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Shared Autonomous Electric Vehicle (SAEV) Operations Across the Austin, Texas Region, with a Focus on Charging Infrastructure Provision and Cost Calculations

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Shared Autonomous Electric Vehicle (SAEV) Operations Across the Austin, Texas Region, with a Focus on Charging Infrastructure Provision and Cost Calculations

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Abstract

Shared Autonomous Electric Vehicle (SAEV) Operations Across the Austin, Texas Region, with a Focus on Charging Infrastructure Provision and Cost Calculations

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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 5,301 square-mile, 6-county region. The simulation works in synch with the agent-based, open-source, simulator MATSim, with SAEVs as a new

mode. Charging stations are placed, as needed, to serve all trips requested over 30 days of initial model runs. This model uses a mixed fleet where one third of the vehicles in use are gasoline hybrid-electric vehicles which serve all trips in excess of 35 miles, to prevent these low-range EVs from being burdened by long trips. Travelers may sometimes share rides, when practical, up to four travelers per vehicle. Hundreds of simulations of distinctive fleet sizes with different ranges and various charge times suggest that the number and location of stations depend almost wholly on vehicle range. Reducing charge times, as well as independently increasing vehicle range, does lower fleet response times (to trip requests). Increasing fleet size improves response times the most. The effects of dynamic ridesharing and the number of charging stations available are also studied here.

The station generation algorithm produced 170 charging stations for a fleet of SAEVs with 60-mile range. A 200-mile range fleet resulted in just 19 stations. When testing a fleet of 200-mile range and 30-minute charge times with the set of 170 charging stations, average response times were low at 6.8 minutes per request. Empty vehicle miles traveled (empty VMT) accounted for 15% of total travel over the course of the simulation day and just 3.7% of this empty VMT was driving to charging stations (or 0.6% of total VMT). It is estimated that this fleet will cost \$0.60 to \$1.09 per passenger-mile assuming a 10 year return on investment for capital costs (e.g. land acquisition and charging facilities). This is compared to a base case of a fully gasoline-powered fleet which can achieve average response times of 6.4 minutes per trip and 9.73% empty VMT for the same sized fleet. A lower-performance fleet, with 60-mile ranges and 240-minute charge times, meets requests with an average response time of 33.1 minutes creating 25.7% empty VMT. 19% of this empty VMT (4.82% of total VMT) is to access charging stations. Cost calculations estimate this fleet would cost between \$0.59 and \$0.97 per passenger-mile to operate. A gasoline fleet is estimated to operate at just \$0.30 to \$0.62

per passenger mile. These savings are thanks to the presence of existing fueling stations that do not need to be maintained by the fleet manager.

For all but very large fleet sizes, DRS showed substantial changes to response times. With a fleet size of 5 travelers per SAEV, response times fell by 32 minutes on average with an average imposed delay of 11 minutes per traveler. DRS also halved empty VMT for a fleet size of 5 travelers per vehicle. Increasing the number of charging stations from 19 to 170 improved response times and empty VMT but for most fleet sizes these improvements were not substantial.

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Chapter 1: Introduction

Motivation

An exciting application of self-driving, automated-vehicle technology is one-way carsharing, similar to services like Car2Go and transportation network companies (TNCs) such as Lyft – but without a driver. Unlike a TNC or taxi fleet with several drivers working largely independently, an autonomous fleet has the advantage of being controlled by an automatic fleet manager, who can assign vehicles to requests in a way that can keep response times as low as possible. Unlike human drivers, autonomous vehicles cannot miss, or ignore trips; they may work unlimited hours and they do not need to return home each night. 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 of 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, 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 with the long term addition of renewable feedstocks to the power grid (Reiter and Kockelman, 2016). Unlike petroleum-fueled vehicles, EVs have the potential to be a zero-carbon transportation option when coupled with zero-carbon electrical generation. For now, EVs are responsible for substantial carbon emissions from upstream electrical production using fossil fuels and are comparable to hybrid vehicles in terms of per-mile carbon emissions (McLaren, 2016). However, as electrical generation becomes cleaner, electrification of the vehicle fleet is a great way to double down on these carbon savings. EVs zero-tailpipe-emissions, even with "dirty" electrical production, will not contribute to local smog and pollution, especially notable in urban cores. As the price of EV technology continues to fall (Nykvist & Nilsson, 2015) and charging facilities become more convenient, EVs will become increasingly financially, as well as environmentally, advantageous over traditional, petroleum-fueled vehicles.

With heavy use of a shared fleet (i.e., over 100 miles per day per vehicle, rather than 20 miles [Fagnant and Kockelman 2015]), vehicle turnover will be faster, leading to quicker adoption of new EV technologies (Martinez, 2015). All-electric, non-hybrid, EVs are, unfortunately, 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 twenty+ times as long as gas station refueling, depending on the power output. Anticipating the number, placement and size of charging stations is also an important prerequisite for an SAEV fleet, since charging stations are rare in most parts of the U.S., 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, compared to a gasoline-powered fleet, should be explored before making this large capital investment, granted such scenarios even exist. Slow charge times and poor battery-capacity have been major barriers for EV adoption by households in the US and elsewhere (Stephens, 2013), but these barriers are steadily falling as charge times under an hour are becoming available in more and more fast-charge locations [see, e.g., https://www.tesla.com/supercharger] (Bullis, 2013). Battery ranges are rising with new vehicles such as Chevrolet Bolt (Chevrolet, 2016) and Tesla Model 3 (Tesla Motors, 2016a) both expected to deliver 200 miles of range for under $40,000. The recent, dramatic, drop in battery prices will also play a big role in EV adoption, now at an estimated $190 per kilowatt-hour (kWh), roughly one fourth what they cost back in 2009 (Voelcker, 2016).

This work simulates what would be a first-to-market, private, SAEV service: there are no identical competing services or available charging infrastructure assumed. This study simulates robust locations around the region for charging station placement, as well as the effects of battery range, charge times, and fleet size on SAEV system performance for the 6-county Capital Area Metropolitan Planning Organization (CAMPO) region surrounding Austin, Texas. The primary metrics for performance are response times, and unoccupied vehicle mileage. 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 created by Bösch et al. (2016), adopting electric charging strategies created by Chen et al. (2016). Both of these works were further improved upon by using a dynamic ridesharing strategy, more realistic vehicle speeds, allowing charging vehicles to respond to requests, using more robust charging strategies, requiring that 100% of demand be met and more. All of these improvements will produce a higher degree of realism and improve the fleet's performance using creative charging and passenger-pickup strategies.

Some of this work (Loeb et al., 2016) is under review for publication in *Transportation Research Part* C with co-authors Kara Kockelman and Jun Liu.

PRIOR RESEARCH

In this section, several prior works related to this paper are summarized. The first three (Chen et al. [2016], Chen and Kockelman [2016] and Bösch et al. [2016]) provide the primary methods and the inspiration for this work. The remaining works are listed in decreasing order of their relevance and/or contributions to this paper. Additional literature review can be found in the appendix.

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 mile × 100 mile homogenous grid with quarter-mile spacing, where each grid cell had different population densities depending on their distance from the network's center. Cells within 2.5, 7.5 and 15 miles were considered downtown, urban, and suburban respectively. Cells not falling within these circles were considered exurban. Every scenario they tested produces 7%-14% empty VMT, though VMT produced by recharging trips are negligible. 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 and a 160-mile effective vehicle range and costs comparable to that of a gasoline-powered fleet with just 6.6% more vehicles. Their systems were estimated to be cheaper than a gasoline fleet with fuel prices as low as $2.50 per gallon assuming $45,000 purchase price for a long-range SAEV, $405 per kWh for replacement batteries assuming the battery will be replaced once in the life of each 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). This led to costs of 43 to 48 cents per passenger-mile or 66 to 74 cents per mile after considering general administration (back office) costs. They assumed no land acquisition costs, or any costs associated with paving, station lighting, etc. To conduct this study, a 2-phase "warm start" began the simulation. The first phase generated charging stations using an oversized fleet. The demand was simulated and a new station was spawned whenever a vehicle needed a charging station but one is not in range. Phase 2, SAEV fleet generation, took place over 20 simulation days using the proposed charging stations from phase 1. A vehicle was spawned whenever a traveler's demand was not met within 10 minutes, and the average number of SAEVs from the twenty days was taken to be the needed fleet size. The model runs scenarios assuming short range and long range EVs (80 or 200 miles) as well as fast charging versus regular charging (4 hours and 30 minutes respectively). Fast charging was assumed to reduce usable range by 20%.

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 by 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; however, automated chargers are important so as not to require 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 a more complex charging strategy (e.g. vehicles may leave charging stations as needed before being fully charged), more realistic charging rates, travel times and congestion are modeled more realistically, the vehicle search algorithm is more advanced and tuned, ridesharing is implemented, far more scenarios were tested, and cost estimates are more thorough.

In order to simulate SAV operations in Zurich, Bösch et al. (2016) created a 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. The simulation takes the MATSim output and will consider a certain number of trips taken as SAV requests, depending on the settings. A registered SAV request will be assigned a nearby SAV which will then travel to the passenger's location. Once the vehicle and passenger are both ready, they will transport to the trip end location. The arrival time is calculated using corrected beeline distances and average speeds found from in the MATSim output. It was found that for low levels of demand, the required fleet is dependent on the number of requested trips. 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). Their study is somewhat limited since traffic assignment is performed prior to SAV simulation. This makes dynamic ride-sharing, as well as vehicle relocation, difficult to represent. Even without these features found in many other models, results still showed improvement over current conditions. Bösch et al.'s (2016) program is a major contribution to this thesis' work, along with Nagel's (2016) MATSim code. By simulating the CAMPO region in MATSim first, 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 6-county Austin region.

Some past studies have been too optimistic in their predictions of response times and replacement rates (the average number of conventional vehicles that can be replaced by each SAV) due to limitations on service area size and person-trip distances. 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 to 11 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 mile × 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-VMT falls with greater spatial intensity of trip-making (thanks to more efficient use of SAVs and more opportunities for DRS).

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 (109 mi), 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). A private taxi fleet needs more vehicles to keep up with a shared taxi fleet and requires considerably more repositioning trips. 18% and 26% more shared taxis and private taxis, respectively, are needed when there is no high capacity public transit. With only 50% penetration/user adoption of SAVs, total vehicle-miles were 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. One policy concern is labor issues involving taxi companies; however, Martínez notes that taxi companies can step up and take an active role in bring SAVs to market. This new, agent-based model, developed for this study was set in Lisbon Metropolitan Area because it is a fairly typical European city/region, in terms of GDP per capita. Lisbon also has a well established subway system which helps to study SAVs interactions with heavy rail transit. Lisbon generates over 5,000,000 person trips per day, 55% of which are commutes to work or school and 1.2 million take place within Lisbon which are the focus of this study. Lisbon has relatively low car ownership at 21.7% and low daily travel at 1.9 trips per person. There are over 60,000 cars, 400 buses and 2,000 taxis circulating simultaneously during peak periods in Lisbon making 60 vehicles per road-kilometer and an estimated 160,000 cars parked simultaneously, a utilization rate of 78%. In Lisbon, 60% of trips are taken by private car which drops to 40% in the city center, where 20% of trips are taken by walking or some other non-motorized mode. A population was synthesized using Lisbon travel survey to generate trips within the city that are allocated at the census block level and timed for a synthetic weekday. Each trip was characterized by its departure time, origin-destination pair, trip purpose and traveler's age. For all modes, access time, waiting time and number of transfers were all considered. Trips were assigned non-motorized mode when less than

1 km (0.6 mi) long, or assigned to the subway when a station is nearby; the rest were assigned to an SAV. Buses were eliminated from the network since the average bus occupancy is only 20% in the base case. When an agent requests a ride, the dispatcher will find the best SAV and have it pick up the passenger. Ridesharing is allowed when an increase of no more than 20% of trip time or trip distance is imposed, capped at 10 minutes and 2 km. SAVs may have a capacity of 2, 5 or 8 passengers. When a vehicle is empty and unassigned, it will park and wait. The scenarios studied are the presence of ridesharing, availability of the subway system, penetration rate (50% or 100%) and time period. The share of mass transit actually increased from the base case when it is available, likely because in real life, walking trips longer than 1 km are fairly common. In addition to the results found above, the simulations show that travel time increases under ridesharing are of little concern. In the peak hours, ridesharing can be achieved more easily because of the high demand. Party size elasticity is 1.07, meaning for each 1% increase in overall demand, party size increases 1.07%. 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. They estimated private-vehicle replacements to be as high as 10 to 1, and as little as 0.9 to 1.0.

Zhang et al.'s (2015) SAV with DRS simulations on a synthetic network predicted a 14:1 vehicle replacement. They also acknowledged the possibility of charging but only predict two 2-hour intervals every 3 days in which charging can take place, which certainly isn't feasible. After considering all costs, trip costs can be reduced by 62.5% over a vehicle-ownership model. Like Fagnant and Kockelman (2016), 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 with low available-vehicle density (relative to expected near-term demands). Each SAV in the system was able to serve one or two vehicle-trips at a time with trip profiles matching the 2009 NHTS in a 10×10 mile grid with one minute timesteps. Similar to in Chen et al., household density was high (4,000 households/mi^2) near the urban core, but drops discretely at more than 10 miles from the center (1,500 households/mi^2) in the corners of the study area. The area was split into grid cells 0.05 miles across. Each household in the study area made approximately 5.66 trips per day and departure times and trip lengths were assigned randomly using the data supplied by the 2009 NHTS. Destinations were based on origin and trip length. To begin the simulation, the fleet was comprised of 500 randomly distributed vehicles. The size of the fleet was increased in increments of 50 vehicles until the reduction in average waiting time was less than 30 seconds for all travelers. The study found 700 vehicles were adequate. Travel speeds were fixed at 30 mph for peak times and 21 mph off-peak. There are criteria that must be met in order for two travelers to share a ride. Travelers must both be willing to share a ride, the cost induced delay must be less than the savings in travel costs for all parties and a detour cannot be made to pick up a new client. Delay cost was estimated using randomly assigned hourly salary rates based on the density function of the 2014 US Census. Results show that only 6.7% of trips participated in ridesharing; however probability of ridesharing was larger when the vehicle-trip is quite long or when the client's salary is lower. Ridesharing was able to reduce average delay from 4.24 minutes to 2.66 minutes during peak times and average detour time was only 0.82 minutes for these trips. Ridesharing reduced VMT by 4.74% but still increases trip lengths by 11% with 0.6 empty VMT per trip, on average. Counter-intuitively, cold starts increased by 6.82% when ridesharing is considered, however this is still 98% fewer cold starts than without an SAV fleet (this assumes these vehicles are able to run 24/7 for extended periods of time). The 700-vehicle fleet was able to replace 9858 conventional vehicles indicating a 14:1 replacement rate, also reducing parking by 92.5%. It is noted that the parking demand could be reduced further by the fact that parked SAVs do not need space to open doors. While DRS tends not to improve passenger experience, it will decrease VMT and thereby reduce congestion.

Atasoy et al. (2015) simulated a conventional taxi-type system wherein passengers select which type of taxi or TNC service they prefer, based on real-time pricing and wait times (as provided by the fleet manager). Passengers could choose from private taxi, shared taxi or minibus. Results showed that a welfare optimizing strategy gives the best results for users, providing request processing times of 1.5-2.5 seconds per user. The vehicle fleet was dynamically allocated, meaning vehicles can take on any one of the three roles as needed. When a passenger requests a trip, (through smart phone or some similar device) the fleet manager determines a choice set for the traveler with quoted prices, arrival time and departure time. A logit system calibrated using constants from Koppelman and Bhat (2006) will then allow the passenger to choose the best option for their needs which may include rejecting all options. The options may lie within or outside of the user's intended arrival window; however, undesirable arrivals are penalized in the logit model, where late arrivals are more heavily penalized than early arrivals. The model is optimized, separately, over vehicle allocation decisions for profit maximization, consumer surplus maximization and multi-objective optimization (social benefit). Profit maximization leads to low passenger satisfaction. The social benefit case is solved using an exhaustive search mechanism. The framework is implemented in C++ and R with a 24-hour time horizon. 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, were ignored. Demand was assumed as 1% of the trips or 5,000 ride requests randomly generated taking into account appropriate daily demand fluctuations and population densities. OD pairs less than 500 meters (0.3 mi) apart were not considered. Costs to operate this fleet are assumed at $200/day plus $0.20/km. For the first scenario tested, taxis cost $5 plus $0.50 per mile, shared taxies were 50% of the taxi fare and bus was $3. Alternative specific constants were $1 for bus and $3 for taxi. For the second scenario, Taxi prices were raised to $6 plus $0.60/mile, shared taxi was 60% of the taxi fare, and the bus was $5. Similarly, the ASC was changed to $8 for bus and shared taxi and $10 for private taxi. The authors tested these 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. This study includes a ridesharing model that is somewhat unique. Ridesharing follows three restraints: passenger loading and unloading is first in-first out (FIFO), ridesharing itineraries are developed to minimize travel times and lastly, if several co-passengers are possible for a vehicle, the passenger whose trip has the closest start time is chosen. For all trips, occupancy is limited to four passengers, boarding and alighting take 2 and 1 minute respectively, and intrazonal trips are proportional to the square root of the zones area. The area of study, the Stockholm network, consists of 421 demand zones, 11,000 links and covers 40 km × 40 km (25 mi × 25 mi). Link speed limits, as well signal timings, are known and travel speed on a link is fixed at 75% of the respective speed limit. A full simulation day consists of 498,732 trips over 132,976 OD pairs where only internal trips are studied. This demand was fit to morning and afternoon peaks using toll data and a Gaussian distribution. Total mileage is 2,606,000 km (1,619,000 mi) with an average trip length of 10 km (6 mi) and 30 min. The maximum allowed detour to rideshare was given several different values which showed it is unlikely that increasing the allowed detour beyond 50% would provide additional gains. This simulation models VMT as more elastic to ridesharing than most studies. 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.

Chapter 2: Methods

This study uses three major steps to simulate SAV operations across Austin, Texas: tour generation, traffic assignment, and SAV simulation. SAV simulation is the primary study and is performed through the following processes: charging station generation, vehicle charging rules, vehicle assignment and dynamic ridesharing.

Tour Generation

The travel data to generate tours 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 a sample of residents of the 6-county region (Burnet, Bastrop, Caldwell, Hays, Williamson and Travis counties). As described in Liu et al. (2016), a 20% 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 are assumed to make no trips on the given travel day, and 22.6% of 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 seeks to optimize individuals' trip patterns in order to approach a network-wide user equilibrium. This is done through a co-evolutionary process of scoring competing travel plans, for each traveler, across desired activity sets. MATSim has a five step iterative process: loading of initial demand, mobility simulation, scoring, replanning and analyses. After each replanning phase, the mobility simulation and scoring are performed again, and this cycle is repeated for several iterations, approaching network-wide user equilibrium. Then analyses of the final iteration may take place.

In the first step, the initial demand is loaded into the program. This is in the form of the tours created by Liu et al. mentioned above. MATSim requires that each traveler has a set of plans with desired end times and desired mode choices. Some activities that travelers may carry out include work, shopping and home. Next, the mobility simulation dynamically loads the provided network, delivering real-time travel time estimates and congestion using a queue model. MATSim's time-step is just one second, so trip departures are scheduled nearly continuously over a 24-hour day plus an additional 6 hours to make sure every tour is completed since tours are not permitted to start mid-way (at 3 am each morning, when the 24-hour day begins). (Note that MATSim developers are experimenting with 72+ hour simulations for more complete results) The first network loading of the simulation will carry out plans just as they appear in the initial demand. After the 1-day simulation is complete, each agent's plan for that day receives a score. Agents receive positive scores for on-time departures and on-time arrivals; likewise their scores will decrease for late or early, departures and arrivals. The agents remember their plans and respective scores, and will store their five highest scoring plans, always rejecting the lowest scoring plan after five have been saved. At the end of each simulation-day (iteration), MATSim creates an event-file containing a list of trips for each agent that can then be used for requests on the SAEV simulation, as described later on.

After scoring, MATSim will randomly select a subset of travelers to attempt to improve each of these traveler's routes, modes, when flexible, and departure time selections, as feasible. Travelers may only replan a mode choice for a sub-tour (e.g. making a shopping trip on one's lunch break).

Then the network is loaded again to simulate another full day and scoring and replanning phases occur once more. After more than one plan has been executed, agents may choose from one of their saved plans as part of the replanning process and the score for that plan is reevaluated. MATSim is unique in that it is a co-evolutionary process meaning each traveler chooses plans independently of other travelers' choices. This mimics real life travel decisions where individuals largely make decisions based on their personal perception and experiences, unlike typical DTA algorithms, which shift travelers in large groups. Replanning is not done through a rigorous procedure; instead it is a randomized trial-and-error process. While this may not seem optimal, empirical studies have shown that this method will converge to a dynamic user-equilibrium over many iterations.

The network used for this study is derived from OpenStreetMap, which contains highly detailed network information for the Austin 6-county region.

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 Zurich. 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.

Their model simulates an SAV fleet which behaves very much like a TNC (e.g. Uber, Lyft, and Fasten) or taxi service where travelers make a request when they wish to travel, and they are picked up by a vehicle and taken to their desired destination. Unlike a TNC or taxi fleet with several drivers working largely independently, an autonomous fleet has the advantage of being controlled by an automatic fleet manager who can assign vehicles to requests in a way that can keep response times as low as possible. Unlike human drivers, autonomous vehicles cannot miss, ignore or reject trips; they may work unlimited hours and they do not need to return home each night.

The trip file outputted by MATSim is loaded into the SAV code to represent demand. The trip file is taken from a late MATSim iteration (10 works well), so these trips are close to a user equilibrium. One weakness of MATSim is evident here in that no convergence criteria given by the software. Future works should use many more iterations to verify the number of iterations needed to reach stable results given adequate time and computing power. The trip file contains the origin and destination of each trip as well as the respective travel times. From these trip files, a random sample of travelers/agents is assumed to use SAVs throughout the day rather than their original modes. Their departure times, as given in the trip file, are taken to be their desired departure time, rather than actual departure time. In their code, it is assumed that every traveler will make a request 5 minutes before their desired departure time. Once the request is registered, the program searches for a vehicle that can reach the agent within 5 minutes of the scheduled departure time (or within 10 minutes of the trip request). The vehicle search is repeated every timestep (i.e., every second) until a suitable vehicle is found; 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 request is dropped and the trip is left un-served. Once an SAV has received an assignment, it drives to the traveler. If the vehicle arrives before the scheduled departure time, it waits for the traveler; otherwise, the traveler boards immediately and heads to their destination.

There are two different types of vehicle speeds that must be modeled in this simulation. Travel time transporting SAV users to their destinations is taken directly from the MATSim event-file and is derived using the DTA algorithm described in the traffic assignment section. Empty-vehicle movement, however, was not modeled in the upstream traffic assignment, so empty SAV travel time must be estimated another way: using average network speed and a Euclidian distance correction factor. Bösch et al. had a separate program to find the average ratio of every trip's actual driving distance to its Euclidean (or "beeline") distance between its origin-destination pair. The SAV code can easily find Euclidean distance between any two locations, so this correction factor gives an estimate as to the actual driving distance between any two points on the network. Bösch et al. used another code to find the average driving speed of every trip on the network as fond in the event-file. The travel time estimated for any empty vehicle is then:

$$(travel\ time) =$$

$$(Euclidian\ distance) \times (correction\ factor) \times (average\ network\ speed) \quad (1)$$

After an SAV drops off its user, it remains at that location until it receives a new assignment. The issue with the travel time given in the trip file is that it is the travel time of the trip departing at the exact time that the traveler makes the request. Given some finite response time, the network conditions will change slightly (or a lot if the pickup is quite late) by the time the vehicle arrives to pick up the passenger. Empty travel speeds is, of course, an even rougher estimate.

CODE MODIFICATIONS TO SIMULATE SAEVS

This code was very attractive for a lot of reasons: it is highly versatile to different data sets, it runs quickly, provides a lot of useful data and is totally open-source. There were, however, a lot of functionalities needed for this study, not available in the code. There were also a few ways in which the code's realism could be improved. The main contribution of this work is the extensive modifications and adaptations of this code.

The first major modification is the simulation of electric vehicles. The original code does not consider the impacts of vehicle range; therefore refueling times and fuel station locations are ignored. This is a reasonable estimate for gasoline-powered fleets, which may be able to serve trips all day on a single fill-up, and refueling times are relatively brief. 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 SAEVs' ability to serve trips throughout the day. The location and number of charging stations also affect the amount of time SAEVs will spend driving to and from them. Adapting this code for EVs involved the tracking of vehicle range, recharging strategies, and placement of charging stations (described below).

The next most important issue is empty traveling speed. Instead of using a single average speed for the whole day, the program will check the event file at every timestep to determine the average speed at that time. The empty speed is then temporally updated in the simulation for every timestep. This is still limited in that empty vehicle travel is identical across the entire network for every road type; however, peak time slow-downs and off-peak free flow speeds are now simulated more realistically.

Another concern is that the code will reject trip requests after a ten-minute, unsuccessful search for a vehicle. This was updated to exclude trip requests exceeding a certain distance, and keeping the remaining requests open until they are met. The trips that were rejected are instead serviced by a hybrid-electric (HEV) fleet, with no range limitation. From an implementation standpoint, this is more user-friendly: customers can know ahead of time if their trip is serviceable by an EV based on its length, rather than be rejected after waiting several minutes. This is especially important to any captive users who may not have had an opportunity to arrange an alternate mode. Wait times are closely correlated to trip length because the probability of finding a vehicle with adequate range goes down as trip length goes up. Therefore setting a cap on trip length is an effective measure to keep wait times reasonable.

A more subtle change is a modification to the search algorithm. The code looked for vehicles that could meet each request within 5 minutes of the desired departure time. This means as the 5 minute deadline approached, the search radius decreased until finally reaching zero, and consequently, the probability of finding a suitable vehicle would decrease as time went on. This was modified to maintain a fixed search radius for a certain period of time. After that period had passed, the code will simply assign the closest possible vehicle, regardless of how far away it is. Tuning these parameters showed that maintaining a 10 second search radius for 9 seconds gave the best response times.

One of the most advanced modifications to the code was the introduction of dynamic ridesharing, or DRS. DRS was implemented to decrease customer wait times, reduce empty travel and decrease vehicle idle time. This is demonstrated to be effective in many simulations including Fagnant & Kockelman (2016), Zhang et al. (2015), Atasoy et al. (2015), Burghout et al. (2015), Martínez (2015), and many more not reviewed here. The dynamic ridesharing algorithm is discussed in detail below.

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

The first step to adapt the code for EVs is to develop a set of charging stations on the network. The stations are generated in mostly the same technique developed by Chen et al. (2015). This is done by first assuming a large/oversized (1 vehicle for every 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. Loeb et al. (2016) determined that extending the station generation phase longer than 30 days had little to no effect on the number of stations generated. 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 visit per hour (after scaling for sample size) are removed due to inactivity. The vehicle fleet is then randomized again and the simulation is given a final run where no new stations can be formed. The flow diagram for the station generation phase can be seen in Figure 2.1 below. This algorithm provides no guarantees of optimality for station locations; however, it does serve to minimize the number of stations given vehicle parameters.

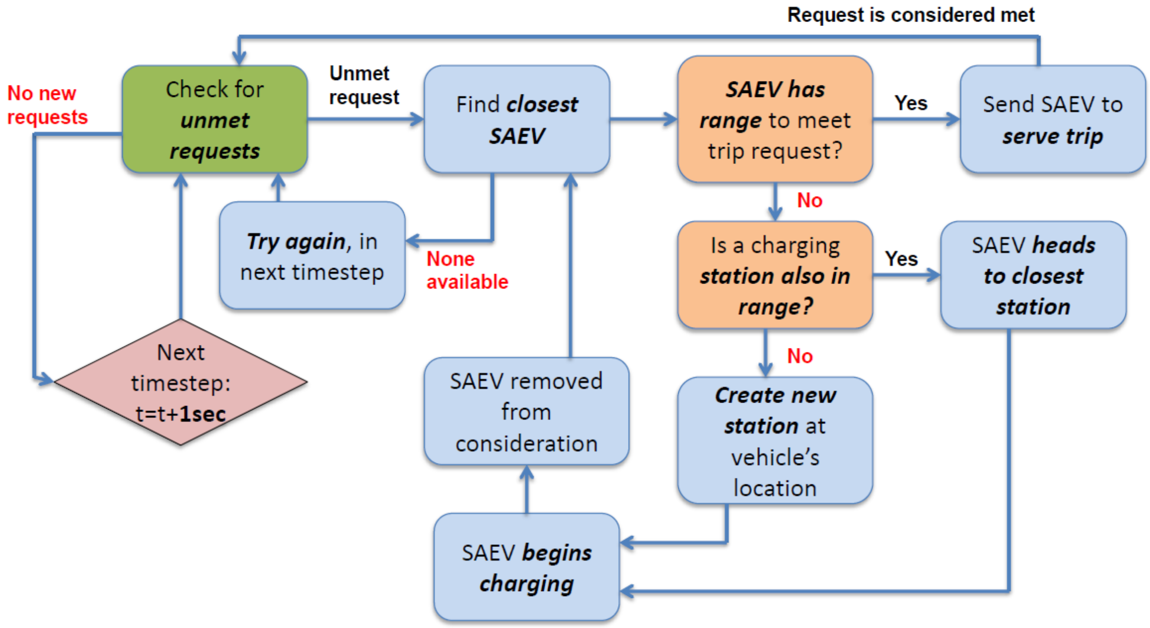

Figure 2.1: Charging Station generation phase flow diagram (this diagram does not show the entire simulation process, but demonstrates how a charging station may be generated.)

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 two conditions under which a vehicle may be assigned to a charging station. First, in every 1-second simulator timestep, SAEVs with a range below 5% of their battery's capacity will be 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 (2016b). This implies two different charging rates:

For remaining range under 80%: $$Rate_{fast} = \frac{0.8Range}{0.5T_{full}} \quad (2)$$

For remaining range above 80%: $$Rate_{slow} = \frac{0.2Range}{0.5T_{full}} \quad (3)$$

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). Long term depreciations in battery range as a result of repeated charges are not studied here. A charging vehicle will cease charging when it has reached a full charge, but will not leave unless assigned to a request. Charging stations should, in theory, be able to operate without any 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.

VEHICLE ASSIGNMENT

When a request is received in the program, it is assigned a vehicle in a way that seeks to reduce the traveler's waiting time. The first step in this process is to define a search radius. This is the area surrounding the traveler inside of which any SAEV is able to reach the passengers within a specified timeframe. If no SAEV lies within the search radius, the request is ignored and will be reevaluated the next timestep. Since this code does not track vehicles on true roads, vehicles just passing through the search radius cannot be evaluated since their exact locations at a given timestep are not known. After several timesteps, the search radius is made infinitely large such that all SAEVs on the network are candidates to service the request. For the results found in this work, a search radius of 10 seconds was maintained for 9 seconds before opening up the radius to the whole network.

When an SAEV is found inside the search radius, it may or may not be eligible to respond to the request. There are several criteria that must be met: 1) The vehicle must have enough range to pick up the passenger, take the passenger to the destination and finally make it a nearby charging station; 2) the vehicle must be the closest eligible SAEV within the search radius; 3) if the vehicle is charging, there must not be any eligible vehicles in the search radius that are not charging; 4) if there are passengers in the SAEV already, the new traveler may not impose a delay of more than 30% on any passenger's original trip time, and there must be 4 or fewer passenger on board at any given time.

This introduces some improvements over both Chen et al. (2016) and Bösch et al. (2016), the most important being the introduction of ridesharing, offered by neither of these works. The DRS capabilities are described in detail below. Also, Chen et al.'s (2016) SAEV simulations does not allow charging vehicles to undocked and fulfill a service request. By allowing this capability, SAEVs do not have to sit idly at charging stations when they are eligible to meet requests. This is also advantageous because batteries charge more slowly as they reach capacity shown in the SAEV charging rules section above; now vehicles only have to sit through these slower charge times if they have no other more productive assignment. Bösch et al. (2016) was limited in their search algorithm by ignoring vehicles already transporting passengers. Besides making DRS impossible, this also excludes from consideration vehicles that are about to be close to a requesting traveler when dropping off another passenger nearby.

DYNAMIC RIDESHARING

Because traffic assignment is performed upstream of the SAEV code, dynamic ridesharing capabilities are somewhat limited. This is because, geographically, only the end points of each vehicle-trip are known, and the SAEV will "teleport" between them. Therefore once an SAEV is headed for a destination, it may not change course before its intended arrival time. The only thing this means for ridesharing is that an SAEV may accept a ride request while carrying a passenger, but it may not change course until it arrives at its intended destination. The way this is dealt with in the code is using a last-in-first-out (LIFO) pattern for pickups and drop-offs. The reasoning may be best demonstrated with an example, shown in Figure 2.2. Suppose a traveler, *traveler A* located at *origin A* on 51st Street, requests a ride downtown to *Destination A* at 09:55. The code determines that the SAEV in the upper right is the closest eligible vehicle and assigns it to *traveler A* and the vehicle's arrive time to *Origin A* is determined to be 10:00. At 09:57, while en-route, the vehicle receives a request from *traveler B*, in Hyde Park headed to South Austin. The vehicle accepts this request, and continues on to pick up traveler A and the vehicle's arrival time at *Origin B* is determined to be 10:06. *traveler A* boards the vehicle at 10:00 and they continue to *Origin B*, but again, on the way, at 10:04, the vehicle receives a request from *traveler C* in West Campus headed to East

Riverside, near *origin B*. This trip is also accepted. The vehicle continues to pick up *traveler B*, and then picks up *traveler C* without interruption. At this point, it might be intuitive to drop off *traveler A* first. Unfortunately, travel times between *Origin C* and *Destination A* are not in the MATSim trip file, and so must be estimated. On the other hand, the trip between *Origin C* and *Destination C* <u>are</u> in the trip file, so that travel time is well estimated through traffic assignment. Therefore in order to preserve the highest degree of realism, the last traveler picked up must be the first to be dropped off. This may appear to be unfair, but the algorithm enforces the rule that no traveler may experience a delay greater than 30% to their in-vehicle travel time (IVTT). For example, suppose that *traveler A*'s initial travel time, given in the MATSim trip file, is 30 minutes. This means that that maximum allowable IVTT for *traveler A* is 39 minutes. When the vehicle received the request from *traveler B*, the code calculated a travel time of 33 minutes, traveling from *Origin A* to *Origin B* to *Destination B* to *Destination A*. Then when receiving the request from *traveler C*, the code verified that the travel time from *Origin A* to *Origin B* to *Origin C* to *Destination C* to *Destination B* to *Destination A* was 38 minutes. This is less than 39 minutes so *traveler C* imposes an acceptable delay on *traveler A*. Likewise, it is verified that *traveler C* imposes an acceptable delay on *traveler B*. For every one of these requests, the four rules from the Vehicle Assignment section still apply and no more than four travelers may share a vehicle. This FILO method of ridesharing is definitely not optimal so a more advanced routing mechanism could improve response times further. Also, the imposed delay estimates are calculated using instantaneous (not predictive) travel time estimates, so it is possible for a traveler to experience a delay greater than 30% if network conditions worsen while picking up fellow passengers.

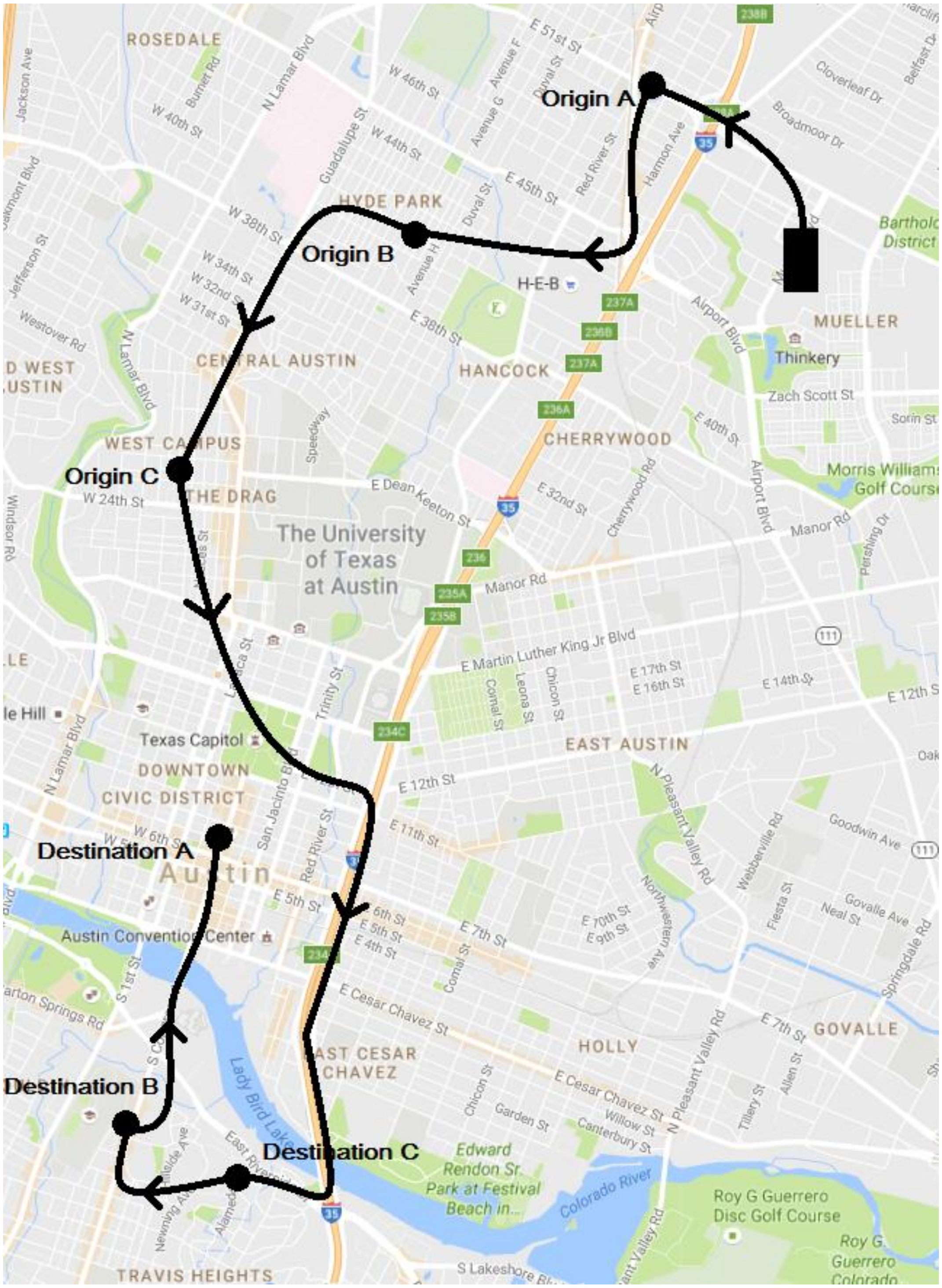

Figure 2.2: Example of a possible ridesharing route in Austin

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 of average ridership per vehicle, or the average number of travelers served per SAEV. These average ridership rates were varied from 4:1 to 8:1 in increments of 1.

The share of travelers assumed to use an SAEV is fixed at 0.5% of the network's demand. This is out of the 20% trip sample of total network demand. In other words 0.1% of the region's travelers or total person-trip-making is simulated in each scenario, in order to keep computation times on the order of hours, to make testing the hundreds of scenarios here a reality. Charging time requirements were varied from 30 minutes through 240 minutes, across scenarios simulated. Battery ranges varied from 60 miles to 200 miles, in 20-mile increments. Unless otherwise noted in the discussion of results (below), the standard or base scenario's range is assumed to be 200 miles with a complete charging time of 30 minutes, and average ridership of 5 travelers or 5 trip-makers per SAEV (Table 3.1). (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.)

EVs have a fairly limited range, so meeting longer trips will usually take many iterations, slowing computation time and yielding poor results. To mitigate this issue, one third of the fleet is considered to be Hybrid-electric vehicles (HEV) and is dedicated to meeting trips greater than or equal to 35 miles. The electric fleet is free to quickly meet the shorter trips that it is better suited for. The HEVs are powered by gasoline, so their refuel times are effectively negligible over the course of a 24-hour day. This means they are able to efficiently serve these long trips without first checking their range. Without this hybridized fleet, meeting 100% of trip requests on the network is practically infeasible.

Chapter 3: Results

This section presents the data found from various simulations along with discussion of those results. Many different parameters underwent sensitivity analysis. When a parameter is not the focus of a certain result it will take the default parameter given in Table 3.1, unless otherwise noted.

Parameter	Default Value
Vehicle range	200 miles
Fleet size	5 travelers per vehicle
Charge Time	30 minutes
Mode Split	0.5% travelers (choosing to use SAEVS as oppose to another mode)

Table 3.1: Default values to assume for given parameters unless otherwise specified in text

STATION GENERATION

A set of charging stations was the first input needed for the rest of the simulations. Loeb et al. (2016) noted that the number, and location, of stations depend almost entirely on vehicle range. Some changes were made to the algorithm, but it is still largely similar. With this reasoning, stations were generated over a set of different vehicle ranges, (60 miles to 200 miles in 20-mile increments) for two different charging speed scenarios (30 minutes and 240 minutes). The 30-day station generation phase was run at least three times for each range and charge time scenario. Some were given as many as six trial runs if there was significant variation in the number of stations produced or there were outlier data. The number of stations generated under each scenario was averaged to get the results found in Figure 3.1. The fleet was oversized at 1 vehicle per traveler and mode split was reduced to 0.25% to reduce run times over this very long simulation.

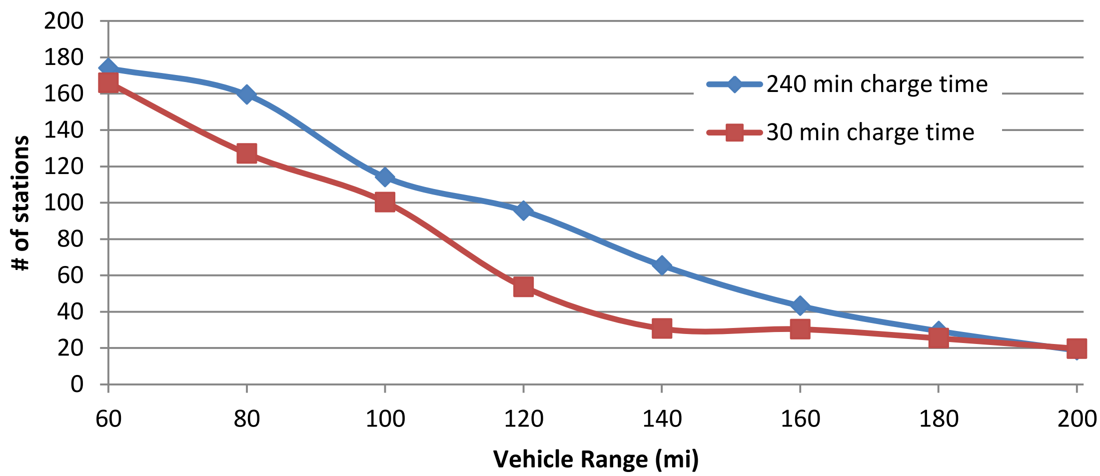

Figure 3.1: Average number of charging stations generated for both fast-charging and slow-charging scenarios across different vehicle ranges

Figure 3.1 shows that, as expected, the number of stations generated depends primarily upon vehicle range and much less on charge times. While the 30-minute charge time shows generally fewer stations, the difference in outcomes is not very consistent or terribly significant considering a factor of four reduction in charge times. For slow-charging vehicles, the number of stations fell almost linearly from 174 stations with 60-mile range to 19 stations at a 200-mile range. For the fast-charging scenario, the number of stations fell from 166 at a 200-mile range to about 20 for a 60-mile range. Some of the scenarios in the following section compare how the SAEV fleet performs with a relatively large number of stations compared to fewer. For these two different sets of stations, the large list of stations comes from the 60-mile scenario and the smaller list comes from the 200-miles scenario. From the three trials run for each vehicle-range scenario, the sets of stations chosen for further runs were selected for being the most representative (the closest to the average for each respective range) and are shown in figures 3.2 and 3.3. Both come from the 240-minute scenario containing 170 and 19 stations respectively.

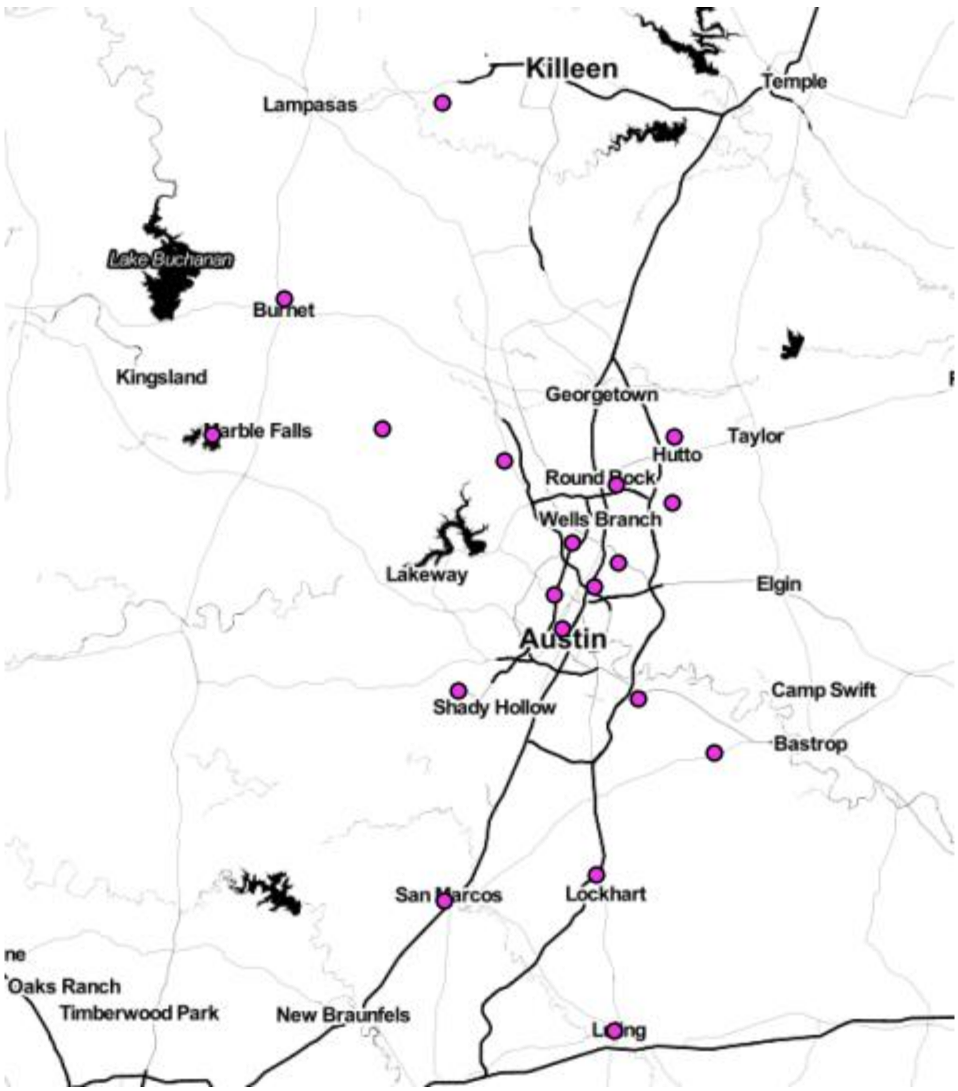

Figure 3.2: Stations developed under 200-mile vehicle range

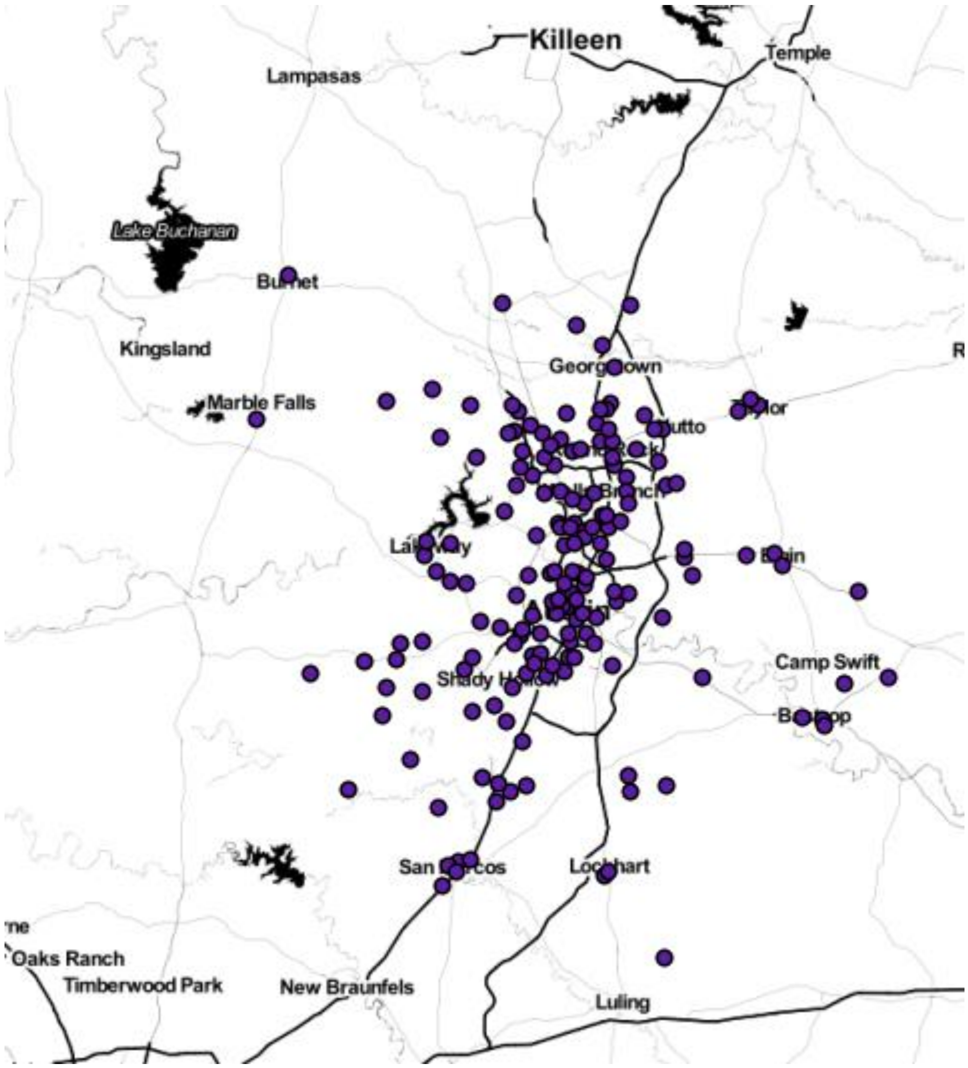

Figure 3.3: Stations developed under 60-mile vehicle range

In Figure 3.3 (the larger number of stations), stations tend to be grouped closer to the Austin urban core, as expected since the highest population density, and hence trip density, lies there. In Figure 3.2 (the smaller number of stations), stations outside of Austin tend to fall right in the center of the surrounding towns, where one might typically expect to find fuel stations. From these diagrams, a visual inspection indicates that nothing is out of the ordinary, and these station placements seem quite reasonable.

EMPTY VMT AND RESPONSE TIME

The primary metrics of performance in these simulations are response times (how long the traveler must wait before picked up) and empty VMT (how much the SAEVs drive around unoccupied). A summary of key results for five major scenarios can be found in Table 3.2, below:

Scenario	Gasoline 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	60	60	200	200	200
Recharge Time (min)	N/A	240	30	240	30	30
# of Charging Stations	N/A	170	170	170	170	170
Avg. Ridership (travelers/vehicle)	5	5	5	5	5	7
Avg. Daily miles per Vehicle	411	288	423	394	349	573
Avg. Daily Trips per Vehicle	20.5	25.5	25.5	25.5	25.5	35.8
Avg. Response Time Per Trip (min)	6.4	33.1	19.1	20.1	6.8	40.4
% Unoccupied Travel	9.73	25.7	30.3	25.8	15.28	30.3
% Travel for Charging	N/A	4.82	8.54	3.29	0.56	4.24
Max % Concurrently Charging Vehicles	N/A	73.5	95.8	79.2	16.5	72.3

Table 3.2: Key findings from 5 simulation scenarios including a gasoline-powered base-case

Many of the response times seen in Table 3.2 may appear far too long for most travelers to tolerate. It is important to find what types of scenarios may yield a feasible SAEV fleet, so several sensitivity analyses were performed to determine the effects of various parameters on fleet performance. The results presented here will not include the statistics from the HEV fleet unless noted otherwise.

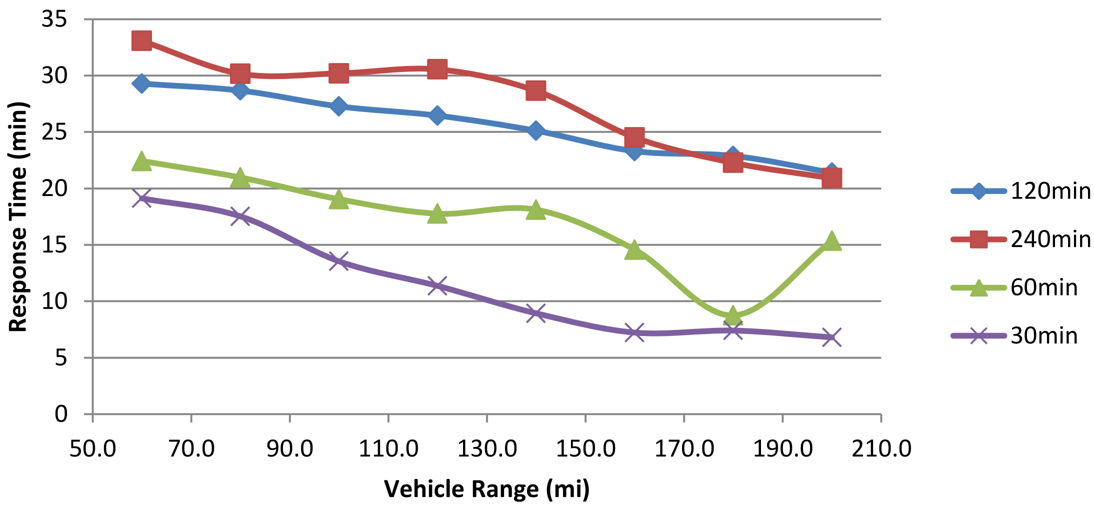

Figure 3.4: Average response times for 4 different charging time scenarios for different vehicle ranges

As seen in Figure 3.4, response times show clear correlation with both charge times and vehicle range. While reducing the charging time from 240 minutes to 120 minutes showed little effect, further reductions to 60 or 30 minutes gave considerable benefit. Figure 3.4 may provide evidence that a charge time of 30 minutes or less is necessary to provide adequate mobility.

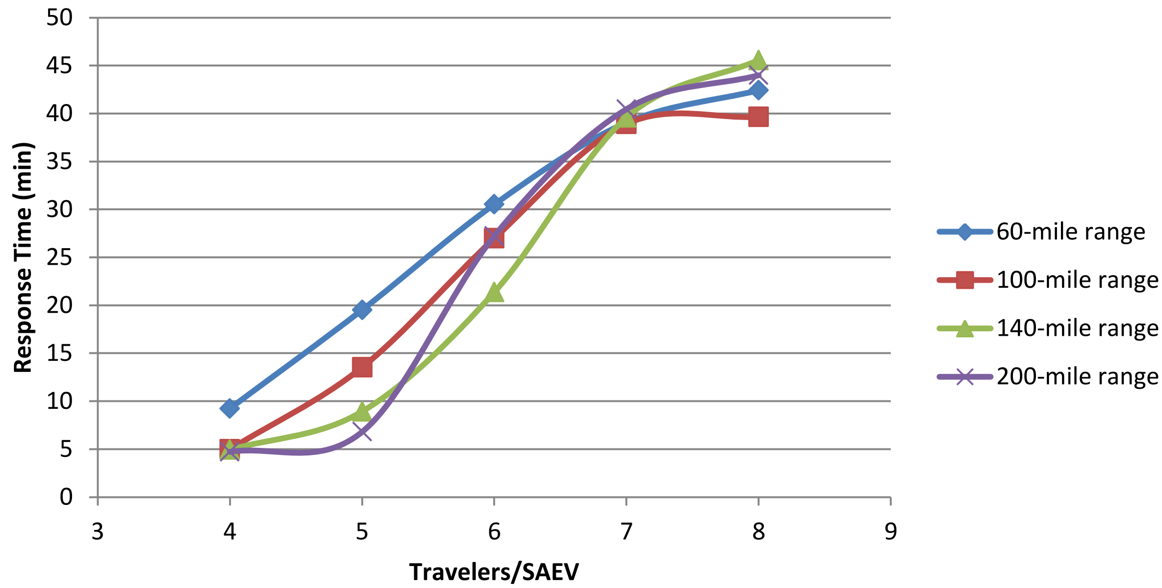

Figure 3.5: Average response times for four different charge time scenarios across different fleet sizes

Figure 3.5 shows response times with respect to fleet size. Fleet size is given in units of travelers per SAEV and includes the HEV fleet as well. This may bias results a bit low, since the two thirds of the fleet that is studied here is left to pick up more than two thirds of the trips. However, this is just a consequence of insisting that every traveler's requests be met.

Fleet size has a much stronger correlation with response times than charge times or vehicle range, though the effects of vehicle range are still evident in the figure. Interestingly, at a fleet size of 7 travelers/vehicle, range seems to make no difference on response times, though this is not the case for smaller or larger fleets.

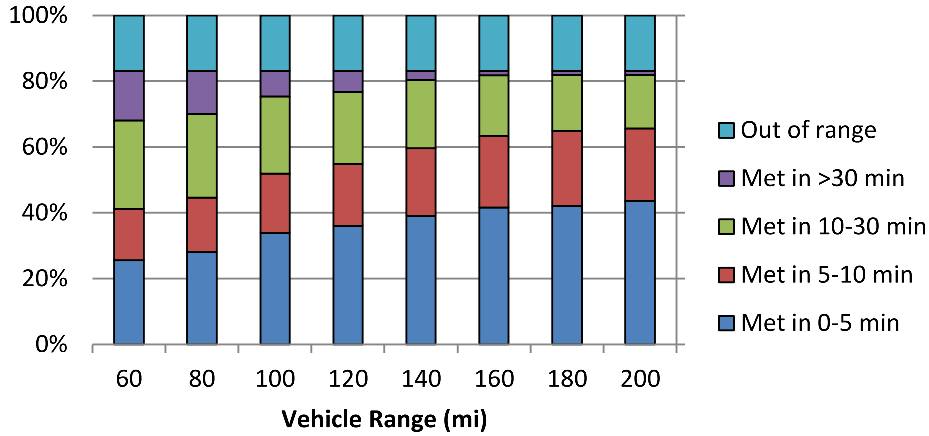

Figure 3.6: Distributions of average response times across different vehicle ranges

Figure 3.6 demonstrates the effects of vehicle range on response time distributions. The blue bar at the top indicates the proportion of trips greater than 35 miles that are handled by HEVs. Response times over 30 minutes carry significant weight in average response time calculations, despite being a very small proportion of all response times.

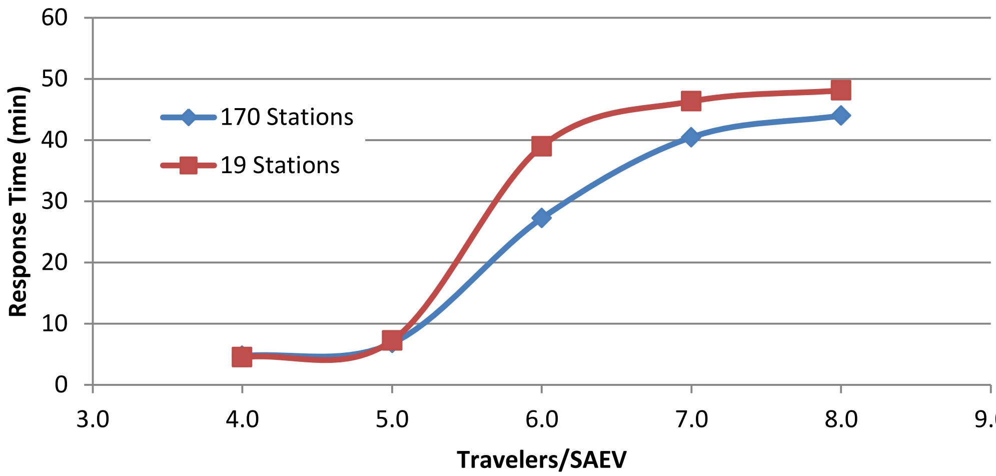

Figure 3.7: Average response times with many and few charging stations, across different fleet sizes

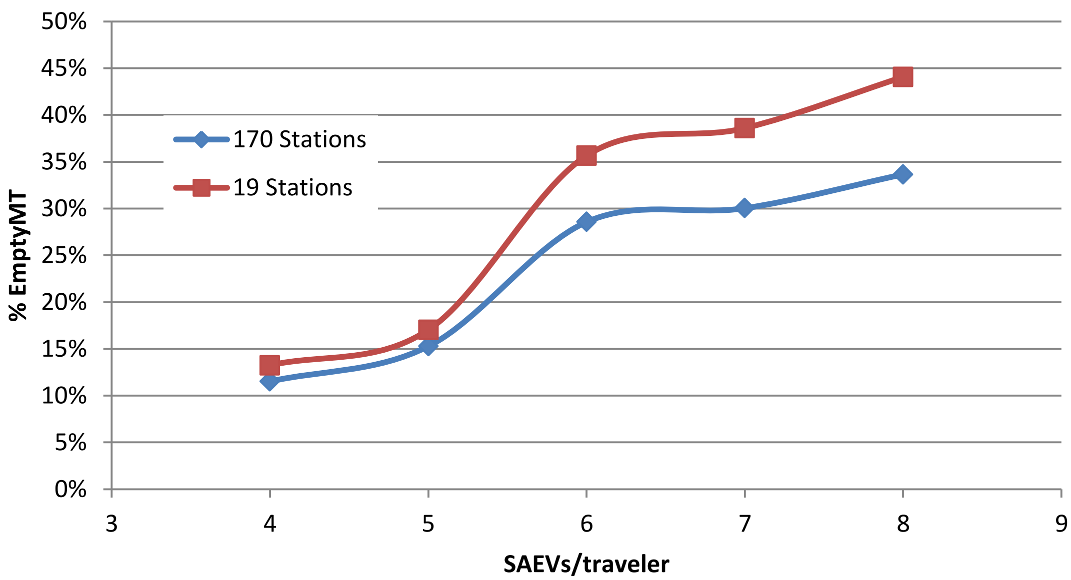

Figure 3.8: Average empty VMT with many and few charging stations across different fleet sizes

As mentioned in the section above, two different sets of charging stations were compared here in Figures 3.7 & 3.8. Surprisingly the nearly-order-of-magnitude difference in charging stations shows little difference in the response. The wide gap in empty VMT is expected, since vehicles are, at any point, further from a charging station when there are fewer on the network, hence needing to traverse more distance to charge.

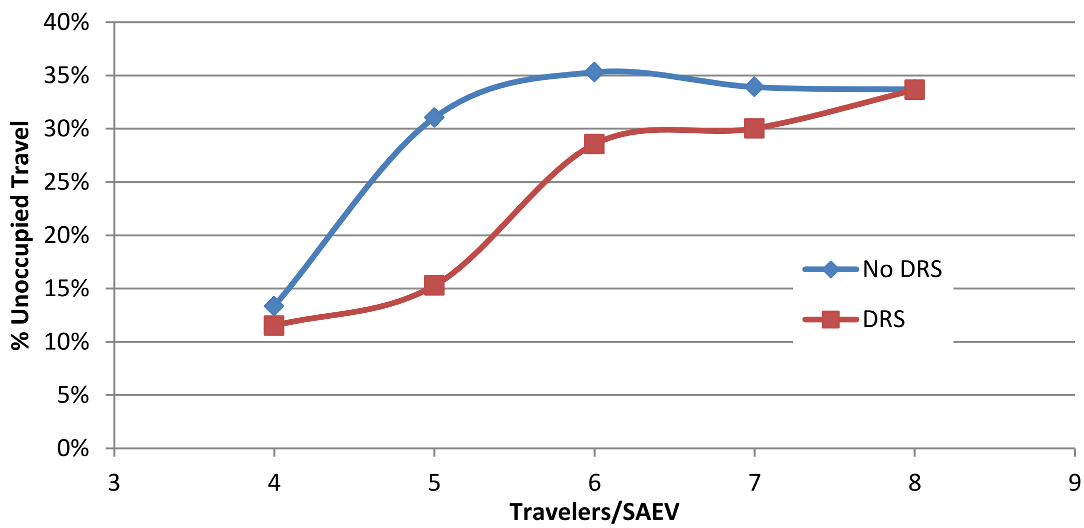

Figure 3.9: Average empty VMT, with and without DRS, across different fleet sizes

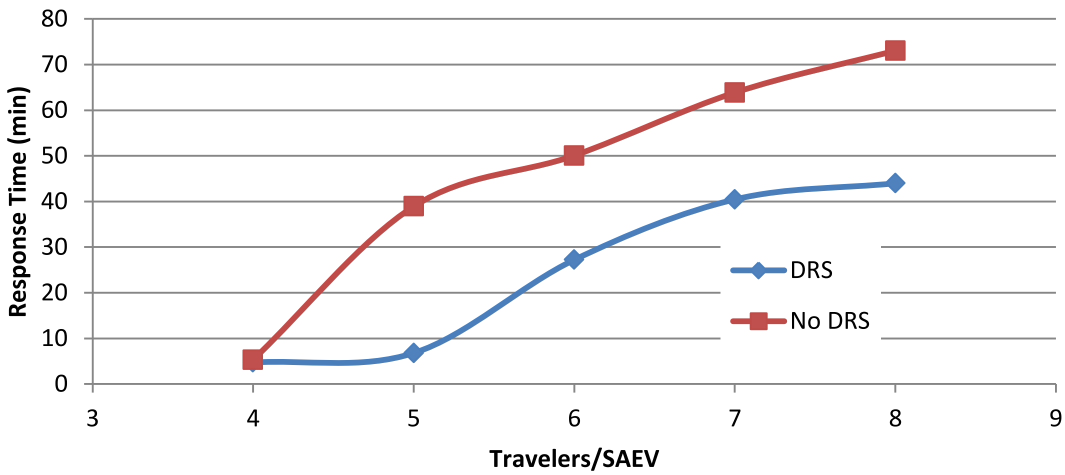

Figure 3.10: Average response times, with and without DRS, across different fleet sizes

Figure 3.9 and Figure 3.10 show clear improvements with the implementation of a DRS system. In the 5 travelers/SAEV case, empty VMT drops by more than a factor of two, and response times drop by more than a factor of four. It is not clear why at a larger fleet size, DRS yields improvements to response times but worsens unoccupied travel proportions. The question remains, however, whether the imposed delay on travelers of sharing a ride is worth the improvements in response times. It would appear that it does, adding an average travel delay of 11 minutes per traveler while improving average response times by 32 minutes with an average vehicle occupancy of just 1.16 (persons per vehicle-trip).

Figures 3.8 and 3.9 together show that empty VMT is considerable for all scenarios studied, never falling below 10% and even exceeding 40% when the number of stations is reduced. This equates to many miles that would be added across the network in addition to current network demand. The mode split here is small (assumed just 0.1% of travelers choose SAEVs) so this will not induce significant congestion feedbacks.

However, with a much larger sample of vehicles studied, this empty travel would begin to have impacts on travel time estimates. Since no network loading is performed by this code, these impacts would not be reflected in the results, demonstrating the need to have built-in dynamic network loading to study SAVs. DRS does reduce the number of occupied miles driven which would mitigate the burden of empty VMT slightly. Besides induced congestion, empty VMT has effects on operation costs which are studied in the financial section below.

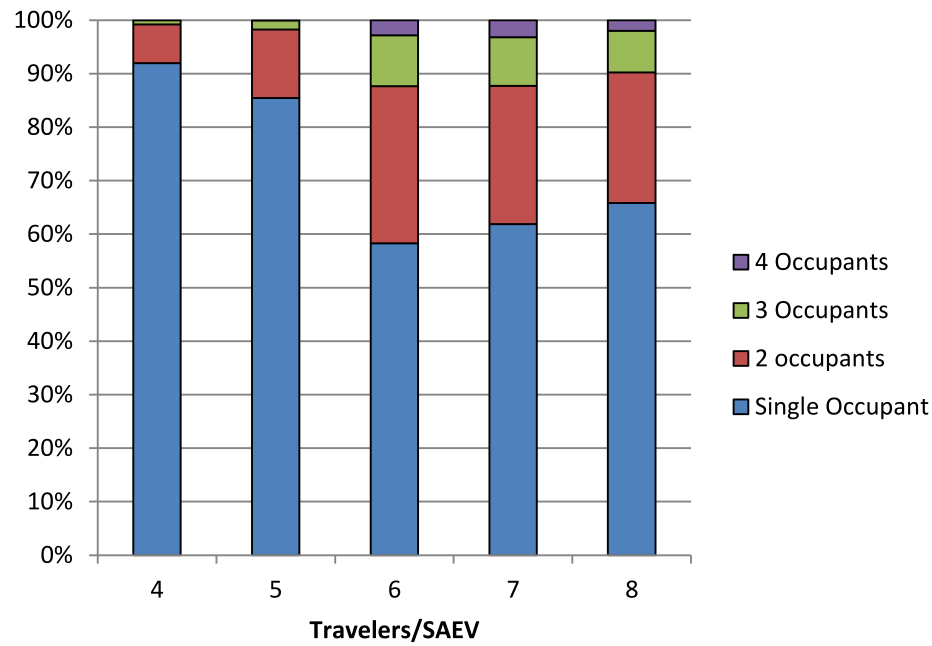

Figure 3.11: Occupancy rates for SAEVs with DRS, across different fleet sizes

Figure 3.11 shows how vehicle occupancies change under varying fleet sizes. Not surprisingly, with a large fleet of 4 travelers per vehicle, the fleet is dominated by single-occupancy vehicles. 4-occupant vehicles are very rare, going from virtually nonexistent to a maximum frequency of 3.2%. Figure 3.11 and Figure 3.9 seem to demonstrate that

DRS may work optimally under certain fleet sizes and may actually be harmful under others. More sensitivity analysis may be needed to determine why this occurs.

The HEV fleet is not the main focus of this study, but it useful to verify that HEV fleet meets demand reasonably. Here, an HEV fleet is not influenced by changes in any EV parameters since it has no notable range limitations (over the course of a day's driving) or long charge times, so only two scenarios for this fleet are studied here. (These two scenarios affect the shortest path problem, but this is not an issue here since no traffic assignment is performed during this simulation.) One of these two scenarios can be seen in Figure 3.12, which shows how the HEV fleet is able to meet all trip requests in under 30 minutes for the case of 6 travelers per vehicle, but response times start to increase, with increasing rate or slope, after that point when there are more than 6 travelers per SAV. This is not a serious problem, since travelers requesting longer trips are prepared to invest more time in their travel and call ahead to schedule a pickup. Response times for the 8 travelers-per-vehicle scenario are reasonable for neither the EV nor the HEV fleets.

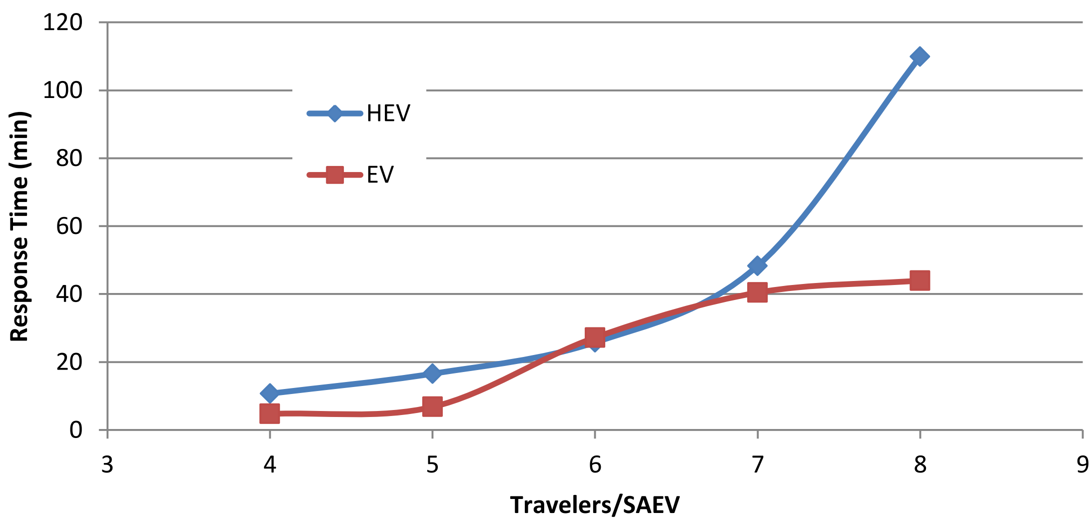

Figure 3.12: Average response times between the EV and HEV fleet across different fleet sizes for the 200-mile range, 30-minute charge time scenario

To get a better understanding of how to improve fleet performance, it was important to understand where the fleet struggles. A plot of request start locations which were served in excess of 30 minutes is shown in Figure 3.13 below. At first glass these trips appear to be very evenly distributed across the region. But considering the high trip density in the urban core, there are relatively very few long-response-time trips represented in that area. This shows that, as expected, trips in these high density areas tend to be met much more quickly than the trips in suburban and exurban areas. Another important consideration is the travel required to pick up each passenger. Figure 3.14 shows the start locations of trips that required SAEVs to travel 15 miles or more to make the pickup. This set of trips has much less disparity than those in Figure 3.13; not one trip lies with the City of Austin. These long pickups will be much more costly to the fleet operator, so this result is very important for fare structuring. This suggests that the city limits of Austin would make a suitable boundary for a pricing zone, where those outside of city limits would be required to pay a premium for their extra empty travel needs. Coupling this surcharge with long response times, these outside trips carry high disutility for travelers and would be mostly eliminated with a logit mode choice model.

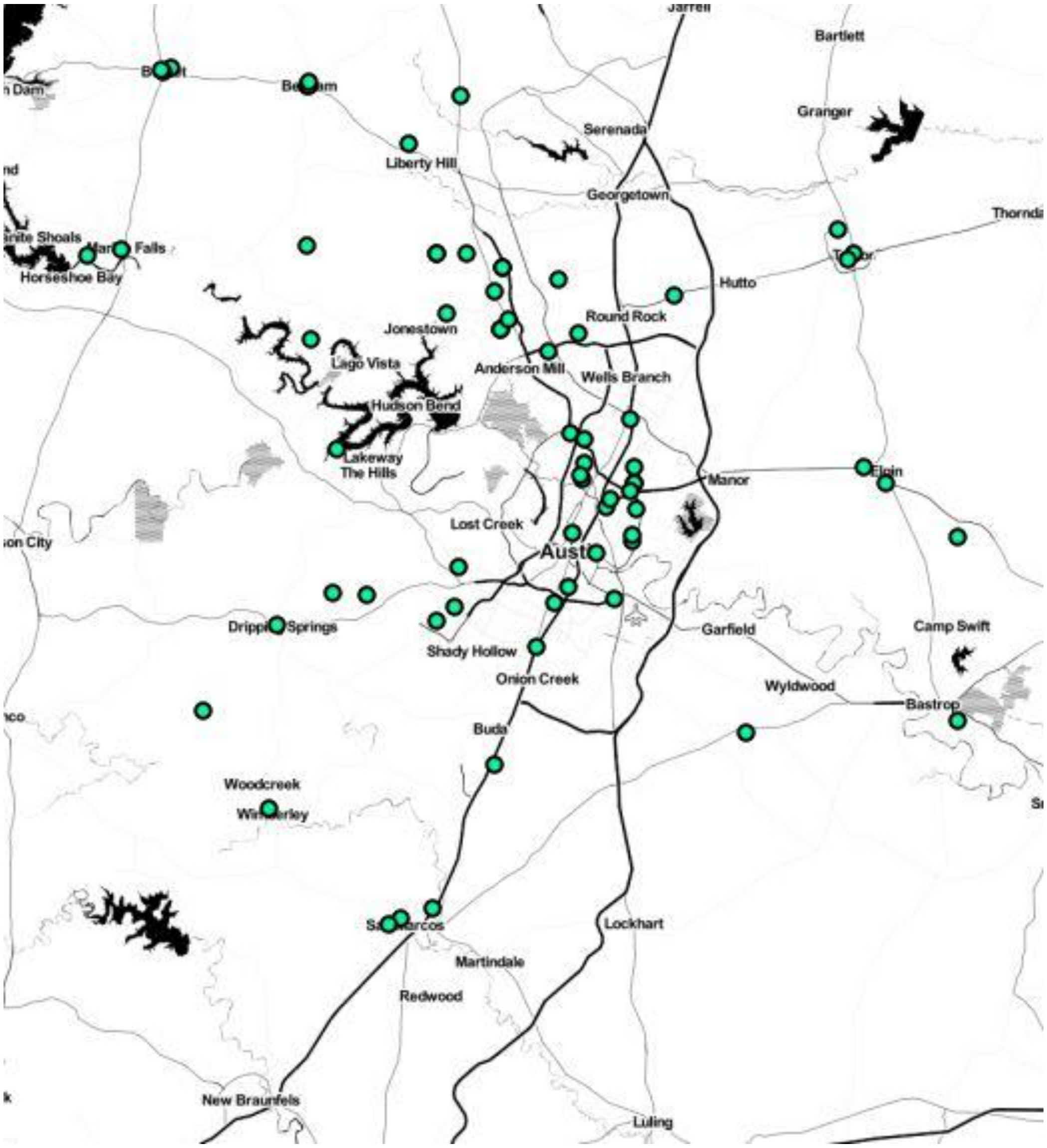

Figure 3.13: Start locations of trips with response times greater than 30 minutes

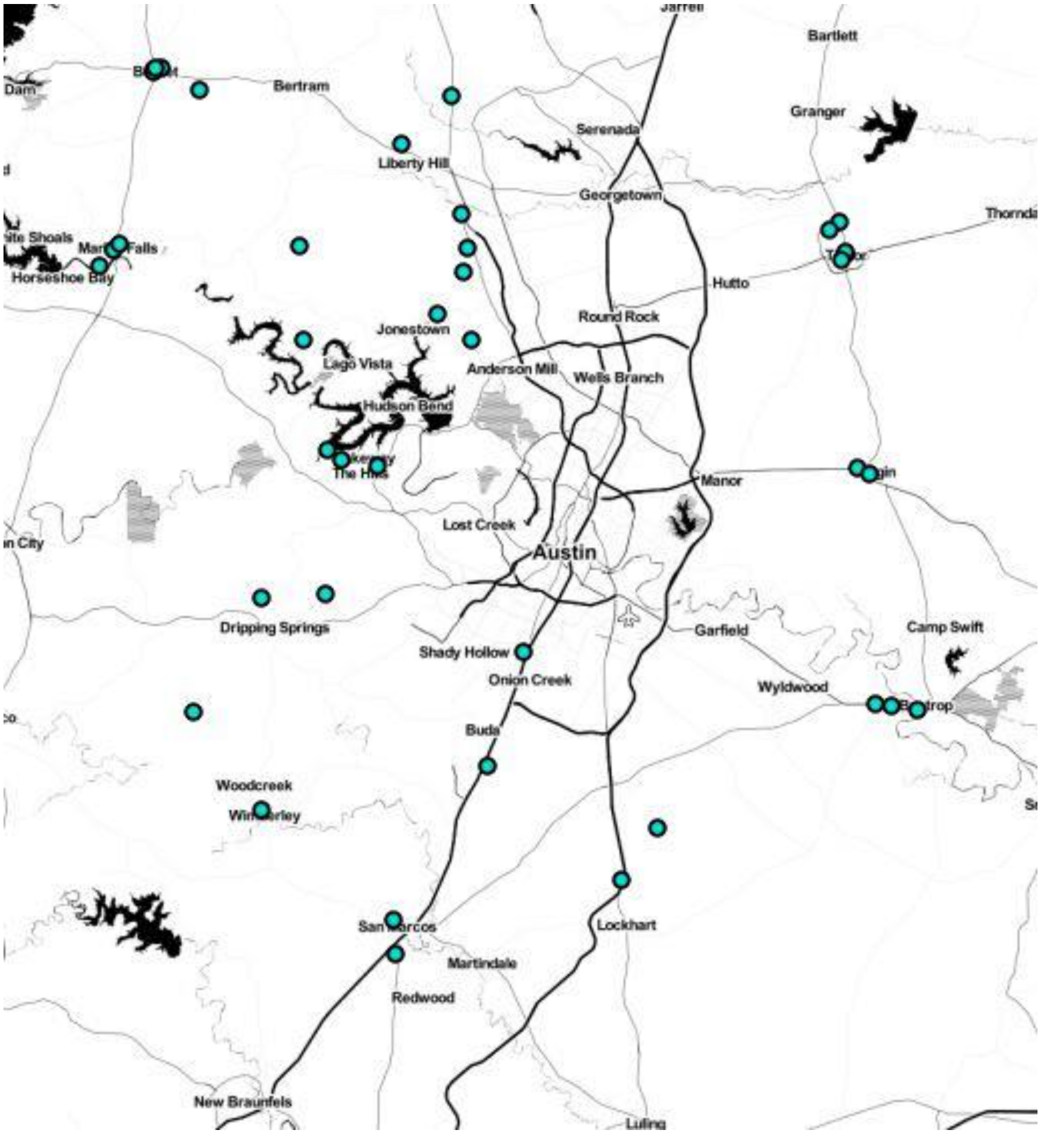

Figure 3.14: Start locations of trips that require an SAEV to travel 15 miles or more to make the pickup

FINANCIAL ANALYSIS

A financial analysis is warranted to find initial estimates for feasibility, recommendations for pricing schemes, and to seed a mode choice model. Costs were estimated from various sources for capital expenses, vehicle and charger maintenance, electricity and vehicle fees. These costs were split into high, low and medium (most likely) estimates, as shown in Table 3.3.

	Low Cost	Mid Cost	High Cost
Vehicle Capital			
SAEV (per vehicle)	$50,000	$55,000	$70,000
LR SAEV (per vehicle)	$60,000	$65,000	$95,000
Replacement batter (per kWh) + $50 install	$100	$145	$190
Vehicle Operations			
Maintenance (per mile)	$0.054	$0.061	$0.066
General Administration	$0.044	$0.11	$0.18
Insurance & Registration (per vehicle-year)	$550	$1,110	$2,220
Electricity (per kWh)	$0.01717 + delivery, demand, adjustment, regulatory and customer charges		
Charging Infrastructure			
Level II Charging (per charger)	$8,000	$12,000	$18,000
Level II Annual Maintenance (per charger)	$25	$40	$50
Level III Charging (per charger)	$10,000	$45,000	$100,000
Level III Annual Maintenance (per charger)	$1,000	$1,500	$2,000
Land Acquisition (per vehicle space)	$990	$1,730	$3,540

Table 3.3: Low, medium and high price estimates for needed expenses to implement an SAEV fleet

Vehicle costs were estimated based on popular production EVs, such as the 2017 Chevrolet Volt and 2017 Mitsubishi i-MiEV, with all-electric ranges (AERs) of 53 and 59 miles, respectively. These ranges are not far from the 60-mile assumption for short-range SAEVs used here. These two models presently have MSRPs of $33,220 (Chevrolet, 2016) and $22,995 (Mitsubishi Motors, 2016) respectively. As for long-range EVs, the 2016 Tesla Model S 90d has a 294-mile range and costs $89,500 (Tesla Motors, 2016c). The Model S is a luxury, high-performance sedan with more range than needed.

Tesla anticipates releasing the Model 3 at just $35,000 in the year 2018 with a range of 215 miles (Tesla, 2016b). This will be Tesla's first experience with an "economy" EV, so this price carries no strong guarantees. These prices do not include government rebates, which are due to be phased out in the near future (IRS, 2016), so should not be depended upon for this study. Vehicle autonomy is reported by ENO (2013) to have an estimated marginal cost of $25,000 to $50,000 but this cost could come down to $10,000 after at least 10 years. For this analysis it is assumed that a regular range SAEV will cost $50,000 to $70,000 ($25,000 to $45,000 + $25,000 autonomy package) and a long range SAEV will be $60,000 to $95,000 ($35,000 to $70,000 + $25,000 autonomy package).

Similar to Chen et al. (2015), SAEVs are anticipated to last 215,000 miles, similar to the average lifespan of a NYC taxicab (New York City Taxi & Limousine Commission, 2014). The type of vehicle and driving environment are extremely disparate between NYC taxicabs and the proposed SAEV fleet, so a sensitivity analysis is warranted here. A battery's usable life is estimated at roughly 100,000 miles based on standard practice by OEMs to warranty their batteries for this distance plus various reports such as Saxton (2013). Then a battery will need to replaced at least once during a vehicle's lifetime, but it would not be a good investment to replace the battery a second time since the vehicle will be very close to (if not in excess of) the end of its service-life. Replacement batteries are expected to cost between $100 and $190 per kWh per estimates from GM and Tesla (Voelcker, 2016), substantially lower than recent estimates of $268/kWh in 2015 and $1,000/kWh in 2008 (IEA, 2016). It's assumed that a trained technician could replace a battery in about an hour working at $50 an hour. Vehicle operation and maintenance costs are assumed to be similar to those for conventional, privately-owned gasoline vehicles, which AAA (2015) estimates to be 5.4 to 6.6 cents per mile for various vehicle types. Changes to insurance premiums are a big unknown pending state and federal legislation and substantial safety research. Some estimate increases to premiums by a factor of 3 or 4 (e.g. Burns et al., 2013) which may be the case in the near term as this technology is in its early stages. Currently three states (CA, NV, and FL) have adopted requirements for $5 million insurance premiums for AVs (Technology Law and Policy Clinic, 2015), with other states looking to follow suit (PennDOT, 2016). On the other hand, a greater number of studies anticipate decreases to insurance premiums (e.g. KPMG, 2015), even the possibility of their elimination (that is by assuming 100% manufacturer liability). AAA's (2015) annual average insurance costs for privately-held cars is $1,100, so an SAV's annual insurance cost is assumed to vary between $555 and $2,200, anticipating both sides of this scenario. SAVs will be used very intensely, but are expected to operate more safely; this uncertainty is represented in the wide range of insurance cost estimates. Electricity costs are estimated using the City of Austin Electricity Tariff for this fiscal year (City of Austin, 2016). Commercial electricity is charged on the basis of a customer charge, electric delivery, demand charge, energy charge, power supply adjustment and regulatory charge. The chargers on the SAEV network will deliver an average power of about 1,360 kW, putting this system clearly in the range of 300 kW to 3,000 kW, and costs are assessed accordingly (energy usage is divided by 0.85, which is the approximate efficiency of most EV chargers as given by many reports such as Forward et al. [2013]). This leads to $65/month customer charge, $4.47/kW electric delivery, $0.01717/kWh energy charge, $0.02761/kWh power supply adjustment (after taking weighted sum for summer and winter rates) and $3.75/kW regulatory charge. The one remaining term is demand charge, which depends on peak energy usage over the day; it will vary substantially under different charging methods. Only one cost scenario was considered for electricity expense since these prices are well known. This should be extended to also emulate regions where electrical costs are very high (e.g. California) and where electrical costs are relatively low (e.g. the Pacific Northwest). Also analyzing these costs at a station level rather than at the network level would provide more detailed and accurate costs.

Land on which charging stations will be built is estimated using Zillow.com's classifieds of land for sale in the Austin area (http://www.zillow.com/austin-tx/land/). By compiling all listings available on November 18, 2016, the average land costs are \$20.81/ft^2 with a median of \$11.84. The first, second (median) and third quartiles of this data can be used for a high, medium and low estimate of land costs: \$6.11, \$11.84 and \$27.24 per square foot respectively. Some of these lots would require paving which is estimated at \$1.25 to \$1.50 per square foot for an average parking lot (Brahney, 2015). To be safe, \$1.50 is added to each estimate for paving. The space occupied by a single vehicle was compared to the compact EV, the Nissan Leaf which is 175 in. long and 70 in. wide (Nissan, 2016). Adding 24 in. to each dimension for a safe spacing between vehicles yields a footprint of 130 ft^2 per vehicle. Multiplying by land and pavement prices gives \$990, \$1,730, and \$3,540 of total pavement costs per vehicle space provided. This does not include any space for vehicle circulation, only for attendants to move about which could be an issue. A more accurate estimate of these land costs would price land by its location in the region instead of assuming an average and would also include some minimum circulations space.

Capital costs, namely acquisition of land and provision of charging infrastructure, are reduced to a per-mile basis by assuming a ten-year return on investment aggregated over all mileage accrued over these years. Increases in demand for SAEV use over this 10-year period are considered accounted for in the increased revenue they provide.

Level II chargers are estimated by the USDOE (2012) to cost between \$8,000 and \$18,000, including installation, hardware, materials, labor and administration fees, with

$25 to $50 annual maintenance cost per Level II charger. The USDOE (2012) and New York City Taxi & Limousine Commission (2013) estimate that Level III charger provision costs from $10,000 to $100,000, including those same fees (listed above) and $1,000 to $2,000 in annual maintenance costs per charger. The number of required chargers at each site is found here by summing the maximum number of SAEVs present at each charging station over the course of the simulation day. General administration costs were estimated by APTA (2015) Public Transportation fact book using the costs found for vanpooling data, since this was the most similar mode. They estimated $57.6 million per year for 1,319 million passenger-miles or 4.34 cents per passenger-mile. Chen et al. (2015) estimate 18.4 cents per mile for this expense, which serves as an upper estimate on this cost.

Gasoline-powered fleets are assumed to have the same associated costs, as applicable, with fuel prices ranging from $2.00 to $4.00 per US gallon, operating at 30 to 50 miles per gallon, similar to the Toyota Camry, Toyota Prius and many similar vehicles. The gasoline-powered vehicles will need attendants to give them fill-ups at fuel stations. Suppose attendants are paid $15/hr and are posted, one each, at a number of fuel stations across the network. Let the number of fuel stations occupied by an attendant vary between the number of charging stations generated in the simulation, that is, between 19 and 170. If fuel stations are manned 24-hours per day, the cost will be $6,840 to $61,200 daily. The costs per service-mile for the three cost scenarios are shown in the Tables 3.4, 3.5 and 3.6 below assuming vehicle lifetime of 215,000 miles.

Since vehicle lifetime is difficult to estimate, a sensitivity analysis was performed over a series of possible vehicle lifetimes to estimate total per-mile cost for each of fleet type studied in Tables 3.4 through 3.6. These results can be found in Figure 3.15 for the mid-range cost estimate

This analysis indicates that starting an SAEV fleet from the ground up is not financially advantageous over a traditionally-fueled SAV fleet. This comes from the high capital cost of vehicles and purchasing and maintaining a system of charging stations. Of the scenarios listed, only the high-range, fast-charge scenario and gasoline scenario yield promising response times of 6.8 and 6.4 minutes respectively. This shows that opting for fast charging and higher range vehicles is definitely worth the additional capital in the long run over a short-range, slow-charging fleet, gaining nearly a fivefold reduction in response times.

A fully electrified fleet is not advantageous to the operator right now, but public EV charging stations are becoming more widely available. EVs are becoming cheaper to own and operate, and the future of fossil fuels is not clear. The cost to run this EV fleet is still quite low on a per-mileage basis--less than driving a personal vehicle 10,000 miles per year (AAA, 2013) for the low- and mid-range cost estimates. It is good to know there are alternatives to fossil fuels that can be profitable for such a fleet with the uncertain future of our climate and fossil fuel prices.

Low-Range, costs per occupied mile (cents/mi)	Gasoline-powered	Standard SAEV	Fast-Charge (FC) SAEV	Long-Range (LR) SAEV	FC, LR SAEV	FC, LR SAEV Reduced Fleet
Electricity/fuel	4.43	3.72	7.29	4.83	5.24	14.0
Maintenance (vehicles and chargers) & General Administration/Attendants	14.9	11.8	14.2	11.7	11.4	13.9
Insurance/Registration	0.41	0.71	0.51	0.52	0.52	0.38
Capital Costs (Land & Chargers)	0.00	3.28	2.20	1.67	0.66	1.93
Vehicle Purchase Costs	14.7	37.7	38.0	43.3	38.5	44.0
Battery Costs	0.00	1.28	1.37	4.21	3.69	4.47
Total cost	29.9	58.5	63.5	66.2	60.0	78.6

Table 3.4: Low-range cost estimates, per occupied-mile, for an SAEV fleet

Mid-Range, costs per occupied mile (cents/mi)	Gasoline-powered	Standard SAEV	Fast-Charge (FC) SAEV	Long-Range (LR) SAEV	FC, LR SAEV	FC, LR SAEV Reduced Fleet
Electricity/fuel	6.65	3.72	7.29	4.83	5.24	14.0
Maintenance (vehicles and chargers) & General Administration/Attendants	40.0	19.4	22.8	19.3	19.1	22.4
Insurance/Registration	0.82	1.42	1.03	1.04	1.06	0.76
Capital Costs (Land & Chargers)	0.00	5.0	9.35	2.56	2.82	8.21
Vehicle Purchase Costs	17.7	41.5	41.8	46.9	41.7	47.6
Battery Costs	0.00	1.85	2.00	6.09	5.33	6.46
Total cost	42.9	72.9	84.2	80.7	75.2	99.4

Table 3.5: Mid-range cost estimates, per occupied-mile, for an SAEV fleet

High-Range, costs per occupied mile (cents/mi)	**Gasoline-powered**	**Standard SAEV**	**Fast-Charge (FC) SAEV**	**Long-Range (LR) SAEV**	**FC, LR SAEV**	**FC, LR SAEV Reduced Fleet**
Electricity/fuel	8.86	3.72	7.29	4.83	5.24	14.0
Maintenance (vehicles and chargers) & General Administration/Attendants	65.4	27.1	31.5	27.0	27.0	31.0
Insurance/Registration	1.64	2.85	2.06	2.08	2.06	1.52
Capital Costs (Land & Chargers)	0.00	7.82	20.7	3.99	6.23	18.2
Vehicle Purchase Costs	26.5	52.8	53.2	68.5	61.0	6.96
Battery Costs	0.00	2.41	2.57	8.00	6.98	8.45
Total cost	62.3	96.7	117	114	109	142

Table 3.6: High-range cost estimates, per occupied-mile, for an SAEV fleet

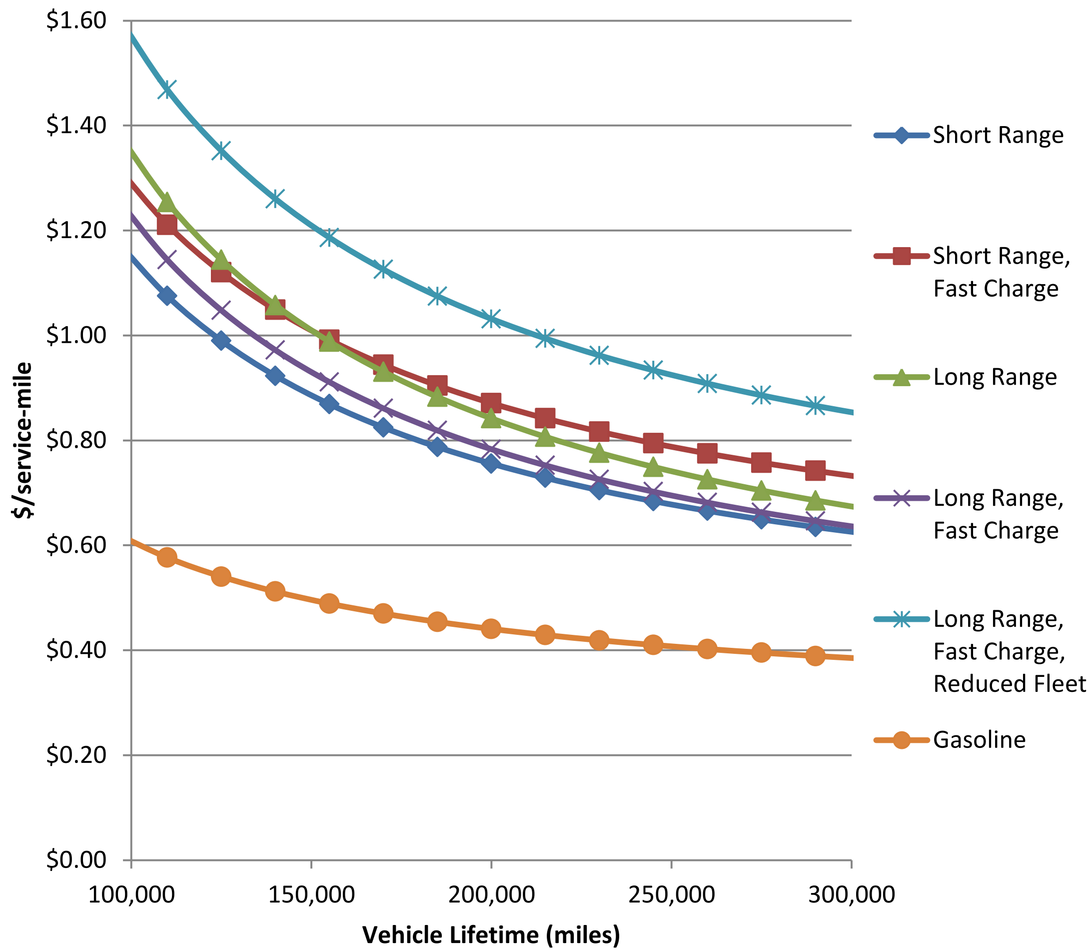

Figure 3.15: Cost per service-mile across different vehicle lifetimes

Chapter 4: 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 more cost-effective and more environmentally sustainable solutions for long-term mobility needs and demands by all types of travelers. This study is unique in that it provides a fleet with mixed fuel-types so as not to leave out a single traveler that requests a ride. It is also unique because of its large, highly detailed network and wide variety of trip lengths. 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.

There are some important aspects of this model that limit realism and fleet performance. The biggest issue is the lack of network loading that occurs for empty travel, since all DTA is performed upstream by MATSim. This results in rough estimates of travel speeds and travel distances. This same problem limits the possibilities of DRS because vehicles are not able to change course en-route when their exact network position is not known. Another valuable extension would to perform a more spatially disaggregated analysis which could establish pricing zones, achieve a better understanding of land costs and provide more realistic vehicle speeds.

After delegating trips above 35 miles to an HEV fleet, a fleet size serving 5 travelers per SAV was able to serve 79% of trips in under 10 minutes with an average response time of 6.8 minutes. Under this same scenario, unoccupied travel accounted for just 15% of VMT, with driving to charging stations accounting for 3.6% 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. If operators wish to offer more charging locations (with fewer chargers, for example), this excess VMT statistic can be brought down. Economies of scale and density in sizing and citing the stations may 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 170 stations for a vehicle fleet with 60-mile ranges, but just 19 stations needed for the same size fleet with 200-mile 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 improve with both increased range and decreased charge times, but reduced charge times (from 240 minutes to 120 minutes) had little effect.

Importantly, increasing fleet size (or SAEVs per traveler) is found to have a profound effect on response times. With 30-minute charge times, a fleet averaging 8 travelers-per-vehicle resulted in average response times of around 40 minutes on the electrified fleet, regardless of vehicle range. A fleet with 5 travelers-per-vehicle delivered average response times under 10 minutes for vehicles with all-electric ranges of 140 miles or higher. At just 4 travelers per SAEV, average response times fell to 4.72 minutes.

Reducing charge times also improves response times. For the fleet with 120-mile range and 5 travelers per vehicle, a charge time of 4 hours resulted in an average response time of 30.1 minutes, which falls to 11.4 minutes with 30-minute charge times. However, differences in response between 240-minute charge and 120-minute charge are not significant, and in fact, in one case, the 240-minute range performs better. Therefore, it is not recommended that a fleet manager expend resources to reduce charge times unless they can fall well below 2 hours. 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. Financial analysis indicated that a fast-charging, high-range fleet has a very small increase in costs over a low-range, slow-charging fleet while providing far better performance. Therefore a fleet manager is recommended to make a larger capital investment in better charge times and bigger batteries for what would likely be a far more profitable fleet in the long term. However, a gasoline-powered fleet is still financially advantageous to EVs. A mode choice will be a necessary future work (similar to the one found in Liu et al. [2016]) to make the demand distribution more realistic. This will also require the development of a fare structure based on a more in-depth financial analysis. Fleet performance metrics are enhanced by employing a dynamic ridesharing (DRS) system, decreasing response times by a factor of four in some cases, and empty VMT by a factor of 2.

Appendices

ADDITIONAL PRIOR RESEARCH

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. They had a unique algorithm where for each scenario, every vehicle has a scheduled departure delay (DD) and a set maximum number of common destinations (CD). These variables allow for ridesharing such that as many travelers appear within the DD can share a ride so long as they have fewer than CD different destinations and the trip length of any traveler is not increased by more than 20%. This 20% figure appears to be a standard in most literature covering dynamic ridesharing. True average vehicle occupancy (AVO) was recorded for different values of departure delay (DD) and CD and results showed that AVO was positively correlated with both CD and DD. With reasonable DD and CD pairs, trip miles can be halved. Using a CD of 5 timesteps and a DD of 5 timesteps lead to VMT cut by two thirds. Rideshare opportunities were shown to vary spatially and temporally, notably increasing during peak periods and at train stations. The New Jersey network was created by pixilating 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. This study models New Jersey because of its geographic variety and mix of open and utilized spaces. The synthetic New Jersey dataset was generated in four steps: creation of a population of individuals who, on aggregate, resemble New Jersey, assignment of workplaces and schools as anchors, assignment of activity patterns and trip ends, and assignment of arrival and departure times. When an individual was created, it took the type of student, worker or other based on age and regional attributes until each of the 8,791,894 NJ residents living in 118,654 census blocks had demographic characteristics. Travelers passing through New Jersey were also studied, where their OD pairs fit into eight discrete buckets. 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. Also, since the road network was based on pixels and Manhattan distance, no real traffic assignment occurs.

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 and Taxi Data which gives the status and location of every taxi in 30 second timesteps. 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 not in use (not tending to request) 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. A conventional human driven (HV) fleet is compared to the SAV fleet for a financial analysis. Estimated cost to own a mid-sized car including parking expenses is approximately $18,000/year. Retrofitting a car for full autonomy is estimated as a $15,000 onetime expense. SAVs are expected to depreciate much faster than HVs and have an expected lifespan of 2.5 years. They will also require significant maintenance and cleaning budgets. AVs can park in low-valued land or provide logistics solutions like shipping parcels when travel demand is low so as to save money and produce revenue. The estimate annual cost of service for the human driven fleet and SAV fleet is $12,563 and $9,728 respectively. Total time spent on vehicle ownership and operations activities were estimated at 885 hours/year in the US and 458 hours in Singapore so the Value of Travel Time Savings from the DOT is used to monetize these hours. Time on business trips on local roads were valued at 100% of the median wage, personal travel 75% and heavily congest travel 150% when using a conventional vehicle. This boils down to a total mobility costs of $1.48 per person-mile in Singapore and $1.14 in the US, for SAV usage when allowing for values of travel and wait times at just 20 percent of the median wage in SAVs compared to the 50 percent that the USDOT in 2011 and others regularly assume (Small, 2012). This is 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 cost $2.77 per person mile in Singapore and $2.20 in the US accounting for travel time valued 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. Spieser et al.'s (2014) study is limited because it does not study congestion.

EXPLANATION OF CODE

The source code created by Bösch et al. (2016) can be cloned from the Git repository `https://github.com/matsim-org/matsim.git`. The project that was modified is called `boescpa` and can be found in the directory: `/playgrounds/boescpa/src/main/java/playground/boescpa/av/st` `aticDemand`. Many classes in this project were modified in some way, especially `staticAVSim` which is the main class. `AVAssignment` was modified to change the search algorithm to assign particular vehicles to requests. `AutonomousVehicle` is the vehicle object class which was updated to include features salient to EVs, such as range and number of chargers performed over the course of a simulation. It was also updated to log more statistics such as empty travel, total mileage and more. `Constants` contains nearly every tunable parameter in the project to prevent magic numbers. This was expanded to support new features and to increase the number of tunable parameters in the code. `StaticAVSim` required major changes to accommodate DRS functionality. In the original code, vehicles are not tracked in real time; when a vehicle receives an assignment, it will not have presence on the network until it completes the assignment. The structure of the primary `for` loop in the main class was rebuilt so that the location of a vehicle is known at each stop that it makes. Many methods were needed to add ridesharing capability. Charging strategies also required many methods in `StaticAVSim` including significant additions to create a charging station generation algorithm. A class called `ChargingStation` was added to make a charging station object. The class `CSAssignment` was added, analogous to `AVAssignment`, to be responsible for assigning vehicles to charging stations. The `Stats` class was updated to record many more statistics and was improved to write a highly detailed summary file which was invaluable when running hundreds of trials back-to-back.

A method written for this study is shown below. Its task is to look at vehicles that are found to have "low charge" and to determine an appropriate assignment for this vehicle. If it is during a station-generation phase, an appropriate action might be to generate a charging station.

```
private static void handleLowCharge(AutonomousVehicle lowChargeVehicle) {
        if (lowChargeVehicle.getDropoffList().size() > 0) {
                throw new  IllegalArgumentException("Busy vehicle charging");
        }
        if (lowChargeVehicle.getStation() != null) {
                System.out.println("Veh ID: " + lowChargeVehicle.getVehicleID());
                throw new  IllegalArgumentException("Charging vehicle given charging
assignment");
        }
        int closestStation = CSAssignment.assignStationToVehicle(lowChargeVehicle,
chargingStations);

        //move it to the right station!
        if (closestStation > -1) {
                chargingStations.get(closestStation).incNumberOfServices();
                lowChargeVehicle.atStation(chargingStations.get(closestStation));
                lowChargeVehicle.incNumberOfCharges();
                lowChargeVehicle.incRange(-
Constants.BEELINE_FACTOR_STREET*CoordUtils.calcEuclideanDistance(lowChargeVehicle.getMyPo
sition(), chargingStations.get(closestStation).getStationPosition()));

        lowChargeVehicle.incStationAccessDistance(Constants.BEELINE_FACTOR_STREET*CoordUti
ls.calcEuclideanDistance(lowChargeVehicle.getMyPosition(),
chargingStations.get(closestStation).getStationPosition()));

        stats.incStationAccess(Constants.BEELINE_FACTOR_STREET*CoordUtils.calcEuclideanDis
tance(lowChargeVehicle.getMyPosition(),
chargingStations.get(closestStation).getStationPosition()));
                double travelTime =
lowChargeVehicle.moveTo(chargingStations.get(closestStation).getStationPosition());
                //if (lowChargeVehicle.getVehicleID() == 269) System.out.println("going to
charge!");
                vehiclesCharging.add(lowChargeVehicle);

                availableVehicles.remove(lowChargeVehicle);
                lowChargeVehicle.setArrivalTime(Math.max(time,
lowChargeVehicle.getArrivalTime()) + (int) travelTime);
                chargingStations.get(closestStation).incCurrentOccupancy(1);
        } else {
                if (warmStartNumber == 0) {
                        System.out.println("Veh ID: " + lowChargeVehicle.getVehicleID());
                        System.out.println("Veh range: " +
lowChargeVehicle.getCurrentRange());
                        System.out.println("Closest Station: " +
Constants.BEELINE_FACTOR_STREET*CoordUtils.calcEuclideanDistance(chargingStations.get(CSA
ssignment.getAbsoluteClosest(lowChargeVehicle.getMyPosition(),
chargingStations)).getStationPosition(), lowChargeVehicle.getMyPosition()));
                        throw new  IllegalArgumentException("Building Station after warm
start");
                }
                //or make a new one if it can't make it
                ChargingStation newStation = new ChargingStation();
                newStation.setStationID(chargingStations.size());
                newStation.setStationPosition(lowChargeVehicle.getMyPosition());
                //newStation.setTimeOfCreation(time);
                newStation.setCreatedBy(lowChargeVehicle);
                chargingStations.add(newStation);
                lowChargeVehicle.atStation(newStation);
                lowChargeVehicle.setArrivalTime(Math.max(time,
lowChargeVehicle.getArrivalTime()));
                newStation.incNumberOfServices();
                Stats.addStation(newStation);
                vehiclesCharging.add(lowChargeVehicle);
```

```
            availableVehicles.remove(lowChargeVehicle);

        }
    }
```

The following sample is a method that looks at each vehicle being charged to determine how to handle that vehicle at each respective timestep. Typically, it will just receive more charge, but full vehicles must be removed from the charging station.

```
    private static void handleChargingVehicles() {
        stats.updateMaxVehiclesCharging(vehiclesCharging.size()); //update max charging
stats
        for (AutonomousVehicle vehicleToBeCharged : vehiclesCharging) {
            //System.out.println("The range on THIS vehicle is: " +
vehicleToBeCharged.getCurrentRange());
            if (time >= vehicleToBeCharged.getArrivalTime()) {
                //We assume the vehicle reaches 80% range in half the charge time,
and
                //the remaining 20% in the remaining half
                if (vehicleToBeCharged.getCurrentRange() < 0.8 *
Constants.EV_RANGE) {

        vehicleToBeCharged.incRange(Constants.SIMULATION_INTERVAL*(0.8*Constants.EV_RANGE)
/(0.5*Constants.EV_CHARGE_TIME));
                } else {

        vehicleToBeCharged.incRange(Constants.SIMULATION_INTERVAL*(0.2*Constants.EV_RANGE)
/(0.5*Constants.EV_CHARGE_TIME));
                    if (vehicleToBeCharged.getCurrentRange() >=
Constants.EV_RANGE) {
                        //System.out.println("full charge occured on " +
vehicleToBeCharged.getVehicleID());
                        vehicleToBeCharged.resetRange();
                        vehicleToBeCharged.incNumberOfFullCharges();
                        vehicleToBeCharged.resetArrivalTime();
                        vehiclesCharged.add(vehicleToBeCharged);
                        availableVehicles.add(vehicleToBeCharged);

        vehicleToBeCharged.getStation().incCurrentOccupancy(-1);
                    }
                }
            }
        }
        //remove charged vehicles
        for (AutonomousVehicle chargedVehicle : vehiclesCharged) {
            vehiclesCharging.remove(chargedVehicle);
            vehiclesCharging.remove(chargedVehicle);
            chargedVehicle.atStation(null);
        }
        vehiclesCharged = new ArrayList<>();


    }
```

ADDITIONAL FIGURES

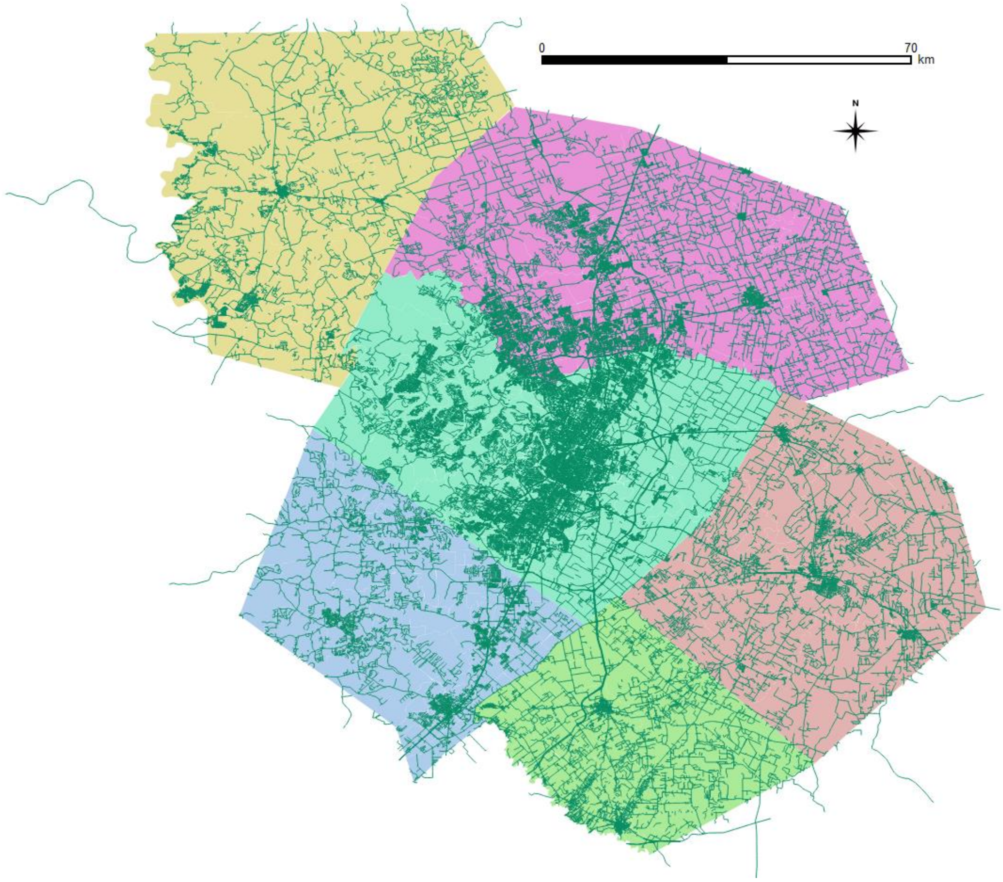

Figure A1: OpenStreetsMap network used for this study overlaid on the six counties of the CAMPO region

Glossary

AV	-	Autonomous Vehicle
AVO	-	Average Vehicle Occupancy
CAMPO	-	Capital Area Metropolitan Planning Authority
DRS	-	Dynamic Ridesharing
DTA	-	Dynamic Traffic Assignment
EV	-	Electric Vehicle
HEV	-	Hybrid Electric Vehicle (gasoline-electric)
IVTT	-	In-Vehicle Travel Time
SAEV	-	Shared Autonomous Electric Vehicle
SAV	-	Shared Autonomous Vehicle
TNC	-	Transportation Networking Company
VMT	-	Vehicle-Miles Traveled

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