SHARED AUTONOMOUS ELECTRIC VEHICLE (SAEV) OPERATIONS ACROSS THE AUSTIN, TEXAS NETWORK WITH A FOCUS ON CHARGING INFRASTRUCTURE DECISIONS

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ABSTRACT
Shared autonomous vehicles or SAVs have attracted significant public and private interest because of the 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 synch with the agent-based simulator MATSim, with SAEVs as a new mode. Charging stations are placed, as needed; to serve all trips requested (less than 75 km 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 and location of stations depend 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 does not appear to improve response times and trips originating in the urban core are served the quickest. Unoccupied travel accounted for

19.8% of SAEV mileage, with driving to charging stations accounting for 23.0% of this empty-vehicle mileage

KEYWORDS

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

MOTIVATION

An exciting application of self-driving automated-vehicle technology is one-way carsharing, 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 and Kockelman 2015). 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). 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 & 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 mi [Fagnant and Kockelman 2015]), vehicle turnover will be faster, leading to quicker adoption of new EV technologies (Martinez, 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 power current. 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 technology 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 and more available in many fast-charge locations [see, e.g., https://www.tesla.com/supercharger] (Bullis, 2013). Battery ranges are rising with the Chevrolet Bolt (Chevrolet, 2016) and Tesla Model 3 (Tesla, 2016b) both expected to deliver 200 miles of range for under $40,000 price.

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 5,301 square-mile, 6-county Capital Area Metropolitan Planning Organization (CAMPO) region surrounding Austin, Texas. The work addresses gaps in much recent research by modeling SAV services across a very large region with a highly detailed (true to life) network of roadways and with variable population densities and land uses. The simulation framework improves upon agent-based simulations by Chen et al. (2016) and Bösch et al. (2016) by using more realistic vehicle speeds, allowing charging vehicles to respond to requests, using more robust charging strategies, and requiring that all demand for trips under 75 km (47 miles) be met, along with other improvements. All improvements deliver greater realism and many improve the fleet's performance, via flexible-charging and passenger-pickup strategies.

LITERATURE REVIEW

While several studies have recently simulated the operations of SAV fleets in urban environments (Fagnant & Kockelman, 2015; Martinez, 2015; Spieser et al., 2014; Zachariah et al. 2014) , only Chen et al. (2016) and Chen and Kockelman (2016) have allowed for electric vehicles or for rural and low-density trip-making locations. They modeled SAEV services over a 100 × 100 mile homogenous grid with quarter-mile spacing. They concluded that an SAEV system could serve all passenger demand with competitive response times as low as 7.7 minutes with 30 minute charge times, 160-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 $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, $1,600 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 minutes. After the initial runs, fleet size and charging stations are fixed and these simulations are performed many times, for a range of scenarios; scenarios include short-range (80 miles) and long-range (200 miles) EVs, as well as fast charging versus regular charging (30 minutes vs. 4 hours, 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-hour charges to 30-minute 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, it relies on a much more realistic network with 234,444 directed (one-way) links, and allows vehicles to leave charging stations as needed, before being fully charged, thereby reducing SAEV downtime and response times (to reach trip-makers).

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 to large-scale networks with reasonable computing times. Like most MATSim users, Bösch et al. (2016) 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 minutes after rejecting 3.8% of trips due to response times over 10 minutes. 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 (2016) program is a major contribution to this paper's work, along with Nagel's (2016)MATSim code. By simulating the CAMPO region in MATSim and modifying and then using Bösch et al.'s (2016) code, this research is able to generate charging stations and then simulate realistic SAEV operations across the Austin region.

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).

Zhang et al.'s (2015) SAVs-with-DRS simulationson a synthetic network predicted a 14:1 vehicle replacement. Like Fagnant and Kockelman (2015), they did not presume that all travelers are willing to share rides with strangers. Their simulation framework employs a straightforward relocation strategy, where empty vehicles can move toward areas/zones with low available-vehicle density (relative to expected near-term demands). Results suggest that only 6.7% of person-trips were able to and elected to participate in ride-sharing, though this share rises and SAV trip-making intensity rises (thanks to greater market adoption).

Atasoy et al. (2015) simulated a conventional taxi-type system wherein passengers select which type of taxi or transportation networking company (TNC) service they prefer, based on real-time pricing and wait times (as provided by the fleet manager). They implemented this framework (with conventional vehicles, not self-driving vehicles) for a network resembling Tokyo's Hino City, but traffic conditions (and thus congestion feedbacks) are ignored. The authors tested several pricing scenarios and found that, in all cases, the shared (taxi-type) fleet delivered greater consumer surplus and profits than a public bus system serving the same demands, even with all human-driven vehicles (where the cost of labor makes taxi or TNC prices quite high).

Burghout et al. (2015) predicted major VMT increases of 24% in the Stockholm, Sweden network with an SAV fleet without dynamic ridesharing; but, interestingly, found that the location of this increased VMT may not contribute substantially to congestion. When ride-sharing was included in their model, VMT fell 11% from the base case, and total travel times fell 7%. Their study performed traffic assignment to anticipate changing travel times. Similar to Fagnant and Kockelman (2015) and Chen et al. (2015), SAVs were created when a request was made (during the test start/initial simulation runs) and no vehicle was available to serve it within 10 minutes or so.

Martínez (2015) concluded that an SAEV fleet should be very plausible when each vehicle has a 30-minute gap or downtime in which to charge every 175 km, by increasing the SAV fleet size only 2%. They simulated the Lisbon, Portugal region in detail, with travelers sharing SAV rides as a specific mode alternative (similar to Zhang et al.'s [2015] approach), alongside subway, buses, non-motorized modes, and private (conventional) cars. They estimated that the same level of personal mobility for Lisbon travelers can be achieved with just 10% of current fleet sizes. Overall, vehicle travel or VMT was simulated to increase anywhere from 6% (with ridesharing and public transport) to 89% (no ridesharing or public transport), while 100% of on-street and 80% of off-street parking was no longer needed, assuming 100% "adoption" (or release of all privately were vehicles). With only 50% penetration/user adoption of SAVs, total VMT was predicted to rise 30% to 90% due to elimination of public transit (for the 90% case) and empty repositioning trips in all cases. Martínez (2015) noted that heavy use of SAV fleet vehicles expedites rapid fleet turnover to newer and cleaner vehicle technologies. Martínez's Lisbon simulations suggested that ridesharing may reduce VMT along arterial roadways, but add substantial VMT to local roads. In the worst case, VMT increased by nearly 90%. Another key finding was that, at 50% penetration, public transit was still needed to meet demand in a reasonable timeframe.

Zachariah et al. (2014) simulated an SAV fleet for travel across the US state of New Jersey, with SAVs making pickups and drop-offs at discrete stations called aTaxiStands. The New Jersey network was created by pixelating the state into half-mile by half-mile squares, with all trips using gridded/Manhattan distances and fixed travel speeds rather than a true and congestible road network. About 50% of the person-trips came from the top 6.1% of trip-producing pixels and 95% of trips came from the top 44%. Their work did not consider fleet size or any kind of empty-vehicle mileage, with all aTaxiStands having an arbitrarily large number of SAVs able to suit any level of demand.

Lastly, Spieser et al. (2014) estimated that in Singapore, SAVs can save drivers, on average, 50% in monetary travel costs per mile as opposed to using a private vehicle by splitting up the hefty cost of vehicle ownership. They concluded that all personal-travel needs in this island-state could be met using an SAV fleet approximately one-third the current passenger-vehicle fleet(or 1 SAV for every 17.28 Singaporeans, rather than the present ratio of 1 to 6.65). They used Singapore's actual road network and trip data from 10,840 of its 1.14 million households. A minimum fleet size was found to be 92,693 vehicles, delivering poor service with peak-period wait times well over one hour. With 200,000 SAVs in circulation, 90% were available for requests at any given moment on an average, simulated weekday, and 50% were available/not in use during peak times of day. With 300,000 vehicles, these availability rates rose to 95% (across a 24-hour day) and 72% during the peak times, with peak-period wait-times averaging less than 15 minutes. Their financial analysis estimates total mobility costs of $1.48 per person-milein Singapore and $1.14 in the US, for SAV usage. This is when allowing for values of travel and wait times at just 20 percent of the median wage (versus the 50 percent that the USDOT and others regularly assume (Small, 2012)), in part because those waiting or en route but not having to drive can often make reasonably productive use of that time. These figures are in contrast to private vehicles, which are estimated to cost, on average, $2.77 per person-mile in Singapore and $2.20 in the US, when including the travelers' value of travel time, at 50% of the median wage. These values are far more than $0.78/mi reported by the American Automobile Association (AAA, 2013) for vehicle ownership and use costs, along with Fagnant and Kockelman's (2015) and Chen et al.'s (2016) full-cost accounting for SAV operator costs.

METHODOLOGY

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. (2016) 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. (2016), 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. These trips were chained for individual travelers, creating a daily tour for performing planned/desired activities. 15.7% of persons make no trips on the given travel day, while 22.6% persons make two trips.

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.

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 reach a network-wide quasi-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 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. MATSim's time-step is just one second, so trip departures are scheduled nearly continuously over a 24-hour 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.

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 SAEVs, along with a few performance enhancements including more accurate speed data, and allowing more trips to be met regardless of wait times. A random sample of travelers/agents is assumed to use SAEVs throughout the day rather than their original modes and request their SAEV trips 5 minutes before their desired departure times. This 5-minute pre-planning (by travelers) is chosen to mimic travelers' tendency to anticipate vehicle response times. Testing that assumption, by changing this variable from 0 to 10 minutes, effects little change on average response times.

Once the traveler's request is registered, the program searches for a vehicle that can reach the traveler within 5 minutes of the scheduled departure time (or within 10 minutes of the trip request). The vehicle search is repeated every time step (i.e., every second) until a suitable vehicle is found (one with sufficient range to serve the trip and then reach a charging station); the first suitable vehicle found is immediately assigned to the request. If no suitable vehicle is found within 5 minutes of the requested departure time, the search algorithm selects the nearest available vehicle. Once an SAEV has received 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 SAEV 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, SAEV travel times are estimated using the beeline/Euclidean distance between each origin-destination pair, a distance correction factor, and the current average speedacross the entire network.The beeline correction factor comes from a separate program that finds the ratio of every trip's/every OD pair's true network distance (using the MATSim assignmentto its beeline distance). The average of these ratios is the beeline correction factor. Average speed is derived from the average speed of every trip on the network that starts within 5 minutes after the SAEV receives its assignment.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.

Code Modifications to Simulate SAEVs

Bösch et al.'s (2016) SAV code assumes all SAVs are gasoline-powered vehicles, and ignores refueling times and locations. In SAEV applications, recharge times are likely to vary from 20 minutes to 8 hours, 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 locations and number of charging stations also affect the amount of time SAEVs will spend driving to and from them. This study examines how station locations, vehicle range, and recharge speeds are likely to affect SAEV fleet performance. Many of the assumptions used here come from Chen et al.'s (2015) charging station generation and SAEV charging algorithms and were added to Bösch et al.'s (2016) SAV codes.

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, 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 re-set 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 fewer than 1.2 visits per day are removed. (1.2 visits per day corresponds to 1 visit per hour after scaling up by a factor of 20, to reflect use of a 5% sample.) 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.

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 responding to a request – but they also now must be able to reach a charging station after delivering the passenger(s). 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 time step, 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 minutes are also sent to charge. Lastly, a vehicle will charge when it receives a request that it has too little range to fulfill and 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 as suggested by many state of charge graphs, a good example of which can be found at Tesla Motors (2016a). This implies two different charging rates:

For remaining range under 80%: $$Rate_{fast} = \frac{0.8Range}{0.5T_{full}} \qquad (1)$$

For remaining range above 80%: $$Rate_{slow} = \frac{0.2Range}{0.5T_{full}} \qquad (2)$$

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). 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. 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.

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 VMT, and number and size of stations generated. Fleet size is pre-determined 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. Charging time requirements were varied from 30 minutes through 240 minutes, in 30-minute 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 minutes, 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.) In order to prevent the simulator from spending an unreasonable number of iterations trying to meet longer trips, 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. Supercomputers will allow for much more comprehensive runs with much larger sample sizes in the near future.

RESULTS

First, various vehicle ranges were simulated and the number and location of stations needed for these scenarios were estimated (as shown in Figure 1).

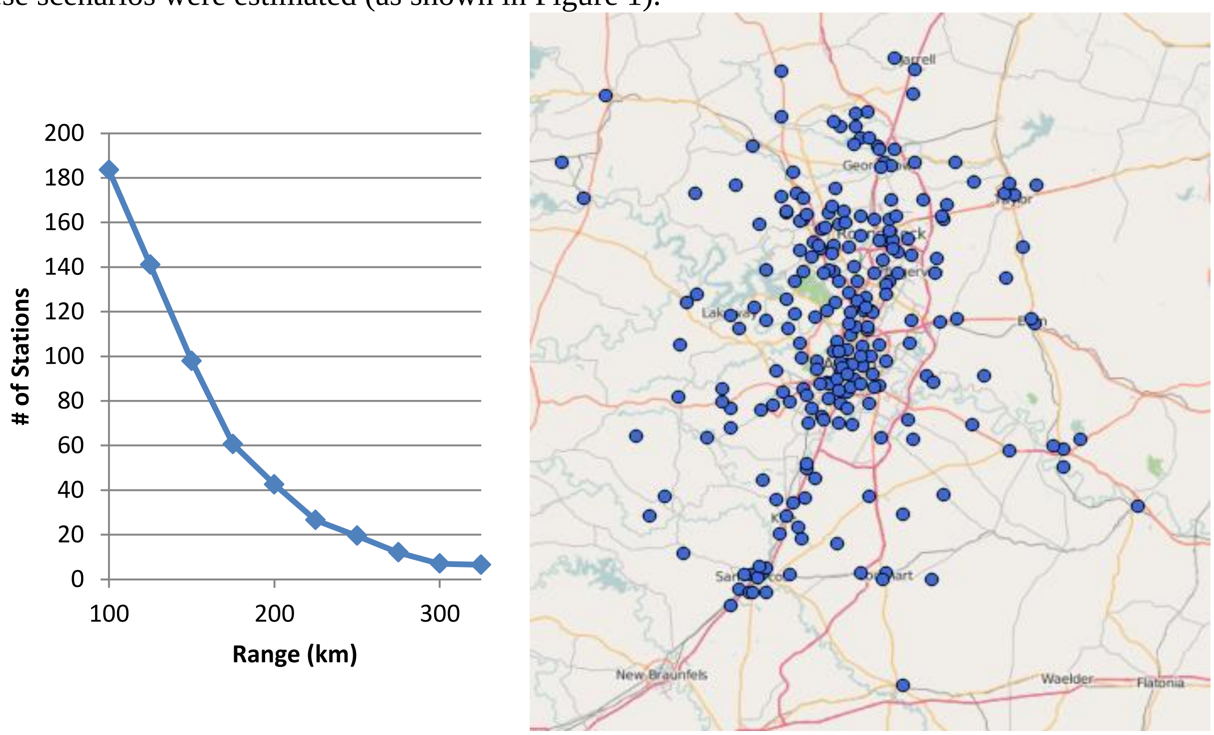


FIGURE 1 Number of stations relative to vehicle range (left) and map of stations for the 100 km-range, 4-hour charge time scenario across the CAMPO region (right)

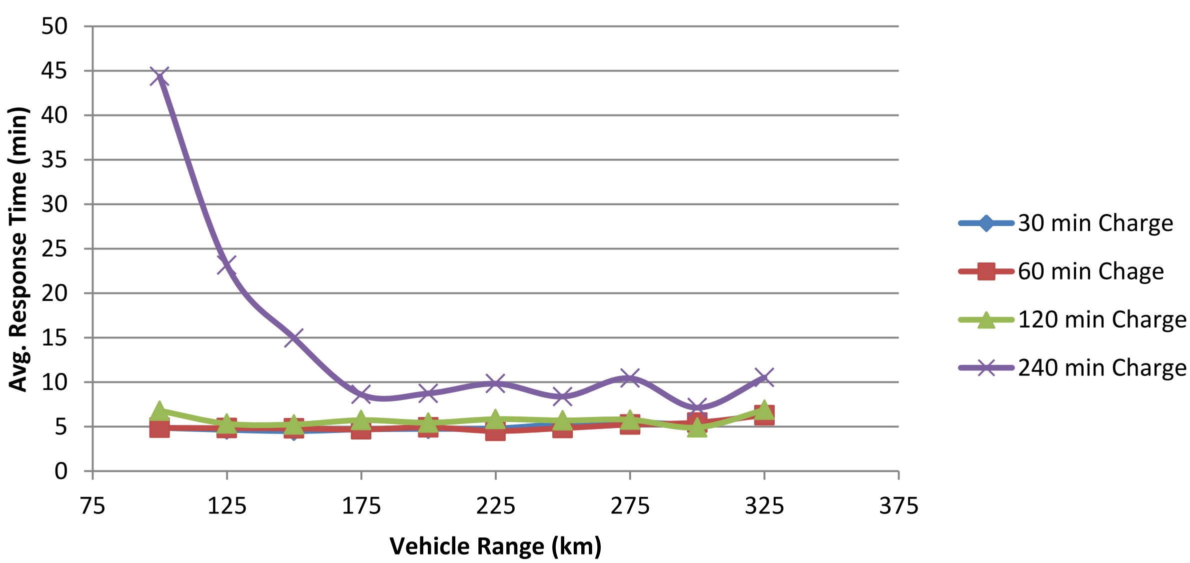
As seen in Figure 1's 4-hour (240-minute) charge time scenario, the number of stations needed to meet demand depends greatly on vehicle range: it goes from 183 stations at 100 km (62 mile) range to just 7 stations when assuming SAEVs have 325 km (201 mile) range. It is interesting to note how, in Figure 1, the rate of change in station counts turns sharply at 175 km, so that may be a type of “sweet spot” for operators electing an optimal range, in a region of this size and trip-making density.

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 Figure 2a, for the 4-hour charge scenario, as range increases, average response times fall: from 44.4 minutes for 100 km range vehicles to 8.61 minutes with 175 km range. After this point, response times show very little change, reaching a minimum at of 7.13 minutes at 300 km and climbing back up to 10.5 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 betweena minimum of 4.51 minutes and a maximum of 6.88 minutes.

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 4.15 minutes.

Figure 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 minutes" indicates the SAEV was 0 to 5 minutes late, and so on. This chart shows that trips met within 5 to 10 minutes late are very rare. Improvements in response times come primarily from shrinking the relatively small proportion of trips met in over 30 minutes: decreasing from 10.04% at 100 km range to 3.38% 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 minutes late reaching a minimum of 2.23% at a 325 km range and trips met on time reaching its minimum of 50.71% at 300 km range.

(a)



(b)

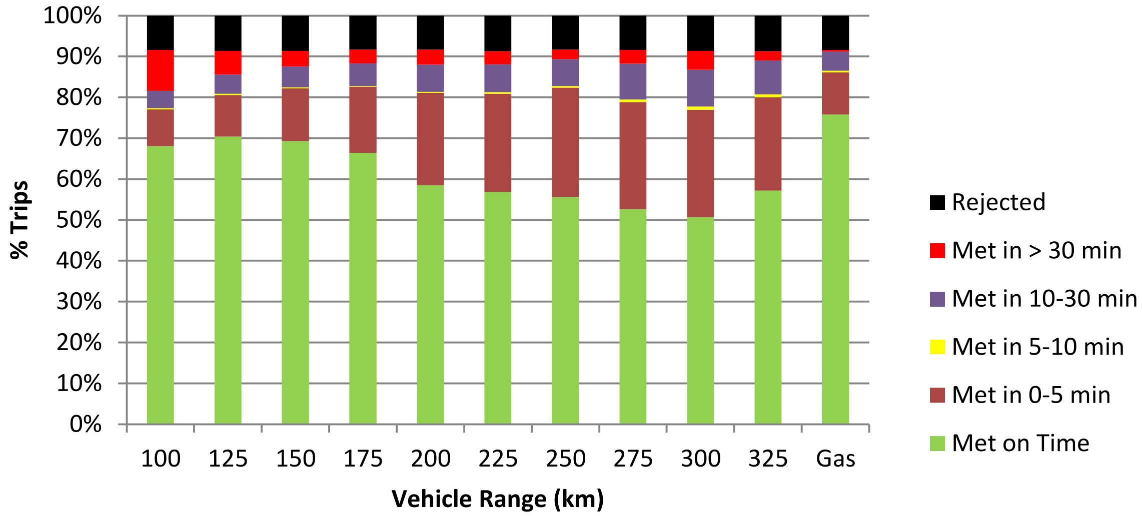
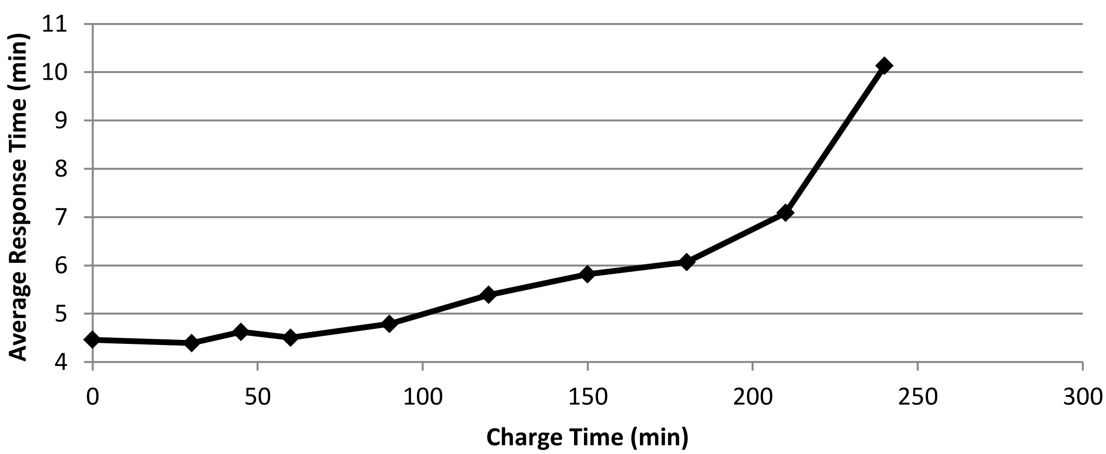


FIGURE 2 Response times relative to vehicle range (assuming 5:1 average vehicle ridership and 240-minute charge times, unless otherwise noted).

Response times were then modeled with respect to charge time (Figure 3) assuming 150 km range, demonstrating that response times are mostly unaffected by charge time until charge times exceed about 90 minutes increasing from 4.78 minutes at 90-minute charge times to 10.12 minutes at 240-minute charge times (Figure 3a). This increase in response times is again heavily weighted by trips more than 30 minutes late (as shown in Figure 3b), which increased from 0.95% to 3.78% for the same scenarios.

(a)



(b)

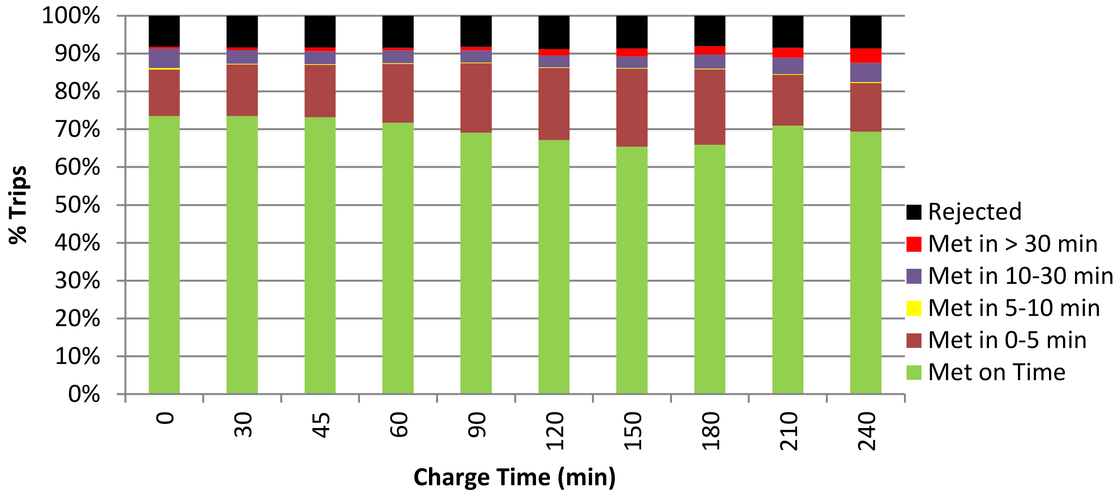


FIGURE 3 Response times with respect to charge times (150 km scenario).

Various fleet sizes were modeled to determine their effect on response times in Figure 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 Figure 5a. The results appear similar, where there is a clear linear relationship up until a "break point" at a ridership rate of 6. Most notably there is nearly 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 array for one of the 100 km range runs was kept fixed for all subsequent runs, and the results are shown in Figure 5b. Somewhat surprisingly, vehicle range does not seem to have an effect response times (at least with 30-minute 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 25.3 minutes, 19.4 minutes, 18.6 minutes and 17.9 minutes for the 325 km, 250 km, 175 km, and 100 km ranges, respectively.

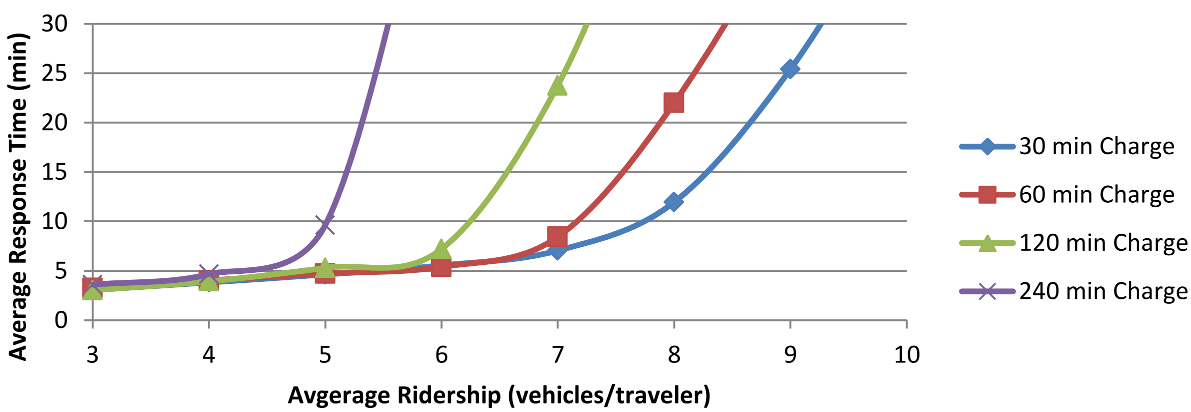
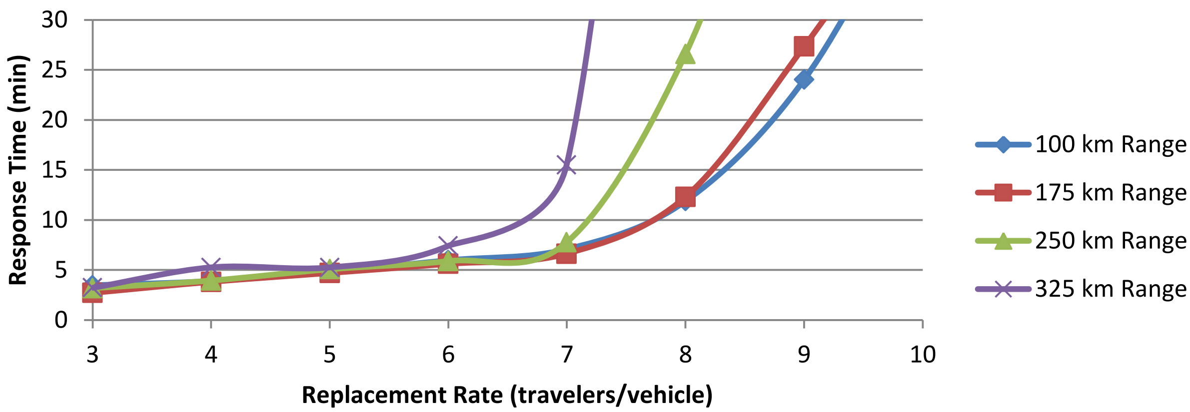


FIGURE 4 Response times with respect to vehicle ridership rates for four charge scenarios.

(a)



(b)

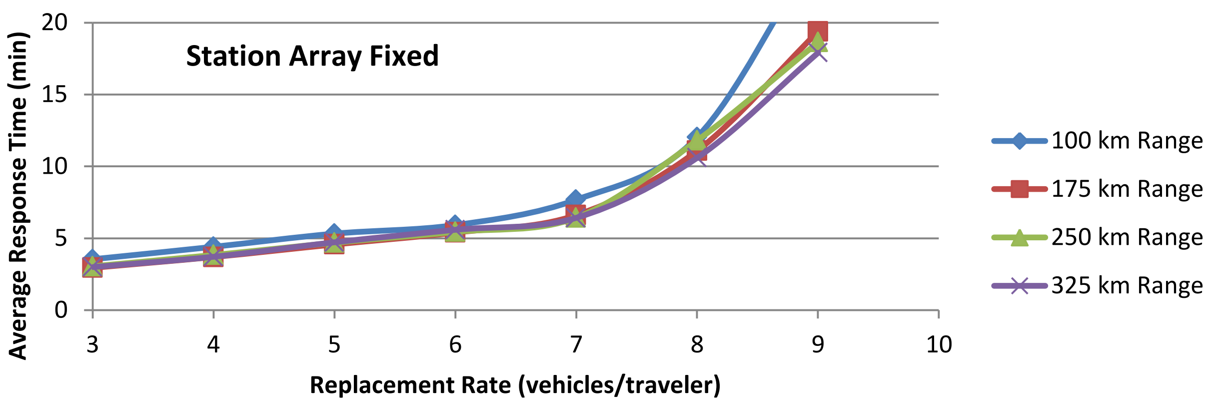


FIGURE 5 Response times relative to vehicle ridership rates for four range scenarios (assuming 30-minute charge times) with station array varied (a) and fixed (b).

Table 2 provides a summary of key results for five major scenarios. Chen et al. (2015) 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. (2015) reduced average wait times was by rejecting trips after a passenger waits for 30 minutes to be picked up.

TABLE 1 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 (mi)	Infinite	62	62	202	202	202

Recharge Time (min)	N/A	240	30	240	30	30
# of Charging Stations	N/A	254	218	5	6	7
Avg. Travelers Served (per vehicle)	5	5	5	5	5	7
Avg. Daily Trips per Vehicle	18.8	18.9	18.9	18.8	19.1	26.8
Avg. Daily Miles per Vehicle	297	328	318	353	331	490
Avg. Wait Time Per Trip (minutes)	3.54	29.8	3.83	7.00	4.95	6.60
% Unoccupied Travel	11.2	18.7	15.3	23.7	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

CONCLUSIONS

The rising popularity of carsharing, 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 SAV was able to serve 91% of travelers within 10 minutes of making their request, with an average response time of 6.6 minutes, assuming 175 km-range vehicles and 30-minute charge times. Under this same scenario, unoccupied travel accounted for 19.8% of VMT, with driving to charging stations accounting for 23.0% of this empty-vehicle mileage. This percentage of empty VMT 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 VMT 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 232 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 to not depend on vehicle range, except when charge times are very long (i.e., 4 hours). 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 not seek vehicles with ranges over 175 km unless the intention is to reduce the number of charging stations.

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-minute charge times, a fleet averaging 10 travelers-per-vehicle resulted in average response times of 44.3 minutes, whereas a fleet with 7 travelers-per-vehicle delivered average response times of just 7.08 minutes. At 3 travelers per vehicle, average response times fell to 3.1 minutes. Reducing charge times also improves response times. For the fleet with 150 km range and 5 travelers per vehicle, a charge time of 4 hours resulted in an average response time of 10.1 minutes, which falls to 4.8 minutes with 90-minute charge times. However, these improvements diminish quickly, since 30-minute charge times deliver an average response time of 4.4 minutes. Therefore, it is not recommended that a fleet manager expend significant resources to achieve charge times less than 90 minutes. Lastly, results suggest that trips originating in the urban center are served best, since every trip within city limits was served in under 30 minutes. 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. Also important will be analyzing the balance of charge times and fleet size with desired response times. A financial analysis of these steps will be useful future work, along with a mode choice model (similar to the one found in Liu et al. [2016]) to determine financial viability of this operation. Fleet performance metrics can also be enhanced by employing a dynamic ridesharing system. Accuracy of these simulations can also be improved by simulating a larger proportion of trips in MATSim (greater than 5%) and by beginning the simulation with a destination choice simulation.

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