreview.com/s/516876/forget-battery-swapping-tesla-aims-to-charge-electric-cars-in-five-minutes/.

Chen, Donna, Kockelman, Kara, Hanna, Josiah, 2016. Operations of a shared, autonomous, electric vehicle fleet: implications of vehicle & charging infrastructure decisions. Transp. Res. Part A 94, 243–254.

Chen, Donna, Kockelman, Kara, 2016. Management of a shared, autonomous electric vehicle fleet: implications of pricing schemes. Transp. Res. Rec. 2572, 37–46.

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

Fagnant, Daniel, Kockelman, Kara, 2014. The environmental implications of shared autonomous vehicles, using agent-based model simulation. Transp. Res. Part C 40, 1–13.

Fagnant, Daniel, Kockelman, Kara, 2016. Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 1–16.

Fagnant, Daniel J., Kockelman, Kara, Bansal, Prateek, 2015. Operations of a shared autonomous vehicle fleet for the Austin, Texas market. Transp. Res. Rec. 2536, 98–106.

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity, London.

ITF, 2015. Urban Mobility System Upgrade. International Transport Forum. Available at: http://www.itf-oecd.org/sites/default/files/docs/15cpb_self-drivingcars.pdf.

Liu, Jun, Kockelman, Kara, Bösch, Patrick, Ciari, Francesco, 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. Transportation 44 (6), 1261–1278.

Loeb, Ben, Kockelman, Kara, 2018. Fleet performance & cost evaluation of a shared autonomous electric vehicle (SAEV) Fleet: A case study for Austin, Texas. Transport. Res. Part A: Policy Pract (submitted for publication).

Nykvist, Björn, Nilsson, Mans, 2015. Rapidly falling costs of battery packs for electric vehicles. Nat. Clim. Change 5, 329–332.

Reiter, Matt, Kockelman, Kara, 2016. Emissions and exposure costs of electric versus conventional vehicles: A case study for Texas. Int. J. Sustainable Transport. 11, 486–492.

Spieser, Kevin, Ballantyne, Kyle, Treleaven, Rick Zhang, Frazzoli, Emilio, Morton, Daniel, Pavone, Marco, 2014. Toward a systematic approach to the design and evaluation of automated mobility on-demand systems: a case study in singapore. In: Meyer, Gereon, Beiker, Sven (Eds.), Road Vehicle Automation (Lecture Notes in Mobility). Springer.

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. Available at: https://www.nrel.gov/docs/fy13osti/55639.pdf.

Tesla Motors, 2017a. Supercharger. Available at: https://www.tesla.com/supercharger.

Tesla Motors, 2017b. Model 3. Available at: https://www.tesla.com/model3.

U.S. DOE [United States Department of Energy], 2017. Model Year 2017 Fuel Economy Guide. Available at https://www.fueleconomy.gov/feg/pdfs/guides/FEG2017.pdf.

U.S. Department of Transportation, Federal Highway Administration (2009) National Household Travel Survey. Available at: http://nhts.ornl.gov.

Yi, Zonggen, Shirk, Matthew, 2018. Data-driven optimal charging decision making for connected and automated electric vehicles: A personal usage scenario. Transp. Res. Part C 86, 37–58.

Zhang, Wenwen, Guhathakurta, Subhrajit, Fang, Jinqi, Zhang, Ge, 2015. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: an agent-based simulation approach. Proceedings of the 94th Annual Meeting of the Transportation Research Board.