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Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure & Pricing Strategies

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Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure & Pricing Strategies

by

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Dedication

To my late grandfather, Ph.D., who continuously advocated for independent, critical thinking despite having experienced violent political persecution for being an intellectual.

To my loving mother, Ph.D., who maintained the drive to seek knowledge despite having witnessed these atrocities against her father, and brought me to a country where I would be able to pursue scholarship without fear of oppression.

To my carefree daughter, may you always remember the sacrifices of those who came in the generations before, and keep a curious and open mind for all of life's possibilities.

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Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure Planning, & Pricing Strategies

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There are natural synergies between shared autonomous vehicle (AV) fleets and electric vehicle (EV) technology, since fleets of AVs resolve the practical limitations of today's non-autonomous EVs, including traveler range anxiety, access to charging infrastructure, and charging time management. Fleet-managed AVs relieve such concerns, managing range and charging activities based on real-time trip demand and established charging-station locations, as demonstrated in this paper. This work explores the management of a fleet of shared autonomous (battery-only) electric vehicles (SAEVs) in a regional (100-mile by 100-mile) discrete-time, agent-based model. The dissertation examines the operation of SAEVs under various vehicle range and charging infrastructure scenarios in a gridded city modeled roughly after the densities of Austin, Texas.

Results indicate that fleet size is sensitive to battery recharge time and vehicle range, with each 80-mile range SAEV replacing 3.7 privately owned vehicles and each 200-mile range SAEV replacing 5.5 privately owned vehicles, under Level II (240-volt AC) charging. With Level III 480-volt DC fast-charging infrastructure in place, these ratios rise to 5.4 vehicles for the 80-mile range SAEV and 6.8 vehicles for the 200-mile range SAEV.

However, due to the need to travel while "empty" for charging and passenger pick-up, SAEV fleets are predicted to generate an additional 7.1 to 14.0% of travel miles. Financial analysis suggests that the combined cost of charging infrastructure, vehicle capital and maintenance, electricity, insurance, and registration for a fleet of SAEVs ranges from \$0.42 to \$0.49 per occupied mile traveled, which implies SAEV service can be offered at the equivalent per-mile cost of private vehicle ownership for low-mileage households, and thus be competitive with current manually-driven carsharing services and significantly less expensive than on-demand driver-operated transportation services.

The mode share of SAEVs in the simulated mid-sized city is predicted to be between 14 and 39%, when competing against privately-owned, manually-driven vehicles and city bus service. This assumes SAEVs are priced between \$0.75 and \$1.00 per mile, which delivers significant net revenues to the fleet owner-operator, under all modeled scenarios, assuming 80-mile-range EVs and remote/cordless Level II charging infrastructure and \$10,000-per-vehicle automation costs.

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INTRODUCTION

Technology is quickly changing the landscape of urban transportation. The privately owned car, once a powerful symbol of social connectivity, becomes an increasingly utilitarian machine as mobile computing devices allow people to work and socialize with location independence. The romance of maneuvering one's status-symbol vehicle at thrilling speeds is fading in the face of a reality filled with congested urban roadways, increasing fuel costs, and emissions-driven climate change. Encouraged by this cultural shift, various transportation trends and technologies are emerging independently. With the rise of the shared-use economy, carsharing is emerging as an alternative mode that is more flexible than transit but less expensive than traditional private-vehicle ownership. Electric vehicle (EV) sales are on the rise and growing plug-in EV adoption can be a key factor in helping regions achieve national- and state-level air quality standards for ozone and particulate matter, and ultimately carbon-emissions standards. Motivated by roadway safety and the growing onerousness of congested urban driving, automated driving technologies are being introduced to make driving more convenient for travelers.

However, the growth of EVs and carsharing are both hindered by technological and social factors. For EVs, the most significant hindrance may be "range anxiety," a user's concern for being stranded with a fully discharged battery and no reasonable recharge option (Bartlett 2012). Meanwhile, as EVs penetrate the private and commercial vehicle fleets, they are also gaining ground in the carsharing world. EVs are a natural match for carsharing operations as existing members of carsharing operations tend to drive smaller and more fuel efficient vehicles than non-carshare members (see, e.g., Meijkamp 1998, Martin and Shaheen 2011a, Ryden and Morin 2005). Cutting edge carsharing operators (CSOs) are already employing EVs in their fleets (such as Daimler's Car2Go and BMW's

DriveNow operations), but the manual relocation of fleets in one-way carsharing systems continues to present profitability challenges to CSOs. AV technology would remove the barrier of manual vehicle relocation and presents a driver-free method for shared EVs to reach travelers' origins and destinations as well as charging stations. In a carsharing setting, a fleet of shared autonomous electric vehicles (SAEVs) would automate the battery management and charging process based on real-time trip demand, and take range anxiety out of the equation for growth of EVs. With the increasing sales of EVs, the rising membership in carsharing organizations, and the recent popularity of on-demand transportation services through transportation network companies, it is possible to imagine a future travel system where AV technologies merges with these transportation trends in a SAEV fleet. Personal transportation will be as easy as hailing a SAEV through a computer or mobile device, waiting for the SAEV to arrive, and sitting comfortably while the SAEV drives to the destination. Automated recharging is easy with wireless inductive charging technology. But can self-driving vehicles be shared, self-charged, and right (battery-) sized for the trip lengths that travelers desire?

This dissertation attempts to answer this question through the simulation of a fleet of shared autonomous electric vehicles (SAEVs) in a discrete-time agent-based model. First, the growth and challenges of each of these transportation trends and technologies (carsharing, EVs, and AVs) is discussed in Chapter 1, which sets the context for the emergence of the SAEV fleet. The chapter discusses who is likely to adopt the SAEV fleet, technology development timeline, direct and indirect benefits of SAEVs, as well as critical challenges for future operators. In Chapter 2, the regional (100-mile by 100-mile) simulation methodology is introduced to model different combinations of vehicles and charging infrastructure to examine the impact of fleet operations when 10% of a city's trips are served by SAEVs. A financial analysis is also conducted to determine the competitiveness of SAEVs against current modes of transportation and to set a baseline feasible price for SAEV service. Chapter 3 builds upon Chapter 2 by adding a mode choice model to look at the impacts of different pricing strategies on SAEV mode share, fleet performance, and revenue. Sensitivity analysis in Chapter 3 shows a range of potential scenarios which can affect SAEVs' ability to compete against private vehicle and transit modes.

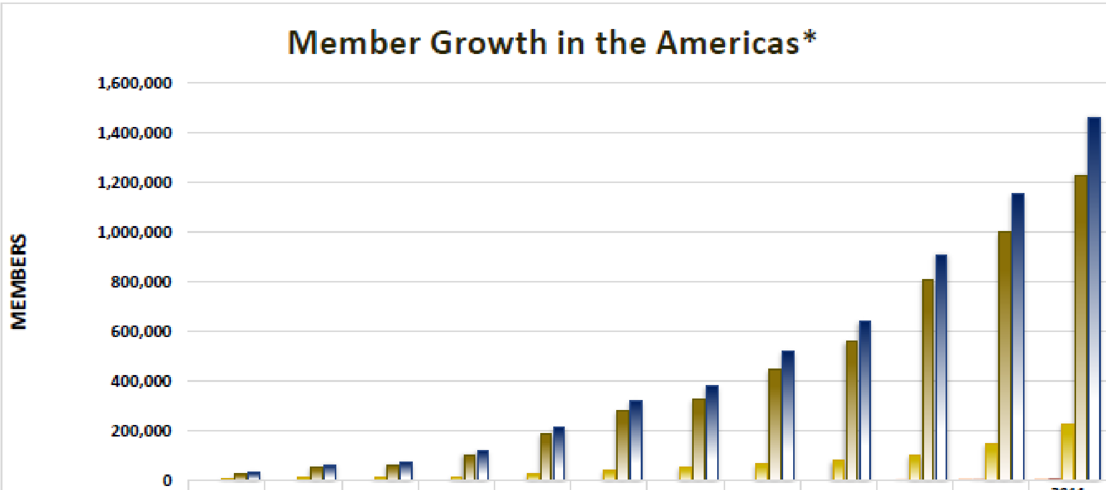
The work demonstrated in this dissertation considers a new mode of transportation that can dramatically change the face of urban passenger transport. SAEVs provide individuals with the ability to travel free from predetermined transit schedules, the burden of vehicle ownership, and the stress of driving in congested traffic. Mass adoption of the SAEV mode will likely decrease private vehicle ownership, demand on roadways and parking infrastructure, and fossil fuel use, while at the same time increasing traffic safety, mobility for non-drivers, and worker productivity.

CHAPTER 1: SAEVS IN A TIME OF CARSHARING, EVS, AND AVS

In order to understand the potential users, environmental impacts, infrastructure considerations, and technological and policy challenges of a SAEV fleet, one must first examine these issues in their current contexts. This chapter discusses present-day critical issues and impacts of carsharing, electric vehicles, and autonomous driving technology. Specifically, the chapter attempts to predict which travelers are most likely to choose SAEV service, the timeline for SAEV deployment based on technology development, direct and indirect benefits of SAEVs, and critical operational challenges as well as policy barriers to the realization of SAEVs.

THE MARKET FOR SAEV SERVICE

To understand the market potential for a SAEV fleet, it is important to understand the current carsharing demographic. Alongside a U.S. trend toward lower private-vehicle ownership (Cohen 2012) and a growing popularity of the collaborative economy (Botsman and Rogers 2010), carsharing is growing rapidly as an alternative model to traditional vehicle ownership. In 2009, for the first time since World War II, the U.S. vehicle fleet diminished in size, as 14 million vehicles were scrapped and 10 million new vehicles were sold (Brown 2010). Internationally, many cities are adopting plans to reduce automotive usage as congestion worsens (e.g., London's costly commuter tax, vehicle registration limitations in Asian cities like Singapore, Beijing, and Shanghai). Both peer-to-peer carsharing (through organizations like Getaround and Relayrides) and business-to-consumer carsharing (through operations like Car2Go and Zipcar) are gaining ground in urban areas, with the majority of growth in recent years in the latter model. Worldwide, carsharing organizations operate in over 1,100 cities across at least 27 countries with 2.8 million members (Shaheen and Cohen 2014). Figure 1 below shows the fast pace of growth of carsharing in the Americas in the last decade, dominated by membership gains in the U.S. and Canada.



	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 (Jan)
Brazil (n=1)								98	347	910	2,884	3,326
Mexico (n=1)										750	2,654	5,634
Canada (n=19)	7,007	10,001	11,932	15,663	26,878	39,664	53,916	67,526	78,856	101,502	147,794	224,523
United States (n=24)	25,640	52,347	61,658	102,993	184,292	279,234	323,681	448,574	560,572	806,332	995,926	1,228,573
The Americas (n=45)	32,647	62,348	73,590	118,656	211,170	318,898	377,597	516,198	639,775	909,494	1,149,258	1,462,056

Figure 1-1: Carsharing Membership in the Americas (Shaheen and Cohen 2014)

Carsharing membership is more appealing for those who travel fewer kilometers and reside in higher-density neighborhoods with good walking, cycling, and transit options (Litman 2000). Thus, carsharing programs tend to concentrate in metropolitan cores, well served by other modes, where travelers can and do rely less on private car use than the average traveler (Stillwater, et al. 2009). In an analysis of 13 U.S. regions with carsharing programs, Celsor and Millard-Ball (2007) found that carsharing neighborhoods are more likely to have higher shares of one-person households and residents with Bachelor's degrees, more workers commuting by transit and non-motorized modes, lower vehicle ownership levels, higher density, and more walkable environments than non-carsharing neighborhoods. Zheng et al. (2009) also found that within the setting of a university town (Madison, Wisconsin), students are more willing to participate in carsharing than faculty or staff (once household income is controlled).

Within carsharing members, usage varies by similar variables. Stillwater et al. (2009) used 16 months of data from one (unnamed) US carsharing operator, and found significant variables which negatively related to carsharing included percentage of drive-alone commuters, wider street widths, and more heavy-rail availability. On the other hand, higher percentages of one-vehicle households, increasing availability of light rail, and increasing history of presence of a carsharing station were positively related to carsharing usage (Stillwater et al., 2009). For station-based systems, Lorimier and El-Geneidy (2011) used data from Communauto in Montreal and found that larger carsharing stations with more vehicle options had a larger catchment area than smaller stations. However, vehicles with child seats had lower usage and higher availability.

For those who use carsharing systems, usage for shopping and socio-recreational activities are the most prevalent, followed by work or personal business trips (Schmoller et al. 2013). Using the same data as Lorimier and El-Geneidy (2011), Morency et al. (2012) sought to examine the pattern of trip transactions for carsharing and used a cluster-based classification process to identify two distinctive behaviors among carsharing users: they tend to either travel short urban trips throughout the week OR long trips just one day of the week. Furthermore, in the German context, very few carsharing trips are round trips (11% of bookings in Munich and 8% in Berlin), highlighting the importance of flexibility in one-way carsharing systems (Schmoller et al. 2013).

In addition to existing neighborhood infrastructure and household demographics, policy can also affect the adoption of carsharing. Using a stated preference survey from Palermo, Italy, Catalano et al. (2008) developed a multinomial logit (MNL) model which simulated that carsharing activity could increase up to 10% with policies which increase parking fees, add reserved parking areas for carsharing and carpooling users, and closing off specific traffic zones for high-emissions vehicles.

While carsharing with driver-operated vehicles is not an omnipresent and universally feasible travel option, its financial benefits do appeal to various populations. Frost and Sullivan (2010) estimated that car owners who drive 12,000 miles (7,460 km) per year at an average speed of 30 mi/hr can save $1,834 by switching to a carsharing service (with those driving less than 12,000 miles reaping even greater savings). Looking specifically at the San Francisco Bay Area, Duncan (2011) estimates that as much as one-third of those households have vehicle usage patterns that would save money via carsharing. Others are not as optimistic: Schuster et al. (2005) estimate that in Baltimore, Maryland, 4.2% to 14.8% of vehicles would be less expensive to share than to own. Surveying 26 existing organizations in North America, Shaheen et al. (2006) estimate that market potential for carsharing is 10% of adults 21 and older.

An understanding of the current characteristics of carsharing members and trips lends insight into who will be the likely users of an SAEV service and what trips are more likely to be served by SAEVs. Like carsharing programs, SAEV fleets will likely to emerge first in areas with higher population densities and more walkable environments, such as metropolitan core areas and university towns. Conceivably, mirroring the current carsharing membership demographics, educated travelers residing in single-person households with low vehicle ownership rates and who actively use alternative modes (e.g., transit, cycling, and walking) for commuting are more likely to be early adopters of SAEV service. In addition, early SAEV users are perhaps more likely to use the mode for personal and recreational trips rather than commute and business trips.

This examination of current carsharing operations also lends insight into characteristics and policies which may make SAEV service more appealing to users. Like carsharing, SAEV services with a heterogeneous fleet will likely be more attractive to users than that which offers a single vehicle type. Cities with efficient parking pricing policies will allow SAEVs to be more competitive with privately owned vehicles. Lastly, while SAEVs will appeal to a greater percent of the population than manually-driven carsharing vehicles, the literature on carsharing seems to indicate that SAEVs will not appeal to all travelers. However, it is likely that the SAEV market potential is greater than the 10% estimate for carsharing. In Chapter 3, a dynamic mode choice model is implemented into the agent-based model framework in an attempt to estimate this market share.

AV TECHNOLOGY DEVELOPMENT

If the market demand for SAEVs already exists (as witnessed by growing carsharing activities worldwide), then the key question becomes when will the AV technology be ready? Perhaps the most well-known project among AVs is the Google Self-Driving Car Project (Google 2014). Retrofitting a test fleet of vehicles including SUVs and sedans, the self-driving vehicles have logged 700,000 autonomous miles as of April 2014 (Google 2014). In May 2014, Google revealed a prototype of their own two-passenger self-driving vehicle, with a possible commercial release from 2017 to 2020 (Gannes 2014). Various vehicle manufacturers are also taking steps toward AV development. General Motors plans to introduce a Cadillac with advanced driver assistance technology that will allow motorist to drive hands free at highway speeds (Muller 2014). Nissan announced plans to have multiple models of commercially viable AVs available by 2020, kicking off the plan with construction of a dedicated autonomous drive proving ground in Japan (Nissan Motor Company 2013). Swedish automaker Volvo has a bold plan for no deaths or injuries in a Volvo branded car by 2020, and has developed a new 500 acre testing facility for active safety systems and AVs near its headquarters in Gothenburg (Volvo Car Group 2014). In July 2014, Daimler demonstrated an autonomous truck along a stretch of the autobahn in eastern Germany, with plans to commercially release the vehicle by 2025 (Eddy 2014).

Estimates of how quickly AV technology will penetrate the vehicle market vary. Consulting firm KPMG estimates that by 2039, half of all new vehicles sold will have fully autonomous driving options (LeBeau 2014). Looking at fleet replacement rates with a 20 year life span, Litman (2014) estimates that AVs will constitute 50% of new vehicle sales by 2045, assuming the first AVs are available for sale around 2020.

Will a full scale SAEV service be feasible as soon as the AV technology is commercially ready? Or will SAEV operators have to wait for travelers to experience AVs in a privately owned setting before being sufficiently comfortable with using them in shared setting? If SAEV service is purely limited by technology development, then such services could be available as early as 2020. However, if travelers are reluctant to adopt AV technology until they reach a certain level of user familiarity, then full scale SAEV services may not be a reality until 2030 or later.

SAEV BENEFITS

There are both direct and indirect benefits to the adoption of SAEVs as a mode. The direct benefits of AVs include improved safety, reduced infrastructure demand (due to more efficient driving and ability to reposition for parking), and optimized driving to minimize energy consumption. In addition to these direct benefits, shared vehicle systems bring a host of indirect energy use and emissions benefits by reducing private vehicle ownership, shifting travel to alternative modes, and creating faster fleet turnover with higher vehicle utilization rates. This section overviews both the direct anticipated benefits of AV technology and the indirect environmental impacts in the context of the current carsharing paradigm, to lend insight into the full range of benefits SAEVs may provide.

Safety Gains

One of the biggest advantages to a fully automated fleet is the elimination of driver error. Bob Goos, chairman of the International Organisation for Road Accident Prevention once stated, “More than 90 percent of road accidents are caused by human error” (Olarte 2011). Certainly human error contributes to a large portion of fatal accidents in the US. According to the National Highway Traffic Safety Administration (2012), alcohol impaired drivers are involved in 31% of all fatal crashes and speeding was a contributing factor in 32% of all fatal crashes. Fagnant and Kockelman (2013) estimate that 93% of all crashes in the U.S. can be attributed to human error, with total annual crash costs valued at $300 billion. With as little as 10% market penetration of AVs on the road, Fagnant and Kockelman (2013) estimate 211,000 fewer crashes per year, translating to a savings of $5.5 billion in crash costs.

Reduced Private Vehicle Ownership

Within carsharing households, early studies estimate that vehicle ownership can be reduced by about 40% to 44% (Whitelegg and Britton 1999, Meijkamp 1998). Zhou and Kockelman (2011) surveyed Austin, Texas households in 2008 and found that 21% of those surveyed (following population correction) would expect to give up/release at least one of their private held vehicles upon joining a carsharing organization. A 2008 nationwide survey found that after carsharing, US households reduced their overall vehicle ownership by 49%, with most of this shift from one-car households to no-car households (Martin and Shaheen 2011b). With autonomous driving technology, the number of households who can access SAEVs will increase compared to traditional carsharing, which is limited by the traveler's distance to available vehicles and restrictively small geofences. This trend of decreased private vehicle ownership will likely continue, as more households maintain mobility and access while going car-free or car-lite.

Modal Shift

Upon joining a carsharing operation, households typically travel by car less than prior to joining carsharing. When use of a vehicle involves reserving a vehicle in advance and the costs of operating a vehicle are made more apparent (generally with a by-the-minute or by-the-mile charge in most manual carsharing operations), households tend to decrease their use of vehicles. Comparing similar households in Montreal, Sioui et al. (2012) found that households who subscribe to and actively use a carsharing organization utilize a car 3.7 times less than neighbors who do not subscribe to these services. However, estimates of how much households reduce their auto travel distances vary greatly. Sperling et al. (2000) estimate carsharing reduces VMT by 30-60%. Frost and Sullivan (2010) estimate carsharing members drive 31% fewer kilometers upon joining a carsharing service. Cervero et al. (2007) looked at members of City CarShare in San Francisco and found that in the long term, carsharing members reduced their annual VMT by 67%. Martin and Shaheen (2011b) found through a North American survey that the average VMT by respondents decreased 27% after joining carsharing (from 6468 km/year to 4729 km/year).

In Europe, these impacts seem to be even greater as Muheim (1998) estimates that members of Mobility Carsharing Switzerland drove 72% fewer kilometers after their first year of joining the program and Meijkamp (1998) reports that members of carsharing organizations in The Netherlands drove 33% fewer miles after becoming car-sharers. Ryden and Morin (2005) used stated preference surveys and found that, on average, carsharing members in Bremen, Germany and Brussels, Belgium reduced their VMT by 45 and 28%, respectively.

So how do carsharing members pursue trips while reducing vehicle ownership and cutting VMT? Overwhelmingly, studies point to increased use of non-motorized modes and transit. In the Netherlands, Meijkamp (1998) reports a 14% increase in bicycling, 36% increase in rail transit use, and 34% increase in bus transit use among carsharing members. In Germany and Belgium, Ryden and Morin (2005) estimate that carsharing members use public transportation 35 to 47% more during weekdays. In Montreal, Canada, households who subscribe to carsharing services use public transportation 55% more often than neighbors who own one private vehicle (Sioui et al. 2012). In the US, a second year evaluation of CarSharing Portland found members reporting 25% increase in walking, 10% increase in bicycling, and a 14% increase in public transit use (Cooper et al. 2000). Similar results can be seen in Philadelphia after one year of joining Philly CarShare, 19% of members reported more walking, 8% reported more cycling, and 18% reported more transit use (Lane 2005). In a survey of 13 car sharing operations in North America, Martin and Shaheen (2011c) found the impact on transit use was statistically insignificant after joining car sharing programs but net use of walking, biking, and carpooling modes increased 2%, 7%, and 3%, respectively.

Just like in the traditional carsharing setting, growing SAEV use means an increased awareness of the cost of each vehicle trip. This awareness will likely lead to modal shifts to less expensive alternatives such as transit, cycling, and walking. As travelers grow accustomed to usage-based pricing, they are more likely to choose closer destinations when a reasonable option is available. In the long run, if SAEVs gain significant market share, land use may also shift towards denser multi-use developments that allow households to work, shop, and pursue recreational activities within a smaller travel radius.

Infrastructure Demand

Reduced vehicle ownership also impacts infrastructure requirements, particularly parking. Most governing authorities' interest in promoting traditional carsharing is motivated by parking demand reduction (Millard-Ball et al. 2005). While numerous studies qualitatively link reduced vehicle ownership and parking demand (see, e.g., Millard-Ball et al. [2005] and Martin et al. [2010]), few studies have quantified the magnitude of that impact. A 2004 study in the U.K. surveyed employers and found that spaces fell from 0.79 spaces per staff member to 0.42 spaces per staff member after starting a carsharing program (Department for Transport 2004). Looking at carsharing and parking at the building scale in Toronto, Engel-Yan and Passmore (2013) found that buildings with dedicated carshare vehicles required 50% fewer parking spaces than those without such dedications. Using survey data from Ithaca Carshare, Stasko et al. (2013) estimated program participants' on-street parking needs or demands fall by 26 to 30%, depending on day of week and time of the day.

In addition to the parking demand reduction from decreased vehicle trips, SAEVs are expected to utilize roadway and parking infrastructure more efficiently than driver-operated vehicles. AV technologies can allow for shorter headways, platooning, narrower lanes, and reduced intersection stops, which all contribute to decrease congestion (Litman

2014). With 10% market penetration of AVs, Fagnant and Kockelman (2013) estimate the annual economic savings in congestion would be $16.8 billion, increasing to $37.4 billion with 50% market penetration rate. With the ability to drop off passengers and drive to different locations to park, parking capacities and prices can also be reduced. Fagnant and Kockelman (2013) estimate average parking savings of $250 per AV per year, with only a 2.0% anticipated increase in travel distance (to travel to the parking spots).

Use Phase Energy Consumption

In addition to reducing use phase energy demand by reducing VMT, members of carsharing operations also tend to drive more fuel efficient vehicles than non-carsharing members. Meijkamp (1998) estimates that shared cars are approximately 24% more fuel efficient than the average car in the Netherlands. Martin and Shaheen (2011a) also found that carsharing vehicles are more fuel efficient than the vehicles they replaced, with the carsharing fleet averaging 32.8 mpg and the vehicles they replaced averaging 23.3 mpg. Using stated preference data from Germany and Belgium, Ryden and Morin (2005) estimated that the average carsharing vehicle is 17% more fuel efficient than the average privately owned vehicle. This phenomenon can probably be attributed to the faster replacement rate of carsharing vehicles since they have higher utilization rates. The average privately owned new vehicle in the U.S. is owned for 71.4 months (or approximately 6 years) before being “replaced”, which may be via sale as a used vehicle, trade-in (when acquiring a newer or different vehicle), shedding an unneeded vehicle, or a serious crash (Seng 2012). On the other hand, due to more VMT and faster wear and tear, the commercial carsharing operations replace cars every 2 to 3 years (Mont 2004). With government mandates like CAFE standards and increasing fuel prices, newer vehicles, on average, are more fuel efficient (and smaller) than older fleets, contributing to a more fuel efficient shared fleet compared to a privately owned fleet.

On top of increased energy efficiency due to faster fleet turnover, SAEVs can also reduce energy consumption by minimizing sudden acceleration and braking, with estimated improvements of 23 to 39% over driver-operated vehicles (Atiyeh 2012). Thus, the combined energy efficiency gains between fleet turnover and driving optimization is estimated to improve 43 to 66% compared to manually-driven privately-owned vehicles.

Other Benefits

SAEVs can also have a number of other benefits, such as allowing alternate use of driving time while in-vehicle (as discussed and incorporated into Chapter 3's mode choice model), reducing driver stress (and decreasing health-related risks that come with commuting stress), and increasing mobility for non-drivers. While these are widely acknowledged benefits, few studies have attempted to quantify them. In a survey of 1,000 Germans, Cyganski et al. (2015) reported that the primary advantages of alternate use of time reported by respondents is the ability to enjoy the landscape and the opportunity to talk to fellow travelers, with only 13% of respondents reporting the primary advantage as the ability to work while in the vehicle.

SAEV CHALLENGES

As discussed, the benefits of adopting SAEV service are plentiful. However, current studies examining carsharing operations and AV adoption obstacles lend insight into critical SAEV operation and adoption challenges. These are discussed below.

Vehicle Relocation

There are a number of operation issues limiting the growth of non-autonomous carsharing systems, with vehicle relocation being the biggest challenge in terms of profitability. Barth and Todd (1999) simulated a case study model applied to a resort community in Southern California and found that while optimal fleet size is in the range of 3-6 vehicles per 100 trips in a 24 hour day, with relocation minimization factored in, the optimal fleet size increases drastically 18-24 vehicles per 100 trips. Correia and Antunes (2012) developed an optimization approach to maximize the profits of a carsharing operator using three separate models. The highest profit model assumes that the carsharing operator has the right to deny any trip from list of requests. The lowest profit model assumes that the carsharing operator must accept all trips requested by clients. Lastly, an in-between conditional service model assumes that trip requests can only be rejected by the operator if there are no vehicles available at the nearest carsharing station. Through a simulation in Lisbon, the study found that an attempt to satisfy all demand always led to negative profit, and that without vehicle relocation schemes, fleet sizes nearing taxi fleet sizes (22.7 vehicles per 100 trips) would be required for full service. Without relocation, carsharing vehicles are also quite under-utilized, with the maximum percentage of vehicles in use any time reaching 31% (lowest percentage of vehicles in use is 5%). The authors note that profit is hard to achieve due to "synergies between commuter trips and more self-balanced trips within the [Central Business District]" and suggest that a variable price policy which encourages trips which balances the demand and availability of vehicles at stations could contribute to more profitable operations. Li (2011) developed a discrete event simulation model under different customer behaviors to examine vehicle utilization, reservation acceptance rate, full parking time, and profit as performance measures. The study found that concentric cities (where large amounts of population are concentrated in a few zones) are best served by one-way carsharing systems and cities with more dispersed populations are better served by roundtrip carsharing systems. Operations of carsharing systems can also be very sensitive to uncertainty. Papanikolaou (2011) proposed a systems dynamics model which simulated one-way carsharing systems with three stock-flow sub-models for stations, users, and vehicles (consisting of 120 equations). A case study on a synthetic network revealed that random events such as breakdowns or changes in reservation schedules can highly compromise the performance of the carsharing system.

Various studies have examined vehicle relocation strategies to optimize the performance of carsharing operations from a system perspective. Earlier works examined the optimized redistribution of carsharing vehicles in a static setting (see, Barth and Todd 1999, Barth et al. 2004, Kek et al. 2009). Fan et al. (2008) proposed a stochastic model which determined vehicle allocation to maximize profit when looking at probabilistic future demand. However, the model does not consider parking availability, a common resource constraint for carsharing operations. Wang et al. (2010) proposed a method to forecast and relocate vehicles using microscopic traffic simulation, forecasting model, and inventory replenishing. Stations with more inventory than predicted demand were defined as candidate supplier stations and stations with less inventory than predicted demand were defined as candidate demander stations. Inventory replenishment at demander stations was determined by the lowest trip cost at the moment of the vehicle relocation from a supplier station as determined by a microscopic traffic simulation model. Nair and Miller-Hooks (2011) developed a stochastic, mixed integer program (MIP) that generates a least-cost vehicle location plan for carsharing systems which meets specified minimum near-term demand. The program allows for exploration between the trade-offs of redistribution costs and level of service. Smith et al. (2013) looked at vehicle rebalancing strategies for a one-way, station-based urban mobility system that blends carshare vehicles with taxi vehicles.

In this setup, the taxi drivers can be employed to rebalance the vehicles at the stations. However, the balancing of the taxi drivers becomes another optimization problem. The algorithm proposes the solution as a function of two linear programs and showed that with taxis blended with a carsharing fleet, the optimal number of drivers is about 1/3 to ¼ that of the total number of vehicles.

The literature on carsharing vehicle relocation indicates that strategic relocation is likely a key component in a successful SAEV service to maximize vehicle usage and minimize fleet size. The specific relocation strategy used in this agent-based simulation is discussed in Chapter 2. These studies on carsharing also point to the importance of a dynamic, supply- and demand-driven pricing scheme for SAEV service (as opposed to the flat distance- or time-based pricing structure of current manual carsharing services). Such a "balancing" pricing structure is explored in Chapter 3 (along with simple distance-based pricing). Dynamic pricing can also help moderate SAEV trip demand and minimize sudden demand "shocks" which are difficult to abate with shared vehicle services. Lastly, to prevent unexpected disruptions in reservation schedules (as carsharing operations are very sensitive to uncertainty), SAEV operators should discourage trip request cancellations, perhaps through a nonrefundable reservation fee.

Charging Station Site Selection

Both shared and privately-owned EVs need to recharge at convenient locations. As discussed in greater detail in Chapter 2, EV charging stations are a costly infrastructure investment. Thus, charging station site selection is a delicate balance between budgetary constraints and user convenience. Research efforts on the front of non-shared EV charging station assignment based on user access can be described by two types of discrete optimization models: coverage and median models. Coverage models determine the minimum number of stations needed to cover all charging demand. Wang (2007) used a coverage model for placement of charging stations for a fleet of electric scooters in Taiwan, minimizing the number of charging stations while satisfying sufficient charging time for scooters to complete intended trips. A downfall of simple coverage models is that they assume no resource limitations (unlimited numbers of charging stations), which is unrealistic in real world EV charging station problems. Looking at coverage as a minimization problem, Dong et al. (2014) use activity-based travel data to locate public charging stations based on the objective of minimizing the number of missed trips. In this model, the total cost of constructing the charging stations is subject to a budget constraint and solved using a genetic algorithm. Another way to look at charging station assignment is to minimize the distance between where EVs are when they need to charge and the nearest charging location. These median models (see, e.g., Hakimi 1964) minimize the distance traveled by EVs to charging stations, weighted by the number of charging requests or charging duration. A limitation to coverage models is that they cannot determine optimal capacity at each charging station, leaving capacities either pre-determined or undetermined. Ip et al. (2010) applied hierarchical clustering analysis to identify demand clusters, then minimized the system's total operation cost by assigning charging stations to select clusters based on demand at each cluster. Frade et al. (2011) proposed a model which maximizes the coverage of demand clusters during morning and evening peak hours for Lisbon, Portugal, constrained to a fixed number of charging stations and fixed capacity at each charging station. Xi et al. (2012) simulated a fleet of public electric vehicles in central Ohio and located charging stations which would maximize charging use, constrained to the total number of charging vehicles. Chen et al. (2013) developed a median model using parking data from Seattle (Puget Sound Regional Council's 2006 household travel survey data) to minimize the distance traveled by EVs to charging stations, weighed by the parking duration. Barouche et al. (2014) developed an optimization model for locating charging stations in Lyon, France, minimizing the total cost of constructing charging stations at the candidate sites and the total energy required for vehicles needing to charge to access the charging stations. However, this model's application is limited to dense urban networks, where charging demand is assigned to a specific demand cluster, and the cluster is associated with only one charging station.

Other researchers have attempted to look at a more comprehensive picture of charging station planning, including power grid infrastructure and EV ownership trends in their respective models. Wang et al. (2010) created a numerical method for the layout of charging stations using a multi-objective planning model. Accounting for charging station attributes, distribution of gas-station demands (rather than parking decisions, as a proxy for charging demands), and power grid infrastructure, among other variables, the researchers tested and verified their model using data from Chengdu, China. Demand was defined as a function of flux in each zone (determined from the number of vehicles leaving and entering each zone). Sweda and Klabjan (2011) used an agent-based decision support system to identify patterns of residential EV ownership and driving activities to determine strategic locations for new charging infrastructure, with the Chicago region as a case study. They find that EV ownership extends beyond the core areas, and they speculate that BEV owners are often those with higher incomes, residing in less dense areas. Wirges et al. (2012) also consider EV ownership in their spatial planning model for charging stations, recognizing the temporal, dynamic aspect of EV ownership at a regional level. The researchers first simulate EV ownership using a Bass diffusion model, then estimate the charging demand from the estimated EV fleet, and lastly, locate the charging stations based on intercity travel data. He et al. (2013) examined optimal charging station locations of PHEVs with the objective of maximizing social welfare, using a hierarchical model which captures the interaction between the regional transportation network and the transmission grid. The convex mathematical program solves for an equilibrium state between electricity prices, origin-destination flows, and power flow.

The existing literature on public EV charging station site selection indicates that for a fleet of SAEVs, the ideal charging infrastructure should simultaneously maximize charging coverage and minimize access travel to charging sites. In this dissertation, the focus of charging station selection is on maximizing charging coverage (as discussed in Chapter 2) while vehicles miles traveled to charging stations is minimized through pricing strategies (as discussed in Chapter 3).

Policy and Public Perception

While private companies (both automotive and non-automotive) have made great investments into development of AV technology, policy on autonomous driving has been more reactive than proactive. Currently, only four states have passed legislation to address the presence of self-driving vehicles on public transportation infrastructure. In 2011, Nevada, lobbied by Google, was the first state in the U.S. to legally allow autonomous driving on public roads by providing the legal framework for licensing and testing of AVs (Knapp 2011). In 2012 and 2013, Florida, California, and Michigan also passed laws recognizing the legality of AVs on public roads, although in the latter two states, a driver is required to sit behind the wheel of the car in case of failure by the robotic system (Ingram 2013). The USDOT has also issued a preliminary statement of policy outlining strategies and recommendations for preparing for AVs on public roads (NHTSA 2013). Nonetheless, there is no standardized framework for AV licensing and insurance (Fagnant and Kockelman 2013), which presents significant barriers for the implementation of SAEV services.

While those in the transportation industry are optimistic about the future of self-driving vehicles, the topic of AVs draws a mixed reaction from the public. A survey of public opinion about self-driving vehicles in the US, the UK, and Australia found that the majority of respondents have a positive opinion about AV technologies and have high expectations about the benefits (Schoettle and Sivak 2014). At the same time, respondents also expressed concern about security and safety issues related to self-driving vehicles with approximately one third of respondents stating they would be “very concerned” about riding in fully self-driving vehicles (Schoettle and Sivak 2014).

SUMMARY

A full understanding of the market share, development timeline, benefits, and challenges of a future SAEV service requires examining these issues in their current contexts of carsharing, EV infrastructure, and AV technology. Existing studies on the characteristics of current carsharing users and trips provide insight into the early SAEV adopter demographic, and, when combined with AV technology development progress, provide a possible timeline for SAEV deployment. Carsharing literature indicates that residents of dense urban zones with low vehicle ownership and access to alternative transportation modes are more likely to be early adopters of the SAEV mode. Deployment of SAEV service hinges on technology maturity and consumer/customer perception. Small-scale SAEV service may be available as early as 2018 in select cities, but will depend on technological advances, cost reductions, public policy, and public perceptions. When full-scale SAEV service becomes a reality, the public will witness safety benefits, a decrease in transportation infrastructure demand, and energy use savings from efficient driving optimization. In the long term, as SAEV users become accustomed to the efficient

SAEV pricing of travel by distance or time, they will likely adopt shifts in travel behavior which will also have significant environmental and energy use impacts. From the literature on carsharing discussed earlier in this chapter, these impacts are likely to include reduced private vehicle ownership and private VMT, modal shift to alternative modes, and energy savings from a more fuel-efficient fleet due to faster shared fleet turnover rates. However, the implementation of SAEV service will also present critical challenges to potential operators. Internally, SAEV operators must address the issue of vehicle relocation to balance vehicle supply and demand to meet traveler needs, and carefully plan charging infrastructure to maximize access for the fleet while meeting budgetary constraints. Externally, future operators are limited by the lack of standardized policies for operations and licensing of autonomous vehicles as well as security and privacy concerns of potential users.

CHAPTER 2: VEHICLE AND CHARGING INFRASTRUCTURE DECISIONS

This chapter examines the impact of vehicle type and charging infrastructure on SAEV fleet performance in a discrete-time agent-based model, examining fleet operations in a 100-mile by 100-mile gridded city. Scenarios combine short-range and long-range electric vehicles with Level II and Level III charging infrastructure to look at the impacts of vehicle range and charging time on fleet size, charging station sites, ability to meet trip demand, user wait times, and induced vehicle miles traveled (VMT). Addtionally, a financial analysis takes a closer look at the tradeoffs between infrastructure and vehicle investment and SAEV fleet performance metrics.

PRIOR RESEARCH

There is a wealth of literature examining carsharing, charging infrastructure planning for EVs, and AVs as separate topics. Studies looking at gasoline-propelled and or electric AVs in a shared setting are more limited. Wang et al. (2006) proposed a dynamic fleet management algorithm for shared fully automated vehicles based on queuing theory. The objective function minimizes wait time of passengers and the number of vehicles used in a certain period. In a simulative environment with five stations and five vehicles, the average passenger waiting time was 3.37 minutes with average vehicle usage rate of 4.3 vehicles per minute, as compared to a fixed dispatch algorithm where average passenger wait time was 4.89 minutes and average usage rate was 3.7 vehicles per minute. Spieser et al. (2014) modeled a fleet of shared self-driving vehicles in Singapore in the absence of any private vehicles, and found that each shared vehicle can replace three privately owned vehicles and serve 12.3 households. Ford (2012), Kornhauser et al. (2013), and Burns et al. (2013) have simulated the operations of shared autonomous taxis, in scenarios where the passengers walk to taxi stands rather than allowing AVs to relocate. In Kornhauser et al. (2013), aTaxiStands (autonomous taxi stands) are placed in every half mile by half mile pixel across the entire state of New Jersey. Douglas (2015) uses the base model proposed in Kornhauser et al. (2013) to size the fleet of an autonomous taxi system in a 5 mile by 5 mile subset of the New Jersey model and estimated that a minimum of 550 vehicles was needed to serve the trip demand. Burns et al. (2013) examined the performance of a shared autonomous fleet in three distinct city environments: a mid-sized city (Ann Arbor, Michigan), a low-density suburban development (Babcock Ranch, Florida), and a large densely-populated urban area (Manhattan, New York). The study found that in mid-sized urban and suburban settings, each shared vehicle could replace 6.7 privately owned vehicles. Meanwhile, in the dense urban setting, the current taxi fleet could be downsized by 30% with the introduction of autonomous driving technology with average wait times at less than one minute. The International Transport Forum (2015) looked at the application of shared and self-driving vehicles in Lisbon, Portugal, and found that with ride-sharing enabled, each shared vehicle can replace approximately 10 privately owned vehicles and induces 6% more VMT than the current baseline. Without ride-sharing, each sequentially shared vehicle can replace 6 privately owned vehicles but induces 44% more travel distances. This study also looked at the impact of electrifying this fleet of shared self-driving vehicles, assuming an electric range of 175 kilometers (108 miles) and a recharge time of 30 minutes, and found that the fleet would need to be 2% larger. Fagnant and Kockelman (2014) presented an agent-based model for Shared Autonomous Vehicles (SAVs) which simulated environmental benefits of such a fleet as compared to conventional vehicle ownership and use in a dense urban core area. Simulation results indicated that each SAV can replace 11 conventional private owned vehicles, but generates up to 10% more travel distances. Still, the overall emissions savings are sizable, with the base case scenario showing 12% energy use and 6% GHG emissions savings over private light-duty vehicle ownership and use. When the simulation was extended to a case study of low market penetration (1.3% of regional trips) in Austin, Texas, each SAV was found to be able to replace approximately 9 conventional vehicles and on average, generated 8% more VMT due to unoccupied travel (Fagnant et al. 2015).

Charging/refueling in a fleet of shared self-driving vehicles has remained a missing component in all of the prior studies mentioned here except ITF (2015) and Fagnant and Kockelman (2014), both of which model the refueling process rather simplistically. Fagnant and Kockelman (2014) modeled the logistics of refueling by assuming the 400-mile range SAVs could refuel at any location within the grid with a 20 minute service lag time. In ITF (2015), recharging of EVs is only looked at in terms of equivalent fleet sizing compared to longer range and shorter recharge time gasoline-propelled vehicles. No study has examined the operations of shared autonomous vehicles looking specifically at the vehicle propulsion system and charging infrastructure, both of which have direct impacts on the vehicle's ability to travel to passengers as well as fueling/charging stations.

The work described here builds from the framework in Fagnant and Kockelman (2014) and analyzes the operations of a SAEV fleet under different vehicle range and charging infrastructure assumptions. There are natural synergies between AVs and EVs, as the "smart" nature of AVs resolve the practical limitations of the non-autonomous EV in the market today. These limitations include the previously discussed all electric range, charging station density, and charging time management. Fleet managed "smart" AVs relieve such concerns from the individual traveler, managing range and charging activities based on predicted trip demand and established locations of charging stations, as demonstrated in the work here.

THE AGENT-BASED MODEL

The discrete-time agent-based model used here is an expansion of the 10-mile by 10-mile urban core model proposed by Fagnant and Kockelman (2014). Here, the model generates a square 100-mile by 100-mile gridded city, divided into 160,000 quarter-mile by quarter-mile cells. The 400-cell by 400-cell city has an origin at the very center (coordinate [200, 200]) which serves as the center of the downtown zone. The gridded city (roughly modeled after the population density pattern of Austin, Texas) is divided into four zones as shown in Figure 2-1: downtown (the innermost 2.5-mile radius), urban (the next ring 7.5-mile radius), suburban (the next ring 15-mile radius), and exurban (the remaining area). Each square cell is considered to be part of a zone if the Euclidean distance from the edge closest to the origin cell (southeast corner for zones northwest of downtown, southwest corner for zones northeast of downtown, and so forth) to the origin falls within the radius limits shown in Figure 2-1. Trip rates for these zones are determined with trip data from the Austin travel demand model segmented by population density. Here, the exurban zone represents Austin traffic analysis zones (TAZs) with less than 500 persons per square mile, the suburban zone represents TAZs between 500 and 1999 persons per square mile, the urban zone represents TAZs between 2000 and 7499 persons per square mile, and the downtown zone representing TAZs between 7500 and 50,000 persons per square mile. In all, the simulated zones represent approximately a 2.9 million people region. Each zone has its own unique average trip generation rate, totaling approximately 680,000 trips per day (representing approximately 10% of all trips in the Austin region inclusive of return trips, reflecting what Shaheen et al. [2006] estimate as market potential for carsharing in a manually-driven setting) and average peak and off-peak travel speeds (derived from sample peak and off-peak trips from the Austin travel demand model), as shown in Table 2-1. It is important to note that the peak and off-peak vehicle speeds can only be calibrated to a granularity that corresponds with the discrete 5-minute time steps modeled here.

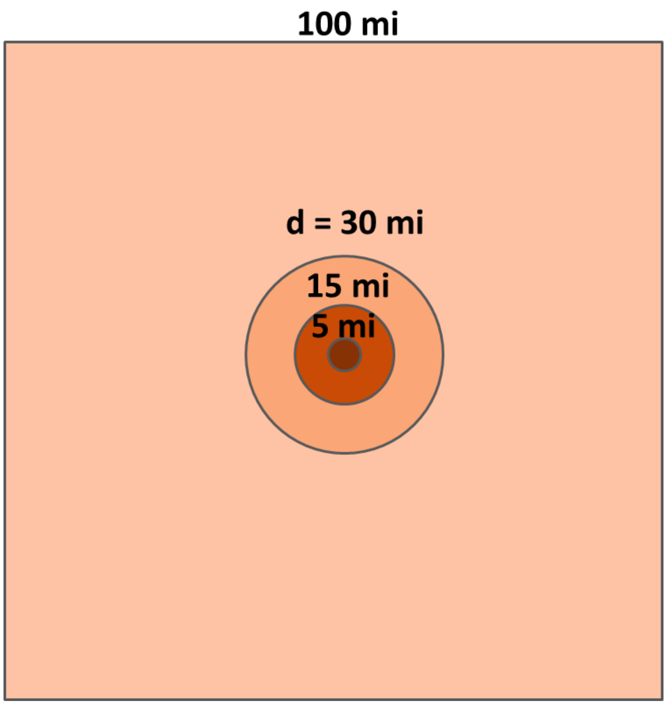


Figure 2-1: Gridded City Zones and Zone Limits

	Avg Trip Gen. Rate (trips/cell/day)	Travel Speed (mi/hr)	
		Peak (7-8am, 4:30-6pm)	Off-Peak (All Other Hours)
Downtown	129	15	15
Urban	39	24	24
Suburban	11	30	33
Exurban	1	33	36

Table 2-1: Zone Trip Generation Rates & Travel Speeds

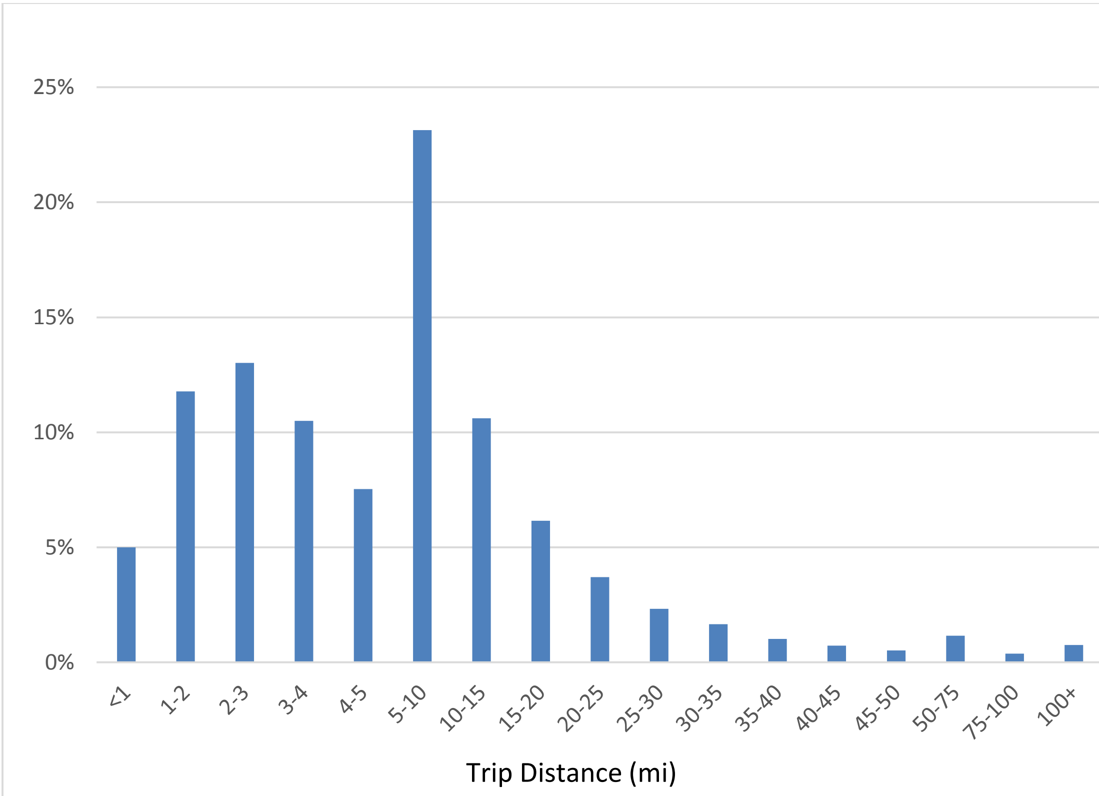


Figure 2-2: U.S. Personal Travel Trip Length Distribution (2009 NHTS Data)

Trips generation rates shown in Table 2-1 represent the average rates for each zone. The actual trip generation rate in each cell is drawn from a Poisson distribution for each 5-minute time step within a 24-hour temporal distribution following the average rates of the 2009 National Household Travel Survey (FHWA 2009). The destination cells for each trip generated are assigned as a function of the trip length (drawn from the 2009 NHTS person-trip length distribution, shown in Figure 2-2) and proportional to the share of cells to the north, south, east, and west of the origin cells. In other words, the trip generation methodology used here favors higher attraction levels toward the city center. For detailed information on the step-by-step trip generation methodology used here, please refer to Fagnant and Kockelman (2014).

The model first runs through a two-phase warm start, during which the number of charging stations and the size of the SAEV fleet is determined. After the warm start completes, the model then runs for 50 consecutive days with the predetermined fleet size and charging station layout to output fleet operation performance metrics. Each phase of the model is discussed in detail in the following sections.

Charging Station Generation

In Phase 1 of the warm start, consecutive 24-hour days are modeled to determine the number of charging stations needed for full service of the SAEV fleet. Figure 2-3 demonstrates the process of how and where charging stations are generated in the warm start.

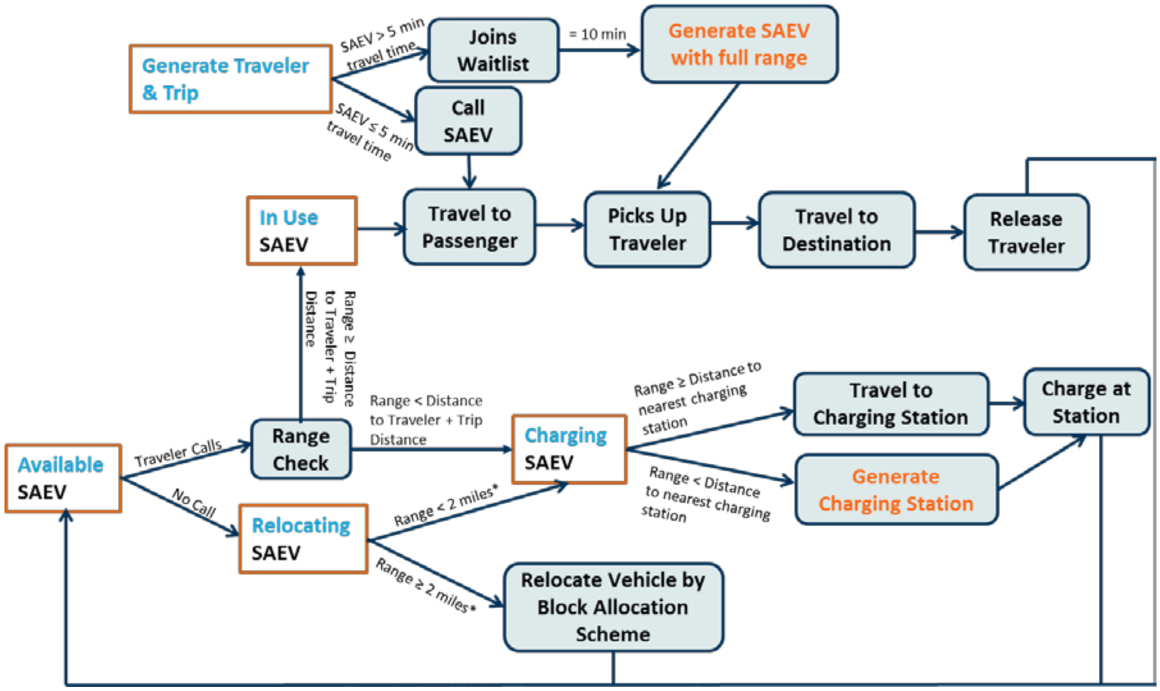


Figure 2-3: Agent-Based Model Algorithm-Charging Station Generation

Once a trip is generated by the process discussed in the Model Setup section, a traveler looks for the closest *available* status SAEV within a 5-minute travel time radius through a greedy search algorithm (searching at increasing distances starting from its own origin cell, followed by a search to the north, south, east, or west drawn at random, and so forth). If an available SAEV is located within a 5-minute travel-time radius, the traveler claims the SAEV and the SAEV falls under *in use* mode for the subsequent time periods to pick up the traveler, complete the assigned trip, and release the traveler. If an SAEV is not available within a 5-minute travel-time radius, the traveler joins a waitlist. In the following 5-minute time step, travelers on the wait list are prioritized and served first, before new trips generated during the current time step are served by SAEVs. When a traveler has been on the waitlist for 10 minutes (or two time steps), a new SAEV is generated with full charge in the cell that the traveler is originating from.

Once an SAEV releases a traveler at the destination cell, the vehicle changes from *in use* to *available* status, and awaits a traveler call in the subsequent 5-minute time step. If the vehicle is not called in the time step, the SAEV changes from *available* to *relocating* status, and its subsequent actions are discussed in the Strategic Vehicle Relocation section below. If a traveler calls, the SAEV checks to ensure that its remaining range is greater than the distance to the traveler plus the distance of the requested trip before accepting the call. If the range is insufficient, the call is rejected and the SAEV changes from *available* to *charging* status. In *charging* status, the SAEV looks for the nearest charging station (by the same greedy algorithm used in trip matching), and if one does not exist within its remaining range, a charging station is generated in the SAEV's current cell. The SAEV then stays in *charging* status at the charging station for the number of time steps proportional to its remaining range, as shown in Equation 1:

Equation 1-1: $T_{charge} = \left\lceil \frac{Range_{full} - Range_{current}}{Range_{full}} \right\rceil T_{full}$

where T_{charge} is the number of time steps an SAEV remains at the charging station cell in *charging* status before becoming *available* for the next traveler, $Range_{full}$ is the number of grid cells an SAEV can travel when fully charged, $Range_{current}$ is the SAEV's current remaining range in grid cells, and T_{full} is the number of time steps required for a fully depleted SAEV battery to fully charge.

Phase 1 of the warm start continues until the number of charging stations on consecutive days converges to within 1%. That is to say, when the number of charging stations added on a subsequent day is less or equal to 1% of the number of charging stations on the prior day, the full set of charging stations is reached.

SAEV Fleet Generation

When phase 1 of the warm start is complete, the charging station layout is set and no more charging stations can be added to the city. The SAEV fleet is cleared to start phase 2 of the warm start, which determines the size of the SAEV fleet. The two phases of the warm start operate independently of each other since the number of SAEVs required in the fleet depends on the number of charging stations available. During the generation of the charging stations, the corresponding SAEV fleet is (temporarily) oversized. The overall algorithm for phase 2 of the warm start is very similar to that of phase 1, as seen in Figure 2-4.

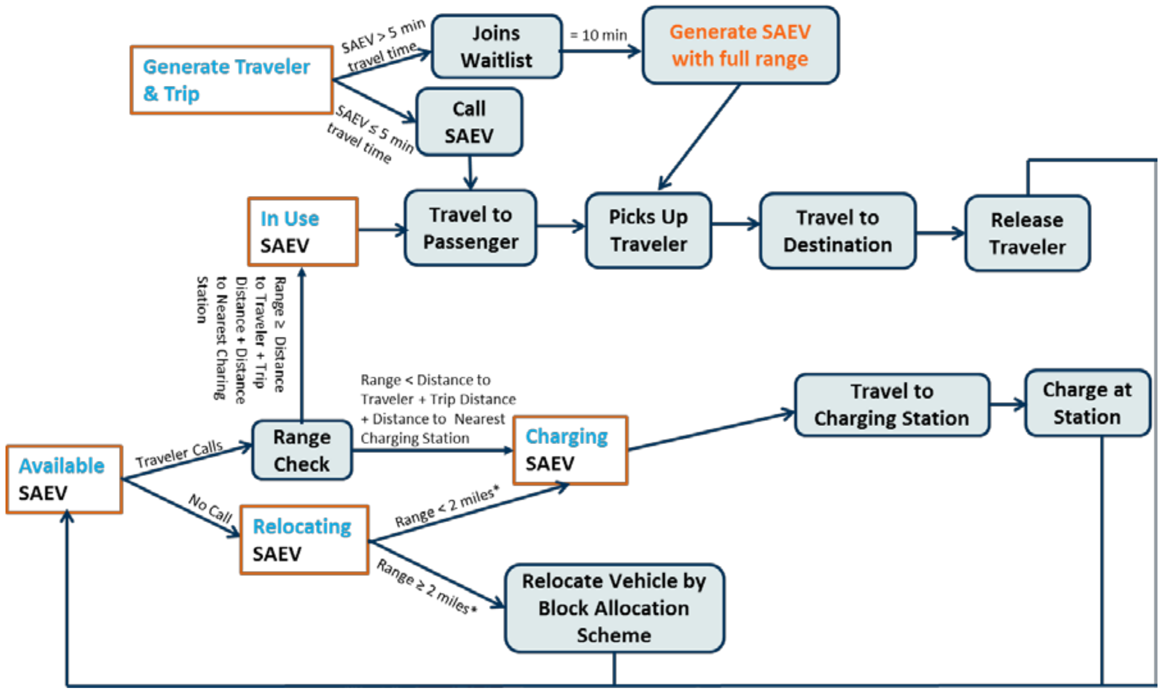


Figure 2-4: Agent-Based Model Algorithm-SAEV Fleet Generation

The SAEVs are generated in a similar process as described in phase 1 of the warm start. Because no charging stations are generated in phase 2 of the warm start, in order to accept a traveler's call, the SAEV must have sufficient range to travel to the traveler, complete the requested trip, and travel to the nearest charging station from destination cell. Phase 2 of the warm start is run for 20 days, with vehicles cleared at the end of each day. The average number of SAEVs generated from the 20 days is taken as the fleet size for the full run.

Waitlist

Once the charging station locations and SAEV fleet size is determined from the two phase warm start, the program runs through 50 consecutive days when vehicles are in continuous operation (no vehicle clearing). The full run's model structure is identical to that of phase 2, except no new SAEVs are generated and travelers remain on the waitlist.

If a traveler's trip request is rejected in 6 consecutive time steps (equivalent to 30 minutes on the waitlist), that trip is considered unserved and is removed from the waitlist. As previously mentioned, in the full run, the entire 2009 NHTS trip distance distribution is used in trip generation. Therefore, trip distances exceeding the range of the SAEVs automatically contribute to the unserved trips metric.

Strategic Vehicle Relocation

During each step of the model (warm start and full run), available SAEVs that are not called by travelers are assigned to *relocating* status for that time step. As discussed in Chapter 1, relocation strategies are key to the success of shared vehicle services. The relocation strategy used in this model first attempts to balance the available SAEVs in the current time step with the expected demand in a 2-mile by 2-mile block in the subsequent time step, then uses two additional strategies to efficiently distribute SAEVs among bordering blocks with a large vehicle supply gap. A block balance is calculated for each 2-mile by 2-mile block to examine the relative surplus or deficiency of SAEVs in each block compared to all other blocks. Blocks with the highest block balance surpluses push relocating SAEVs into adjacent blocks (prioritized by greatest deficiency) while those with the highest deficiencies pull relocating SAEVs from adjacent blocks (prioritized by greatest surplus). After balance is optimized in the larger 2-mile by 2-mile blocks, two subsequent relocation strategies further spread vehicle supply on a smaller scale from cell to cell. The first strategy moves surplus available vehicles (in excess of 2) to cells within a half mile which have zero available vehicles. The second strategy moves surplus available vehicles (in excess of 3) to an adjacent cell with the highest deficit of vehicles. This combination of relocation strategies was deemed the most effective out of several that were tested in Fagnant and Kockelman (2014). To ensure that vehicles in *relocating* status have sufficient range for relocation, a check ensures that the SAEV has sufficient range to travel a distance equivalent to 5 minutes of travel time from its original cell (roughly equivalent to 2 miles but varies with whether the vehicle is in the downtown, urban, suburban, or exurban zone) plus the distance to the nearest charging station to the relocation destination.

VEHICLE AND CHARGING INFRASTRUCTURE SCENARIOS

The agent-based model described here is run for several scenarios to examine the sensitivity of various fleet operation metrics to model inputs, as shown in Table 2-2. Model run times ranged from 131 to 186 minutes per scenario on a high-performance desktop computer. A non-electric SAV scenario (assuming 400-mile range and 15 minute refueling time) is run as a reference case for comparison to the results in Fagnant and Kockelman (2014), which examined the operations of a SAV fleet across a smaller space (with higher rates of trip generation) with a 20 minute refueling-time assumption (for vehicles to essentially refuel in place, since gas stations are rather ubiquitous in North America). Next, the SAEV scenario assumes the vehicle has an 80 mile range (similar to that of current models of the Nissan Leaf, Chevrolet Spark, Honda Fit EV, and BMW i3) and 4 hour full recharge time, corresponding to charging times of current market BEVs with a 240-volt AC Level II charger. A SAEV Fast Charge scenario assumes the same 80 mile vehicle specifications with a recharge time of 30 minutes, mimicking the specifications of current market BEVs with a Level III 480-volt DC high-current charger. Following current fast charging guidelines, the SAEVs in the fast charge scenario will only be charged to 80% full, to protect the batteries from losing capacity from repeat fast charging, which effectively reduces the range to 64 miles. The last two scenarios looks at various types of charging in combination with long-range BEVs matching the 200 mile range specification of the recently announced Chevrolet Bolt and Tesla Model 3 (both with 2017 planned release dates). The LR SAEV scenario combines a 200-mile range with a 4 hour recharge time while the LR SAEV Fast Charge scenario combines a 160-mile effective range with a 30 minute fast charge time.

Scenario	SAV	SAEV	SAEV Fast Charge	LR SAEV	LR SAEV Fast Charge
Range (mi)	400	80	64	200	160
Refuel/Recharge Time (min)	15	240	30	240	30
# of Charging/Fueling Station Sites	1062	1562	1573	1555	1517
# of Chargers/Fuel Pumps*	2231	30,113	16,502	16,554	2378
Fleet Size	29,939	57,279	39,593	41,179	31,859
Avg Daily Miles per Veh	259	131	197	190	241
Avg Daily Trips per Veh	22.3	11.4	16.9	16.3	20.8
Veh Replacement Rate	7.32	3.73	5.53	5.33	6.82
% Trips Unserved	2.13%	3.94%	4.36%	2.29%	2.73%
Avg Trip Distance (mi)	10.06	9.41	9.08	10.02	10.02
Avg Wait Time Per Trip (min)	9.29	8.10	7.67	8.44	9.53
Avg Range Remain. at Recharge (mi)	1.62	43.09	40.72	5.42	2.47
% Total ”Empty” Miles Travel	6.64%	10.69%	14.02%	7.09%	7.05%
Max % of Concurrent Charging Vehicles	7.45%	52.57%	41.68%	40.20%	7.46%

*As proxied by the maximum number of concurrent charging/refueling vehicles in the day.

Table 2-2: Performance Metrics from Vehicle & Charging Infrastructure Scenarios

Simulation results show that the number of vehicles needed in a fleet is highly sensitive to charge time and, to a slightly lesser degree, vehicle range. Substituting Level III in place of Level II chargers for SAEV and LR SAEV fleets reduced the required fleet size by 30.9 and 23.3%, respectively. On the other hand, increasing the electric range of vehicles from 80 to 200 miles reduced the fleet size by 28.1 and 19.5% respectively for Level II and Level III charging schemes. Combining these effects, the necessary fleet for the SAEV scenario is almost double the size of that for the LR SAEV Fast Charge scenario. Using 2009 NHTS rates for 3.02 private car trips per licensed U.S. driver and 0.99 household vehicles per licensed driver (Santos et al. 2011), the private vehicle replacement rate is highest at one shared vehicle for every 7.3 private vehicles in the SAV scenario, in line with the results from the mid-sized urban and suburban models in Burns et. al (2013) and the regional model in Fagnant and Kockelman (2015). However, once the fleet is electrified, the private vehicle replacement rate ranges from a comparable 1:6.8 vehicle ratio in the LR SAEV Fast Charge scenario to a much lower 1:3.7 vehicle ratio in the SAEV scenario. The non-electric SAV fleet requires the fewest number of vehicles (29,939) for full service, and the closest competitive EV scenario (LR SAEV Fast Charge) increases that fleet size by 6.6%, a slightly larger difference than estimated in ITF (2015) despite longer EV range assumption. As seen in Figure 2-5, a snap shot of each vehicle's activity during the peak 5-minute period (defined as the time step with the most *in use* vehicles) demonstrates that with longer charging times and shorter ranges, vehicles are simply tied up at charging stations not able to service trip demand. While the number of *in use* vehicles is relatively consistent across all scenarios, the number of *charging* vehicles increases significantly with longer vehicle charge times and shorter electric range.

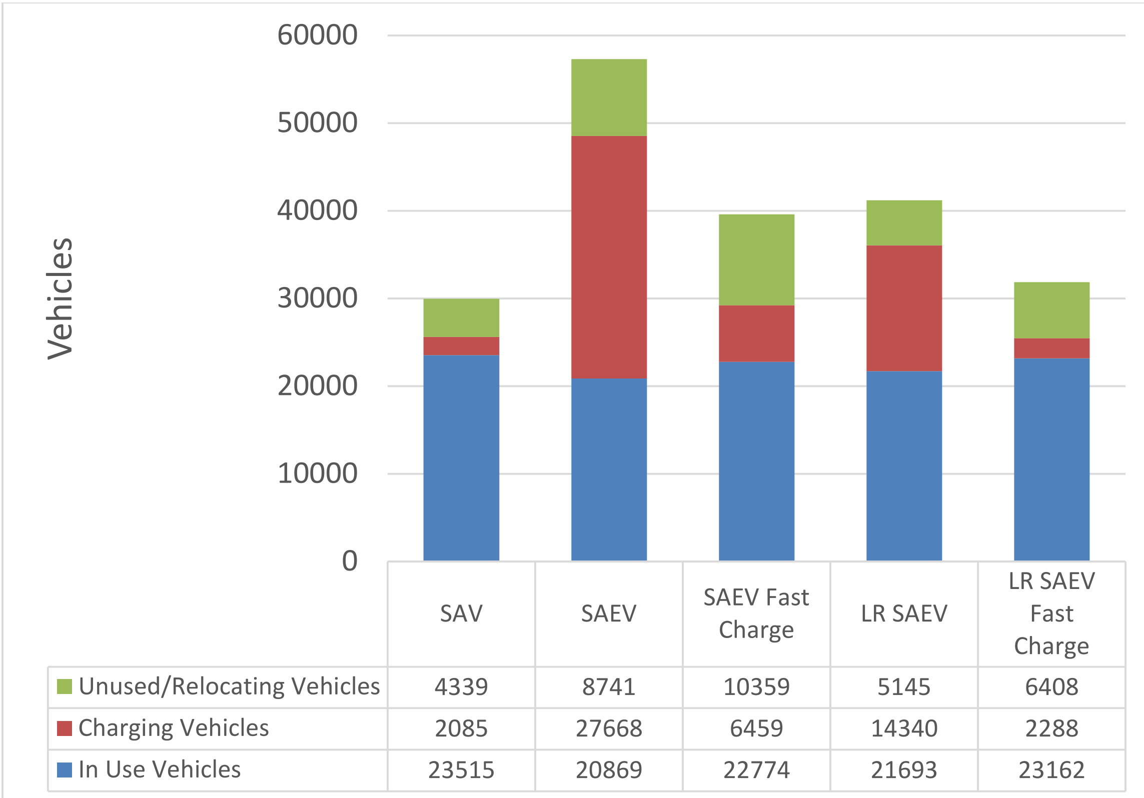


Figure 2-5: Peak (5-Minute) Period Vehicle Use

As seen in the results in Table 2-2, for full service, all EV scenarios produced similar numbers of charging station sites. This result suggests that the number of charging station sites (cells with charging stations) necessary for full service has an inelastic relationship with the vehicle's electric range, but is more determined by the geography of the city (or size of the geo-fence of the service area). Conversely, the total number of chargers needed (as proxied by the average number of charging vehicles in the time step with the most concurrent charging across 50 days) is highly sensitive to charge time and vehicle range. Using Level III chargers cuts the charge time for SAEV and LR SAEV fleets by 87.5%, and correspondingly, the number of needed chargers by 45.2 and 85.6%. Holding charging infrastructure constant, substituting LR SAEVs for SAEVs in the fleet (and increasing vehicle range by 150%), the number of chargers needed decreases 45.0 and 85.6%. Generally speaking, the time steps with higher number of trip requests correspond with the time steps with more concurrent charging vehicles. Simulation results suggest that the LR SAEV Fast Charge scenario is best at spreading out charging demand across the day, with a maximum of 7.46% of vehicles in the fleet concurrently charging during any time step. On the other hand, in the base SAEV scenario, as many as 52.6% of the vehicle fleet charge concurrently during the peak charge time period of the day.

Consistent with what intuition would suggest, simulation results show that longer vehicle range translates into higher percentages of trips served, as vehicles simply cannot serve trips longer than its maximum range. In the 2009 NHTS, 1.05% of the trips are over 80 miles long. In the simulation results, the difference between trips served between the 200-mile LR SAEV and the 80-mile SAEV is 1.65%. However, longer vehicle range is generally associated with longer wait times in the simulation results, primarily due to the inefficiency of serving trips originating in low-demand suburban and exurban areas a shared setting. As seen in Figure 2-6, longer-range vehicles spend more of their "empty" VMT for passenger pick-up while shorter-range vehicles spend more of their "empty" VMT for relocation. Due to the higher trip generation rates in the urban core, the relocation strategy employed here moves unused vehicles in each time step closer to the city center. This positioning strategy decreases shorter-range vehicles' ability to serve trips generated in low-demand outlying areas. As a result, a fleet of shorter-range SAEVs has a relatively lower vehicle utilization rate compared to longer-range SAEVs (as seen by the greater numbers of relocating and charging vehicles in the peak use 5-minute period in Figure 5), but are also able to relocate themselves to serve trips originating in high-demand areas efficiently, translating to shorter average wait times per trip.

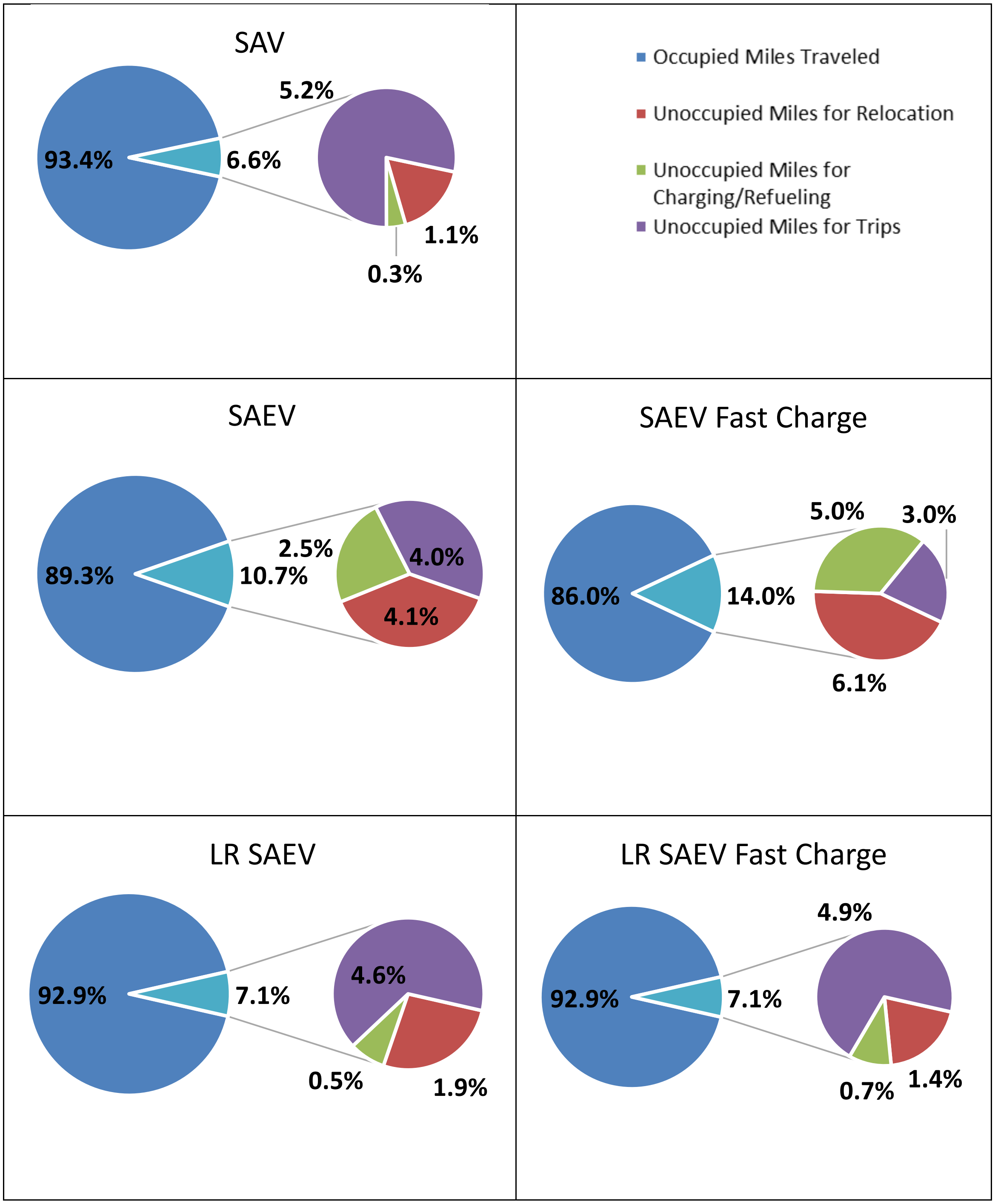


Figure 2-6: Occupied vs. Unoccupied Travel Miles for Trips, Charging & Relocation

Each autonomous driving scenario produced an additional 7.1 to 14.0% of unoccupied VMT, in line with estimates in ITF (2015) and Fagnant et al. (2015). As seen in Figure 2-6, for vehicles with longer range (SAVs and LR SAEVs), the greatest portion (65.6 to 78.4%) of that induced travel can be attributed to unoccupied vehicles traveling to pick up passengers. Unoccupied travel to charging/refueling stations played a relatively minor role in inducing additional VMT, summing to 0.5 to 0.7% of total VMT (or 4.5 to 10.0% of "empty" miles traveled) for longer range vehicles, as seen in Figure 2-6. Due to the more frequent need to recharge, induced miles traveled for recharging is greater for scenarios with shorter range vehicles. SAEVs registered an additional 2.5 to 5.0% miles for charging activity, consisting of 23.6 to 35.4% of their total "empty" miles traveled. As discussed previously, shorter-range vehicles relocate more to position themselves for trips from high-demand zones. Thus, unoccupied travel for strategic vehicle relocation increased with shorter vehicle range, accounting for 4.1 to 6.1% of total VMT (or 38.5 to 43.5% of total unoccupied VMT). For SAVs and LR SAEVs, unoccupied travel for relocation consisted of only 1.1 to 1.9% of total VMT (or 4.5 to 10.0% of total unoccupied VMT).

Not only do shorter range vehicles charge more frequently, simulation results in Table 2-2 also show that they utilize a smaller percent of their range before a charging event. The phenomenon of shorter range vehicles recharging with higher baseline remaining range can be attributed to the demand-based charging strategy employed here, where a vehicle is assigned to charging status after rejecting a trip request due to insufficient range. With shorter ranges, the SAEVs are more frequently assigned to charging status due to increased probability of having insufficient range for trips. To explore whether charging less frequently would improve the fleet performance of the shorter range SAEV scenarios, a distance-based charging scenario was employed in which SAEVs (with Level II chargers) are assigned to charging mode only when its range reaches

10 miles or less. The results comparing the two charging strategies (shown in Table 2-3) show that a distance-based charging strategy reduces the frequency of charging trips (with SAEVs charging on average with 1.2 miles of remaining range compared to 43.0 miles of remaining range in the trip-rejection charging strategy) and correspondingly the induced empty-vehicle (unoccupied) VMT (by -15.7%, with the bulk of the reduction coming from reduced VMT for charging trips). As discussed previously, holding a shorter-range fleet to an even more restricted range (by limiting recharge frequency) has the effect of serving trips originating in high demand zones more efficiently. In this case, the distance-based charging strategy reduced average wait times by 7.9% compared to the demand-based charging strategy. However, this improvement comes at the cost of more unserved trips (increased 35%) and a larger necessary fleet size (increased 3.0%).

Charging Strategy:	**Recharge Upon Trip Rejection**	**Recharge When Range ≤ 10 mi**	**Δ**
Fleet Size	57,279	59,000	3.00%
% Trips Unserved	3.94%	5.30%	34.5%
Avg Wait Time (min)	8.10	7.46	-7.90%
Avg Range Remaining at Recharge (mi)	43.01	1.15	-97.3%
% Total "Empty" Miles Traveled	10.69%	9.01%	-15.7%
% New Travel for Charging	2.52%	3.35%	-42.5%
% New Travel for Relocation	4.12%	1.45%	-18.7%
% New Travel for Trips	4.05%	4.21%	3.95%

Table 2-3: Demand- vs. Distance-Based Charging (SAEV with Level II Charging)

Scenarios incorporating both demand- and distance-based charging strategies were also run. Table 2-4 displays simulation results where SAEVs are assigned to charging status after the vehicle has rejected a trip due to insufficient range and met a maximum range threshold. Results show that combining demand-based charging with a 75% (60-

mile) maximum range criteria yielded the best fleet performance metrics from a user perspective. Average wait times reduced to 7.37 minutes per trip and percent of trips unserved decreased to 1.70%, competitive with the SAV scenario results in Table 2-2. From the operator perspective, applying this charging strategy increases the necessary fleet size slightly (by 0.1%) and decreases induced travel by 12.7%. Increasing more stringent recharging distance criteria continually decreases induced VMT (as shown in Tables 2-3 and 2-4), primarily from reduction in relocation miles. However, as relocation miles decrease, induced miles to pick up travelers increase (and subsequently increases wait times), demonstrating the inherent tradeoffs between reducing extra VMT and enhancing user experience (as measured by wait times and percent of trips served).

Charging Strategy:	**Recharge Upon Trip Rejection, Max Range=80 mi**	**Recharge Upon Trip Rejection, Max Range=60 mi**	**Recharge Upon Trip Rejection, Max Range=40 mi**	**Recharge Upon Trip Rejection, Max Range=20 mi**
Fleet Size	57,279	57,354	57,278	57,174
% Trips Unserved	3.94%	1.70%	3.01%	3.38%
Avg Wait Time (min)	8.10	7.37	8.22	8.45
Avg Range Remaining at Recharge (mi)	43.01	22.17	13.15	6.38
% Total "Empty" Miles Travel	10.69%	9.33%	9.11%	9.04%
% New Travel for Charging	2.52%	3.28%	3.09%	3.11%
% New Travel for Relocation	4.12%	1.91%	1.64%	1.48%
% New Travel for Trips	4.05%	4.14%	4.38%	4.45%

Table 2-4: Demand- and Distance-Based Charging (SAEV with Level II Charging)

FINANCIAL ANALYSIS

Simulation results offer some insight into how combinations of vehicles and charging infrastructure impact fleet operations, but a financial analysis is necessary to truly grasp the tradeoff between additional capital investment (into vehicles with bigger batteries or more expensive fast charging stations) and user benefits (measured in additional trips served or decreased wait times). For each vehicle and charging station type, analysis was conducted for three cost levels: low-, medium-, and high-cost scenarios, as shown in Table 2-5.

	Low Cost	**Medium Cost**	**High Cost**
Vehicle Capital			
BEV (per vehicle)	$35,000	$40,000	$55,000
LR BEV (per vehicle)	$45,000	$50,000	$80,000
Replacement battery (per kWh)	$240	$405	$570
Vehicle Operations			
Maintenance (per mile)	$0.06	$0.06	$0.07
Insurance & Registration (per vehicle-year)	$1,280	$1,600	$1,920
Electricity (per kWh)	$0.11	$0.13	$0.26
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

Table 2-5: Vehicle & Charging Infrastructure Cost Assumptions

For vehicle capital costs, the non-autonomous BEVs are assumed to cost from $25,000 (similar to the Mitsubishi i-Miev and Smart Fortwo Electric Drive BEVs) to $45,000 per vehicle (approximate retail cost of BMW i3 BEV), with a most likely price of $30,000 (comparable to price of Nissan LEAF and Ford Focus Electric BEVs). The non-autonomous LR BEVs are assumed to cost between $35,000 (the projected price of the future 2017 Tesla Model 3 and Chevrolet Bolt) and $70,000 (retail price for the currently available Tesla Model S), with a most likely price of $40,000 per vehicle as some critics and experts believe the current projected pricing for LR BEVs is too optimist (see, e.g. Anderman 2014). These vehicle costs do not consider government rebates and incentives for electric vehicles. AV technology is assumed to add $10,000 to the cost of each vehicle, per estimates from IHS (2014) and Schultz (2014). To convert vehicle capital costs to a per-mile basis (as illustrated in Table 2-5 and Figure 2-6), each SAEV is assumed to be in operation for 231,000 miles before replacement, equivalent to the average mileage life span of a current New York City taxicab (New York City Taxi & Limousine Commission 2014). The battery is assumed to be replaced once during the SAEV's service span (or per 115,500 miles), in line with most BEVs' 100,000-mile battery warrantees and evaluations of EV batteries (see, e.g. Knipe et al. 2003). Cost for replacement batteries (24 kWh for SAEVs and 60 kWh for LR SAEVs) are assumed to cost between $380 to $570 per kWh, per estimates from Plotkin and Singh (2009).

For vehicle operation costs, maintenance (including tires) is assumed to cost between 5.5 and 6.6 cents per mile, similar to current non-autonomous vehicles (AAA 2014). Insurance and registration are assumed to be on the order of two to three times the cost of current privately owned vehicles, similar to assumptions in Burns et al. (2013), which translates to $1,280 to $1,920 annually (AAA 2014). Per mile fuel costs assume electricity ranges 11 to 26 cents per kWh, with a mid-range cost of 13 cents per kWh, mimicking the US national residential electricity average (EIA 2015). The high cost scenario allows flexibility in accommodating future variable priced electricity, a growing possibility with the introduction of smart metering technology.

For charging infrastructure, Level II chargers are assumed to cost between $8,000 and $18,000 each, including costs for installation, hardware, materials, labor, and administration (Chang et al. 2012, USDOE 2012). Annual maintenance cost for Level II chargers are assumed to be minimal at $25 to $50 per year (USDOE 2012). Level III chargers are assumed to range from $10,000 to $100,000, with average cost at $45,000 per station (USDOE 2012, New York City Taxi & Limousine Commission 2013). This cost includes installation, hardware, materials, labor, administration, and transformer upgrades. Annual maintenance cost for Level III chargers are assumed to range from $1000 to $2000 (New York City Taxi & Limousine Commission 2013). To convert charging infrastructure to a per-mile basis, the service life span of charging stations is assumed to be 10 years (Chang et al. 2012). Table 2-6 breaks down the cost per occupied mile of travel (costs are incurred for total miles of travel but allocated to each occupied mile of travel) for each vehicle and charging infrastructure combination in the mid-cost scenario.

	SAEV	**SAEV Fast Charge**	**LR SAEV**	**LR SAEV Fast Charge**
Vehicle & Battery	$0.249	$0.250	$0.346	$0.346
Vehicle Maintenance	$0.071	$0.071	$0.066	$0.066
Insurance & Registration	$0.038	$0.026	$0.025	$0.020
Electricity	$0.045	$0.045	$0.042	$0.042
Charging Station Capital	$0.015	$0.030	$0.007	$0.004
Charging Station Maintenance	$0.000	$0.010	$0.000	$0.001
TOTAL	**$0.417**	**$0.433**	**$0.486**	**$0.479**

Table 2-6: Equivalent Cost Per Occupied Mile Traveled (Mid-Cost Scenario)

This financial analysis reveals that under the most likely mid-cost scenario, a fleet of SAEVs or LR SAEVs can be operated at an equivalent per occupied mile traveled cost of $0.42 to $0.49. The most uncertain component of this per-occupied-mile operating cost estimate is the AV technology. While $10,000 per vehicle is assumed in the base results presented in Table 2-6, the range of estimates for the cost of AV technology when it is first market-ready is large. Various sources report the cost of the retrofitted AV technology on current Google self-driving cars to range from $75,000 to $250,000 (Rogers 2015, Tannert 2014). A key component of that cost is the $75,000 Velodyne 64-laser unit lidar system currently in the Google self-driving cars (Shchetko 2014). The precision of the 64-unit lidar system is useful for research and mapping, but unlikely necessary for mass produced AVs (Shchetko 2014, Davies 2014). In 2010, Velodyne introduced a 32-laser unit lidar system that retails between $30,000 and $40,000 and in 2014, a 16-laser unit system that retails for $8000 (Davies 2014). Some experts believe that 16-unit is the minimum required for automated driving while others are even more optimistic, suggesting that a 4-unit system could be sufficient for self-driving (Shchetko 2014). Once the technology is mature, IHS (2014) estimates AV technology will cost between $3500 to $5000 per vehicle after 5 to 10 years on the market. Figure 2-7 shows how the equivalent per-mile SAEV scenario operation cost varies with a range of AV technology costs from $0 to $100,000. At the upper range of the estimates for AV technology costs, SAEV operation costs can be double the $0.42 to $0.49 estimates shown in Table 2-6.

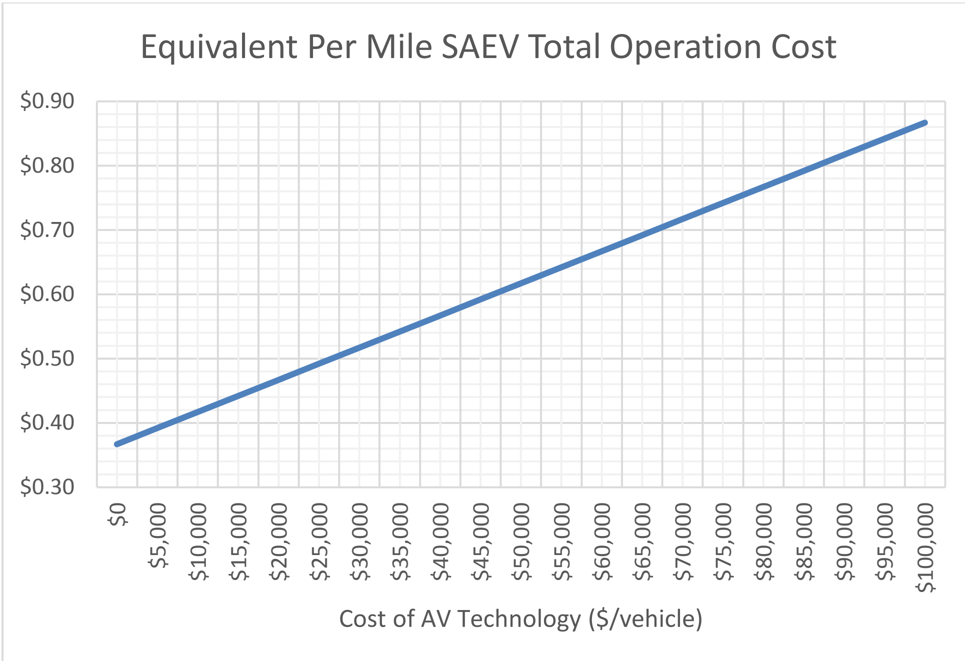


Figure 2-7: Per-Mile Cost Sensitivity to AV Technology Cost

Using APTA (2013a) statistics, for a transit system that serves 2.4 billion passenger-miles per year, general administration expenses (including facilities and salaries) add approximately $0.184 to the per-mile operational costs. Assuming operating margins of 10% (similar to others in the transportation industry) and using mid-cost estimates from Table 2-6, SAEV service can be offered at roughly $0.66 to $0.74 per occupied mile of travel. These costs are on the low end of current manually-driven free-float carsharing services such as Car2Go, which charges roughly $0.70 to $1.23 per mile in Austin, Texas (assuming trips are between 2 to 10 miles and travel speeds are between 15 to 35 mph). Under this pricing assumption, SAEV users would pay roughly 21 to 49% of what is currently charged by transportation network companies like Uber and Lyft (whose equivalent per-mile pricing is $1.50 to $3.18 in Austin for trips between 2 and 10 miles and travel speeds between 15 and 35 mph). In fact, these costs are competitive with

AAA (2014) estimates of average costs per mile of private vehicle ownership, which ranges from $0.40 to $0.95 cents per mile depending on annual mileage and vehicle type, suggesting that availability of a SAEV fleet can have significant impacts on private vehicle use (and ownership), particularly for those who drive fewer annual miles.

Cost estimates in Table 2-6 are derived from fleet size and induced VMT estimates with a demand-based charging strategy with no maximum range restriction (Table 2-2). Employing a demand-based charging strategy with 75% maximum range restriction (Table 2-6) on the SAEV base scenario reduces the cost by $0.020 per mile, yielding the most cost efficient scenario at $0.397 per mile. It is worth noting that cost estimates used for charging infrastructure here are based on traditional, wired charging infrastructure. Currently, a residential Level II wireless (inductive) charger can deliver similar charge times as traditional corded units while costing approximately $2500 more per unit (Evatran n.d.). This translates to a minimal $0.002 to $0.003 increase in equivalent per-mile costs for the SAEV fleets modeled here. Level III inductive chargers are not currently commercially available. If wireless charging is not available for the SAEV fleets, an alternative would be to install traditional corded charging infrastructure and hire charging station attendants at each of the 1500 some odd charging station sites. Assuming one attendant per charging station site and each attendant's wage at $15 per hour, this would add a significant increase of $0.077 to $0.085 per equivalent occupied mile traveled to the costs in Table 2-6.

Of course, outside of AV technology costs, each vehicle capital, operations, and charging structure cost component impacts the total cost per mile differently, as seen in the tornado graphs in Figure 2-8. Here, the baseline (y-axis) value represents the mid-cost scenario for each vehicle and charging infrastructure combination (as shown in Table 2-6). The bars associated with each cost category show the fluctuation in total per-mile cost associated with changing that cost assumption from the mid-cost scenario to low- or high-cost, while all other cost categories remain at mid-levels. These graphs illustrate the sensitivity of per-mile costs to the estimates in each cost category. As seen in Figure 2-8, total per-mile costs are most sensitive to vehicle and battery costs, followed by cost of electricity. Charging station capital costs are only important in the SAEV Fast Charge scenario, where the high number of expensive chargers needed can have significant impacts on per-mile costs.

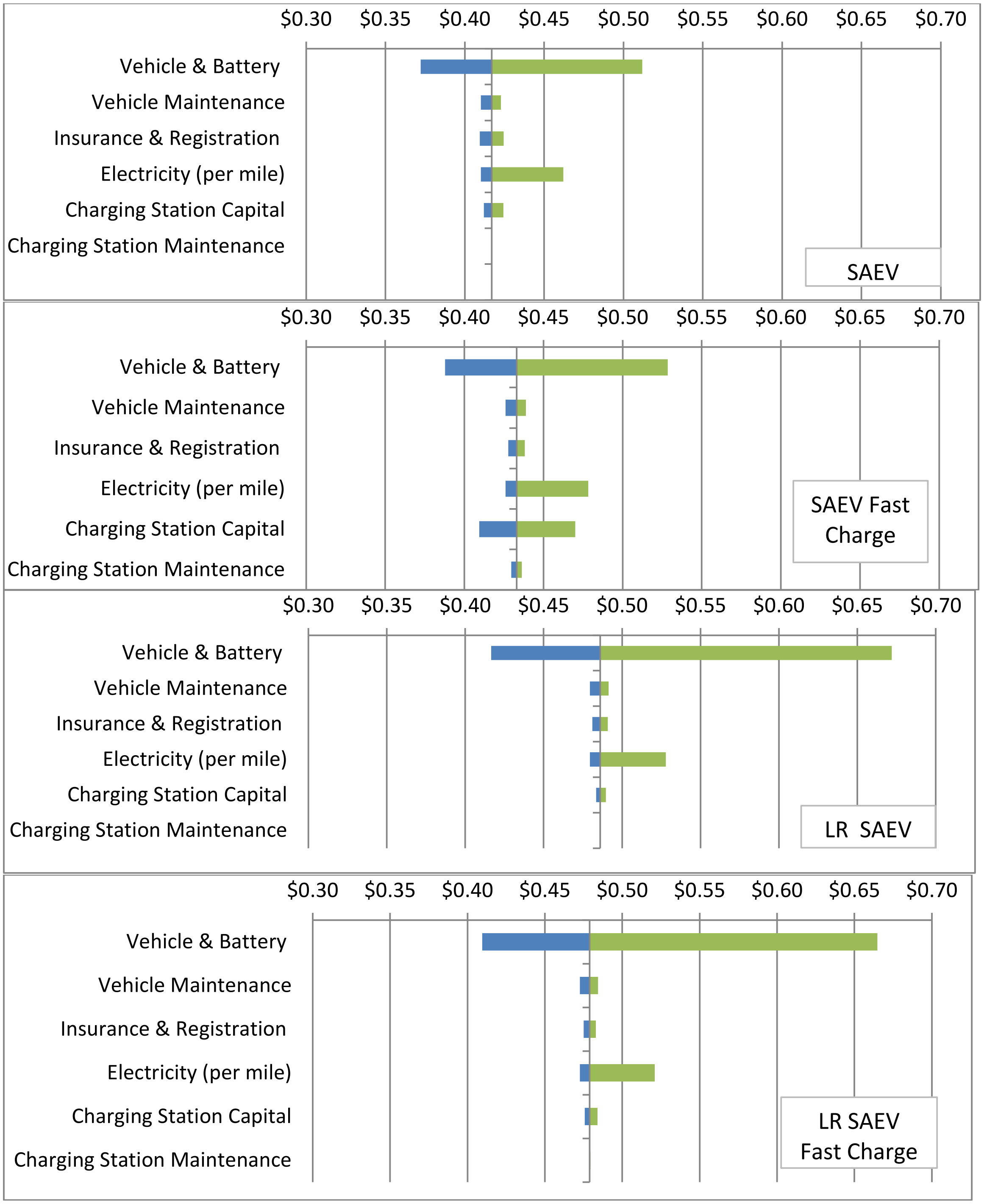


Figure 2-8: Per-Mile Cost Sensitivity to Cost Inputs

While these per-mile costs are lower than current carsharing services and competitive with private car ownership, their ability to compete with a fleet of non-electric SAVs depends on the availability of wireless recharging infrastructure and government tax incentives on EV purchase prices. Assuming SAVs utilize existing gasoline stations with no additional infrastructure investment, a fleet of SAVs can be operated for $0.400 per mile with a 231,000-mile vehicle life span, $30,000 per SAV purchase cost ($20,000 for the vehicle, $10,000 for AV technology), 30 mile per gallon fuel economy, $3.50 per gallon gasoline price, $15 per hour wage for one attendant per gasoline station to service the fleet, and the same AAA-based costs for maintenance, insurance, and registration prescribed to SAEVs. Of course, this per-mile cost is highly sensitive to gasoline prices. Figure 2-9 below shows the equivalent gasoline price per gallon for a fleet of SAVs to be at the same operating cost as a fleet of SAEVs with various purchase price incentives (e.g., federal tax rebate) for both wireless charging and attendant-assisted charging.

Figure 2-9: Equivalent Gas Price ($/gallon) for SAEV & SAV Equal Operating Costs

With EVs purchased at full price, SAEVs with wireless recharging are competitive with SAVs on a per mile basis when gasoline is at $3.50 per gallon. With current federal tax incentives of $7500 per EV, SAEVs become price-competitive with SAVs when gasoline is at $2.50 per gallon. Without wireless recharging infrastructure (and using station attendants at charging sites), SAEVs purchased with the $7500 federal tax rebate are not price-competitive with SAVs until gasoline reaches $4.69 per gallon. Without the federal rebate, this increases to $5.70 per gallon.

CITY OF AUSTIN, TEXAS CASE STUDY

Even though the Poisson-based trip generation process modeled in the simulated monocentric city introduces some variation in specific cell trip generation rates, actual trip generation rates in real city geographies are significantly less "smooth." In exurban areas, an overall low population density is often reflected by pockets of relatively denser residential development among much larger areas of very sparse population. Moreover, travel demand varies significantly by time of day, with peaking in the morning and late afternoon/early evening, as well as some strong mid-day travel. Therefore, a case study using Austinites' year-2010 trip generation (and destination choice) rates with U.S. departure time choices (varying every 5 minutes) was performed. The region's 1413 traffic analysis zones (TAZs) and personal trip tables (by origin versus destination zone) were used to appreciate the effects of real-world (heterogeneous) trip-making behaviors.

The 1413 TAZs in the Austin area were mapped onto the 400-cell by 400-cell gridded region with each TAZ's generated and attracted trips assigned to one quarter-mile by quarter-mile cell. The TAZ closest to the geographic centroid of the Austin region (as determined by the mid-point value of all TAZ centroids' longitude and latitude coordinates) was identified as the center (cell [200,200]) of the simulated region. Then, each of the remaining 1412 TAZs corresponded to a cell in the simulated region by indexing the TAZ centroids' latitude and longitude coordinates relative to the city center. This process effectively created an extremely "spiky" trip generation pattern, where only 1413 out of the 160,000 cells (less than 0.9%) in the simulated region served as trip origins and destinations, rather than permitting every cell to generate (and attract trips). If more time had been available, identification of additional trip generation and attraction points within the larger TAZs (e.g., the 491 that are bigger than 2 square miles) would have been useful. The charging strategy of trip rejection plus a maximum 75% remaining range was employed here, as this strategy showed improved fleet performance metrics as compared to a charging strategy based solely on trip rejection (Table 2-4).

Trip departure times were assigned to five-minute time steps according to 2009 NHTS departure time distribution, as shown in Figure 2-10. As with the trip-generation points, these departure times are excessively spiked. This time effect comes from individual's preferring to report their trip start times at 15-minute increments (e.g., rounding to 10 am or 10:15 am, rather than identifying and reporting 10:03:22 am and 10:11:46 am departure times).

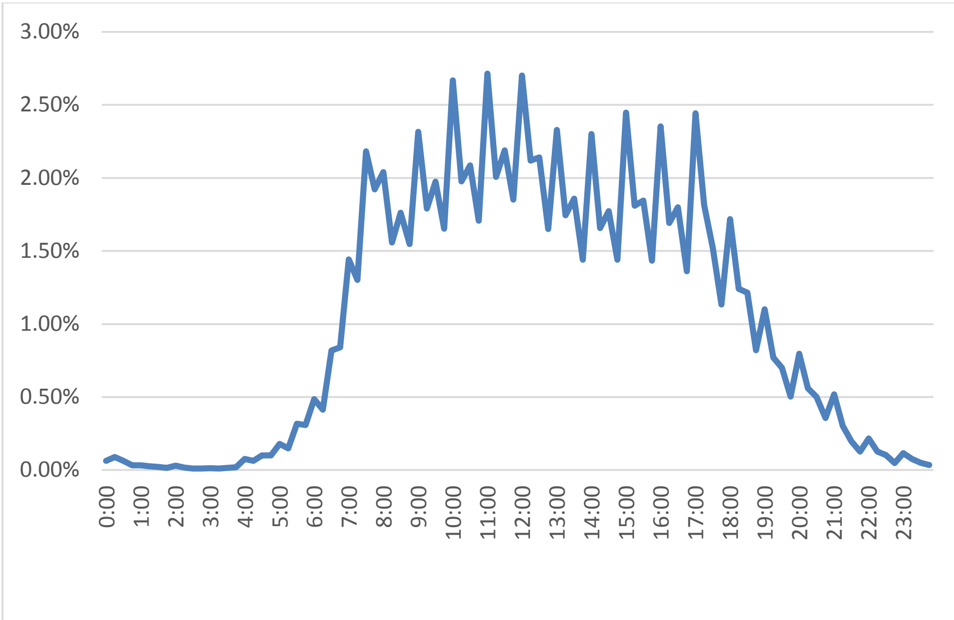


Figure 2-10: Trip Departure Time Distribution

Scenario results from the Austin case study are shown in Table 2-7. Despite the significantly more concentrated (spatial and temporal) patterns of trip generation, the average daily miles per vehicle are very close to Table 2's results, which used much smoother, simulated trip generation rates (and destination-choice and time of day patterns). However, because the average trip distance (across all ground modes, not exclusive to auto trips) in the Austin case study is only 5 miles (as opposed to the 9 to 10 mile average trip distances in Table 2-2's NHTS-based results), the daily trips per vehicle (and corresponding private vehicle replacement rates) are higher. SAEVs with Level II charging infrastructure are now estimated to replace 5 private vehicles and LR SAEVs with Level III charging infrastructure replacing 9 private vehicles. Intrazonal trips are modeled as zero distance trips here, and are thus excluded from the model. This is an important result: working with trips that average almost twice as long (using the NHTS trips, which can end far outside the oriogin region, unlike MPO-based trip tables which end at the boundary of a region) keeps the vehicles almost twice as “busy”, resulting in nearly half the vehicle replacement rate.

Austin Scenario	SAV	SAEV	SAEV Fast Charge	LR SAEV	LR SAEV Fast Charge
Range (mi)	400	80	64	200	160
Refuel/Recharge Time (min)	15	240	30	240	30
# of Charging/Fueling Station Sites	21	25	26	23	25
# of Chargers/Fuel Pumps*	1053	16,334	9889	8852	1080
Fleet Size	14,802	26,758	16,772	21,859	14,750
Avg Daily Miles per Veh	253	137	216	171	253
Avg Daily Trips per Veh	27.4	15.2	24.2	18.6	27.5
Veh Replacement Rate	8.98	5.00	7.95	6.09	9.02
% Trips Unserved	0.52%	0.44%	0.25%	0.48%	0.41%
Avg Trip Distance (mi)	5.15	5.13	5.14	5.14	5.15
Avg Wait Time Per Trip (min)	3.49	2.86	3.01	3.15	3.25
% Total ”Empty” Miles Travel	3.15%	4.03%	4.19%	3.25%	3.38%
Max % of Concurrent Charging Vehicles	7.11%	61.04%	58.96%	40.50%	7.32%

*As proxied by the maximum number of concurrent charging/refueling vehicles in the day.

Table 2-7: Performance Metrics from Austin Case Study Scenarios

While the Austin trips cannot go past the 5-county regional edge or border, trips under 1 mile are included here (as long as the origin and destination differ). Thus, these vehicle replacement rates are likely biased high. Restricting trip origins and destinations to less than 1 percent of the total geographic area means higher concentrations of SAEVs in select trip-active cells, which has the effect of reducing the number of unserved trips (less than 1% in all Austin case study scenarios), decreasing average wait times (between 2 and

4 minutes in all Austin case study scenarios), and reducing "empty" VMT (between 3.1 to 4.2% in all Austin case study scenarios), thanks to vehicles needing to travel less for next-passenger pickup. Furthermore, restricting all trips to travel between these 1413 cells also drastically reduces the number of charging station sites necessary, down to just 23-25 cells with charging stations. These charging station sites as estimated to have as many as 653 charging pads per station in the 80-mile SAEV with Level II infrastructure scenario down to 43 charging pads per station in the LR SAEV with Level III infrastructure scenario (in order to meet the maximum 5-minute demand per day experienced at that site), and their locations represent just 1.8% of the 1413 trip-active cells, and just 0.0002% of the 160,000 cells across the 100-mile by 100-mile region. Such results underscore the fact that charging station locations are a function of both the geography of the service geo-fence and travelers' trip-making patterns.

Financial analysis results from the Austin SAEV scenarios show operating costs of \$0.386 to \$0.472 per occupied-mile traveled, with 80-mile range SAEVs and Level II charging infrastructure ranking lowest in operation costs, also consistent with findings from the simulated trip generation scenarios.

CONCLUSIONS AND LIMITATIONS

Motivated by natural synergies between autonomous driving technology and EVs in a shared setting, this chapter employs an agent-based model to simulate the operations of a fleet of SAEVs in a medium-sized metropolitan area under various vehicle and infrastructure scenarios. Simulation results show that fleet size is highly dependent on charging infrastructure and vehicle range. For the non-electric SAV scenario, each shared vehicle can replace 7.3 private vehicles. For a fleet of 80-mile range SAEVs with a 4 hour full recharge time, this replacement rate drops to one shared vehicle for every 3.7 private vehicles, since more than half of the fleet is tied up in charging activities during any time period (and thus necessitating a larger overall fleet for operation). Simulation results also suggest these shared fleets can serve 95.6 to 97.9% of all trips with average wait times between 7 and 10 minutes per trip, while producing an additional 7 to 14% of "empty" VMT for traveling to passengers, strategic repositioning, and accessing charging stations. While this induced travel can be reduced slightly with strategic charging, model results also reveal the inherent tradeoffs between reduction of induced "empty" travel and improvement of user experience (as measured by wait times and percent of trips served). These tradeoffs highlight the need for a dynamic pricing scheme for SAEVs which penalizes trips that incur more relocation miles (and thereby increase subsequent trip wait times) and incentivize trips that coincide with strategic relocation (and thereby decrease subsequent trip wait times).

Financial analysis reveals that despite requiring the largest fleet and the most charging stations, the base 80-mile range SAEV fleet with Level II charging stations is the cheapest to operate on a per-mile basis of all the EV scenarios. This is primarily due to the high sensitivity of per-mile operating costs to vehicle purchase price (with SAEVs assumed to cost $10,000 less per vehicle compared to LR SAEVs in the mid-cost scenarios). On the other hand, per-mile costs of SAEV operations are not very sensitive to charging infrastructure costs. While SAEVs with Level II charging infrastructure is cost effective, the scenario is ineffective in spreading out charge demand, with as much as 53% of the fleet concurrently charging during the peak charging period of the day. If SAEVs become a widely adopted mode, this type of fleet can translate to significant demand increases on the electric grid during peak hours. LR SAEVs with Level III fast charging infrastructure, while costing 14.9% more per mile compared to SAEVs with Level II charging stations, is very effective at spreading out charge demand with only 7.6% of the fleet concurrently charging during the peak charging period.

With aggressive estimates for overhead costs and profit margins, SAEV service can be offered at $0.84 to $0.98 per mile, a rate competitive with private vehicle per-mile costs for low-mileage households. The price would also be competitive with current manually driven carsharing services and significantly less expensive than on-demand transportation services via transportation network or taxi companies. With wireless charging infrastructure and purchase incentives (e.g. tax credits and rebates) between $0 and $10,000 per vehicle, the 80-mile SAEV fleet with Level II charging infrastructure is price-competitive with its non-electric SAV counterpart when gasoline is between $2.18 and $3.50 per gallon. On the other hand, if recharging of SAEVs requires a station attendant for traditional corded chargers, this gasoline equivalent increases to $4.35 to $5.70 per gallon.

A case study using person-trip rates from Austin, Texas' 2010 travel demand model explores the sensitivity of model results to variability in geographic trip concentration in a region. Each of the 1413 Austin TAZs was tied to one cell in the 160,000-cell gridded region, producing relatively few trip-making zones with extremely high trip rates, amid large areas of zero trip activity. This concentration of trip activity produced much lower shares of unserved trips, shorter average wait times, and fewer "empty" VMT. The shorter trip distances in this within-region simulation also resulted in a much higher private vehicle replacement rates, of 1 to 5.0 in the 80-mile SAEV with Level II charging infrastructure scenario and 1 to 9.0 in the LR SAEV with Level III charging infrastructure scenario, rather than 1 to 3.7 and 1 to 6.8 in the simulated region relying on the longer NHTS-based trips.

Certainly, the agent-based model presented here has its limitations. First, the charging station generation process in this agent-based model mimics the objective of a coverage model (as discussed in Chapter 1). While this method ensures full coverage of all charging demand, it does not take into account budgetary constraints and allows for an unlimited number of charging stations. The charging strategies modeled here varies the criteria for when SAEVs are sent to charge, but do not allow them to partially charge before returning to service. An optimization of the charging strategy process can possibly further improve fleet metrics. Additionally, the scenarios modeled here assume that SAEVs will serve 10% of a city's trip demands and that the temporal and spatial distributions of SAEV trips are the same as the overall trip-making patterns of the city. In reality, SAEV's fleet metrics are highly likely to be sensitive to density of trip demand. Furthermore, SAEV mode may be more attractive to specific types of trips rather than equally appealing for all trips. These questions of mode choice and SAEV market share are the focus of Chapter 3's analysis.

CHAPTER 3: PRICING STRATEGIES

In the previous chapter, scenarios for various combinations of vehicle types and charging infrastructure were modeled to examine their effects on the operations of a fleet of SAEVs. The combination of 80-mile range SAEVs with Level II charging infrastructure was found to be the most cost efficient on a per-mile basis compared to other SAEV scenarios. Once a demand- and distanced-based charging strategy (in which vehicles are sent to charging stations upon rejection of a trip request due to insufficient range and are at most 75% of its full range) is adopted, the user performance metrics (as gauged by percent of trips served and average wait times) are comparable with the other three more costly vehicle and charging infrastructure combinations examined. However, these results presume that the trips which will utilize the SAEV mode are proxied by 10% of the gridded city's total trip demand, in which the trip types (as defined by trip length and time of day) served by SAEVs are proportional to overall trip demand.

When SAEVs make their debut in cities, these vehicles will not exist in a vacuum. SAEVs will be competing against existing modes (private owned vehicles, transit, non-motorized modes, etc.) for trip share. In this chapter, a dynamic mode choice model is introduced to the agent-based framework discussed in Chapter 2 to approximate SAEV market share (with a fleet of 80-mile range SAEVs paired with Level II charging infrastructure) and its impact on other modes under various pricing schemes. Unlike traditional travel demand models where trips traveling between the same origin and destination pair are modeled at the aggregate level, the agent-based framework here allows for mode choice to be applied for each individual trip with its unique characteristics: time-of-day, trip distance, and value-of-travel time.

PRIOR RESEARCH

Recent research has examined the operations of self-driving vehicles in a shared setting, primarily focusing on metrics like empty-vehicle-miles traveled (VMT), average wait times, and private vehicle replacement rates (Kornhauser et al. [2013], Fagnant and Kockelman [2014], Spieser et al. [2014], ITF [2015], etc.). Very few have yet simulated AV effects in competition with other modes of travel. Levin and Boyles (2015) recently simulated mode choice of privately-owned AVs (versus transit, private car travel, and walk/bike) with a fixed trip table for a small (downtown) section of Austin, Texas. Their model allows such AVs to strategically re-position themselves to avoid high parking fees (while incurring added fuel costs, but no traveler time costs), and uses dynamic traffic assignment over a 2-hour peak (morning) period. Their special test cases showed transit demand falling as more user classes (segmented by value of travel time) had access to AVs, with 61% of low- VOTT travelers decreasing their transit use. They allowed link capacities to rise as a function of the proportion of AVs on each link, so congestion did not worsen as the number of vehicle trips rose sharply (due to empty-vehicle parking repositioning). Childress et al. (2015) used Seattle, Washington's activity-based travel model (including short-term travel choices and long term work-location and auto-ownership choices) to anticipate AV technology impacts (from higher roadway capacities, lowered VOTTs, reduced parking costs, and increased car-sharing) on regional travel patterns. Their model estimated that higher income households are more likely to choose the AV mode, as expected (since the technology is costly and VOTT reductions for higher-VOTT travelers are likely to be more significant). With SAVs priced at $1.65 per mile (reflecting costs of current ride-sharing taxi services, like Lyft and Uber), drive-alone trips were predicted to fall by one-third and transit shares rose by 140%, as households released traditional vehicles and acquired AVs or turned to SAVs along with other travel options, since they were no longer "tied" to the fixed cost (and round-trip restrictions) of vehicle ownership and storage.

The above two simulations are largely limited to private AV ownership (except for one scenario [out of four] in Childress et al. [2015]). Furthermore, their mode choice simulations assumed fixed prices/costs for AV (and SAV) use. Due to the variable nature of SAV availability and user wait times, as well as different costs associated with empty VMT for refueling SAVs and passenger pick-up, SAV pricing may best be "smart-priced" to improve fleet performance metrics. The agent-based framework employed in this dissertation allows for mode choice in the context of each trip (based on a trip's time-of-day [to allow for "surge pricing" during peak demand periods] and distance, and its traveler's VOTT) and follows SAEV fleet utilizationthrough a series of simulated travel days to appreciate the effects of various dynamic pricing strategies on mode shares and SAV trip-making behaviors.

VALUE OF TRAVEL TIME

While travel pattern vary by time of day, they also vary by the type of traveler and corresponding travel purpose. Some individual travelers (with specific trip purposes) are willing to pay more than others to save time, distance, and fuel. This willingness-to-pay for travel time savings is defined as value of travel time (VOTT), and varies by traveler, trip type, day of week, and even driver's mood. Thus, VOTTs are regularly segmented in many different ways, including by household income, trip purpose, vehicle occupancy, vehicle class, and time of day (Perez et al. 2012). VOTTs play a significant role in determining mode choice, as some travelers are willing to pay more (as measured by tolls, higher transit fares, etc.) to save travel time while others are willing to tolerate longer travel times to save money on out-of-pocket transportation costs.

In Chapter 2, the trip generation process produces a trip based on an average daily rate for each cell, then assigns the destination cell based on trip distance (drawn from the National Household Travel Survey distribution). In this chapter, the trip generation process remains the same, except the average daily trip rates (shown in Table 3-1) represent 100% of trips in the gridded city (as opposed to 10% in Chapter 2, the assumed share of SAEV trips out of all trips in the city). Again, these rates roughly follow the population densities and trip generation rates of the Austin travel demand model.

	Population Density (persons/mi^2)	**Avg Trip Gen. Rate (trips/cell/day)**	**SAEV Travel Speed (mi/hr)**	
			Peak	**Off-Peak**
Downtown	7500-50,000	1287	15	15
Urban	2000-7499	386	24	24
Suburban	500-1999	105	30	33
Exurban	<499	7	33	36

Table 3-1: Total (Motorized) Trip Generation Rates and Travel Speeds by Zone

To relate each trip to an individual traveler and his/her mode choice, a VOTT is generated for each trip, based on trip purposes and wage rates (per hour). According to the 2009 NHTS, 18.7% of person-trips per household are for work and work-related business trips (Santos et al. 2011). The other 81.3% of trips (for shopping, family/personal errands, school, worship, social, and recreational activities) are combined here, as non-work. After randomly assigning a trip purpose, an income is assigned for the individual traveler based on US Census (2009) data on personal income of individuals residing inside metropolitan areas. SAVs presumably operate more efficiently in densely developed locations than sparsely populated areas (Burns et al. 2013, Fagnant and Kockelman 2015), and individual incomes in metro areas tend to be higher than those in rural areas (with personal incomes averaging 33 percent higher, according to US Census [2009]). Using USDOT (2011) guidelines, VOTT is assumed to be 50% of hourly wage for non-work trips and 100% of hourly wage for business/work trips, yielding Figure 3-1 and 3-2's VOTT distributions.

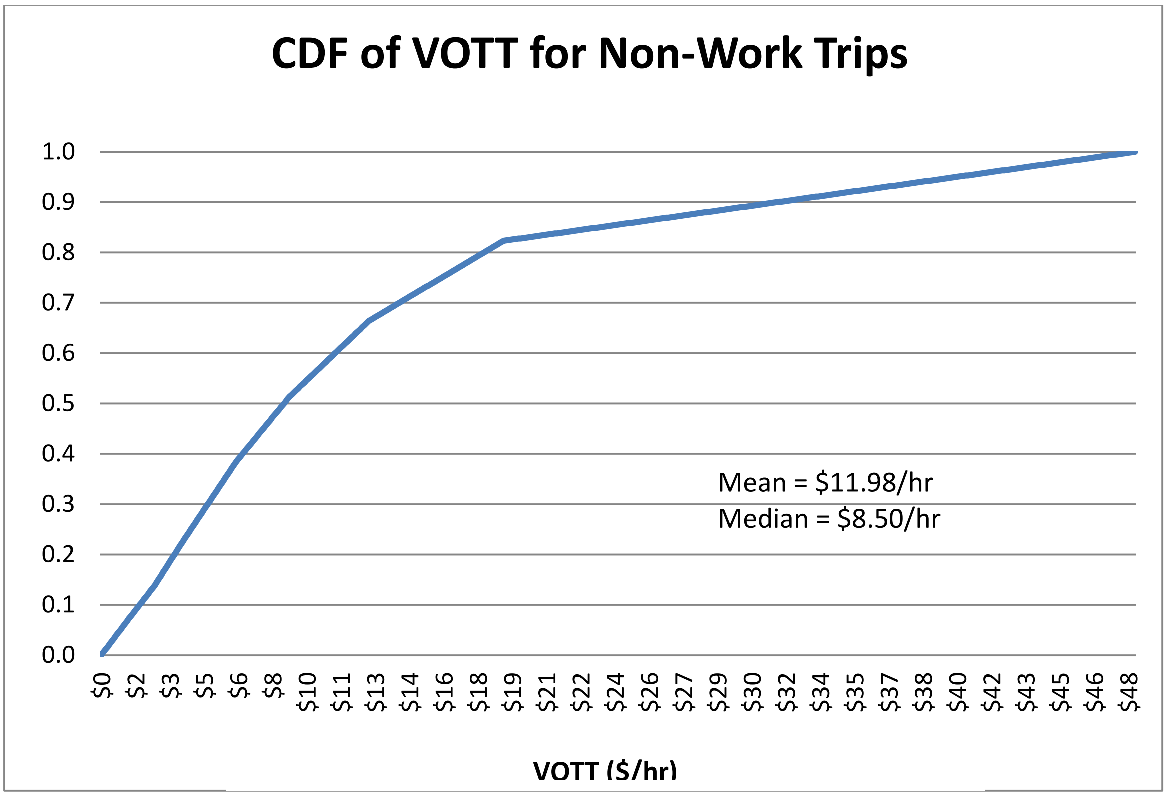


Figure 3-1: VOTT Distribution for Non-Work Trips

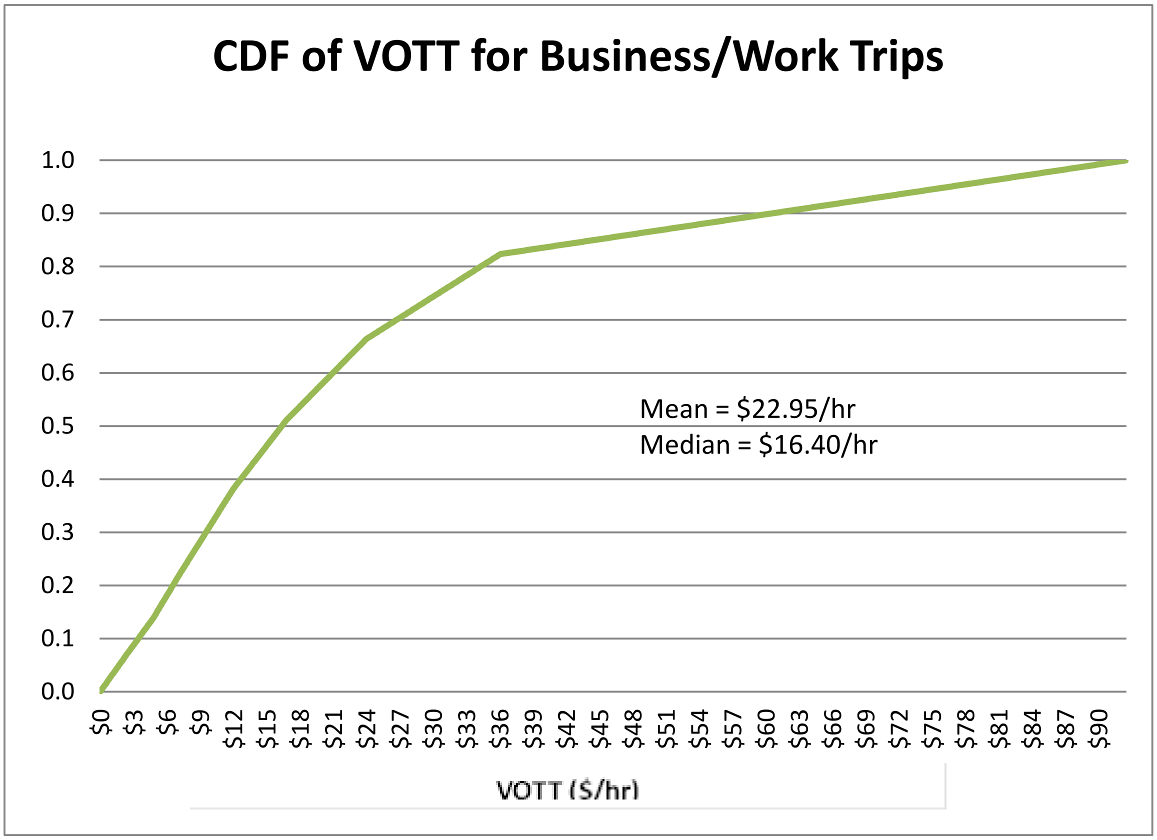


Figure 3-2: VOTT Distribution for Business/Work Trips

MODE CHOICE METHODOLOGY

Once a trip distance, destination zone, time of day, and VOTT has been assigned in the trip generation process, the next step is to determine mode choice. Perez et al. (2012) recommends that a mode-choice model be implemented in a travel demand model using a logit or nested logit specification. For the demonstration in this dissertation, mode choice is limited to three modes: SAEV, (single-occupancy, non-autonomous) private vehicles, and transit in a multinomial logit (MNL) model structure seen in Figure 3-3. Since trips less than 1 mile are not considered in the agent-based model, non-motorized modes are not included in this model.

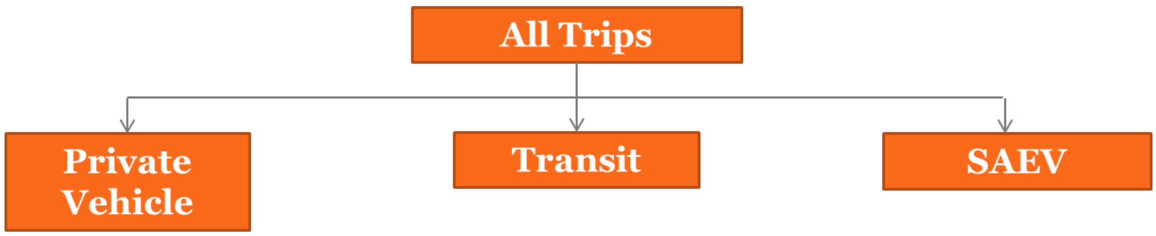


Figure 3-3: MNL Mode Choice Model Structure

In an MNL model, the probability of an individual choosing an alternative is assumed to monotonically increase with the systematic utility of that alternative (Koppelman and Bhat 2006), and can be expressed as the following:

Equation 3-1: $\Pr(i) = \frac{\exp(V_i)}{\exp(V_{PV})+\exp(V_{Transit})+\exp(V_{SAEV})}$

Where i stands for the alternative for which the probability is being computed V_{PV}, $V_{Transit}$, and V_{SAEV} respectively stand for the utilities of private vehicle, transit, and SAEV for a specific trip. Utility valuation for each of these modes is discussed further in the subsections below.

Private Vehicle

In this mode choice model, private vehicle utility is modeled as a function of VOTT, operating costs, and parking fees in the destination zone, as seen in the following equation:

Equation 3-2: $V_{PV} = -VOTT\left(\frac{Distance_{trip}}{Speed_{PV}}\right) - \$0.152\ (Distance_{trip}) - Parking_D$

where $VOTT$ is the individual monetary valuation of value of travel time drawn from distributions in Figures 3-1 and 3-2, $Distance_{trip}$ is the distance of the requested trip (measured in cells), $Speed$ is equivalent to SAEV average speeds (as shown in Table 3-1), \$0.152 is the equivalent vehicle operating cost per cell based on AAA's (2014) estimate of \$0.608 per mile, and $Parking_D$ is the parking fee in the destination zone. In this model, parking cost is assumed to be \$0 for all business trips, since 95% of commuters who drive to work park for free at the workplace (Shoup and Breinholt 1997) and other business transportation are often priced in a distorted market with expense accounts. For personal trips, parking for private vehicles is assumed to be \$0 for trips that end in suburban or exurban cells, \$2 for trips that end in urban cells, and \$4 for trips that end in downtown cells.

Transit

For simplification, the transit mode modeled here emulates local city bus service, the most common form of transit in US cities. Similar to private vehicles, the utility of the transit mode is also dependent upon travel speeds and VOTT. In addition, access time and fare are considered in the transit utility equation below:

Equation 3-3:

$$V_{transit} = -(2)\left(\frac{VOTT}{60}\right)(AT_O + AT_D) - VOTT\left(\frac{Distance_{trip}}{Speed_{transit}}\right) - Fare_{\ transit}$$

Where $Speed_{transit}$ is modeled at 25% slower than Table 3-1's SAEV speeds during off-peak hours and 20% slower during peak hours due to stops, \$2 is the assumed one way $Fare_{transit}$ based on the \$2.04 per unlinked trip fare average from the 2013 National Transit Database Urbanized Data (APTA 2013), and AT_O and AT_D are the access and wait times in minutes based on the trip's origin and destination cell following Table 3-2.

Zone	Transit Access Time (min.)
Downtown	3
Urban	9
Suburban	21
Exurban	60

Table 3-2: Transit Access Time by Zone

Transit access and wait time for exurban cells are penalized (valued at 60 minutes) in the utility function due to the fact that most transit trips to and from exurban areas require transfers (either from private car to transit, or one bus route to another bus route) in the majority of local bus service route designs. Furthermore, access time for transit is modeled at double the VOTT compared to in-vehicle travel time (IVTT). This penalty reflects the general discomfort of time spent walking, bicycling, and waiting outside of vehicles as compared to being inside a vehicle, as recommended in Wardman (2014). Though seated IVTT on transit modes is typically valued as less onerous than IVTT in a private car (presuming that the traveler can perform more productive or leisure activities while seated on a bus as compared to driving a car), standing IVTT on transit modes is considered more onerous than driving a private vehicle (Wardman 2014). Thus, in this model, transit IVTT is simplified to be valued the same as private vehicle IVTT.

SAEV

The structure of the SAEV utility valuation (Equation 3-4) is similar to that of transit, except where transit utility is modeled with a simplified flat price, the SAEV mode incorporates several pricing schemes to examine the impact of pricing on SAEV mode share and fleet operations. The SAEV utility is expressed as:

Equation 3-4:

$$V_{SAEV} = -(2)\left(\frac{VOTT}{60}\right)(2.5 + 5n_{wlist}) - (0.35)VOTT\left(\frac{Distance_{trip}}{Speed_{SAEV}}\right) - Fare_{SAEV}$$

where n_{wlist} is the number of time steps a trip has been on the SAEV waitlist and $Fare$ is the traveler out-of-pocket cost. The first term of this utility function models the onerousness of waiting for an SAEV, is valued at double the IVTT, as also done in the transit utility equation. When a trip is generated, the traveler assumes the wait time is 2.5 minutes (half of a time step). If the trip is waitlisted, the traveler re-evaluates mode choice in each of the subsequent time steps the trip remains on the waitlist, and adds 5 minutes to the wait time for each time step the traveler has been on the waitlist. In other words, the longer a trip remains on the waitlist, the more the SAEV utility decreases, and the less likely the traveler will choose SAEV mode.

The second term of this utility function models the cost of SAEV IVTT. Unlike transit, a traveler will not have to stand in an SAEV. Thus, a traveler can use the IVTT in an SAEV to work, read, listen to music, or pursue other productive or leisure activities. In the base case, this reduction in travel time cost is modeled at 35% of the IVTT in a non-autonomous private vehicle (where the traveler would be driving), equivalent to the valuation of seated riding time on transit (Concas and Kolpakov 2009). This value is varied in the sensitivity analysis section to examine the impact of IVTT valuation on SAEV mode share. SAEV speeds (shown in Table 3-1) are assumed to be the same as private vehicle speeds.

The last term of the SAEV utility function is the fare. In this model, four pricing strategies are explored: simple distance-based, origin-based, destination-based, and combination pricing. Each pricing scheme is discussed in detail below.

Distance-Based Pricing

In simple distance-based pricing, the fare is determined proportional to the trip distance as seen in Equation 3-5. This pricing scheme is similar to the usage-based (by mileage or time) pricing schemes of current non-autonomous carsharing services.

Equation 3-5: $Fare_{SAEV} = \$0.2125 * Distance_{trip}$

Scenario results in Chapter 2 show that a fleet of SAEVs can be offered at a conservative price of $0.66 to $0.83 cents per mile, depending on type of fleet vehicles and charging infrastructure. To be conservative, $0.85 per mile ($0.2125 per cell) is used here as the base fare for simple distance-based pricing. This per-mile fare is also varied in the sensitivity analysis to examine the effects of higher and lower fares on SAEV market share.

Origin-Based Pricing

As discussed in Chapter 1, vehicle relocation is one of the biggest challenges facing operators of non-autonomous carsharing services. The origin-based pricing in Equation 3-6 builds off of Correia and Antunes's (2012) suggestion that variable pricing policies which encourage trips to balance the demand and availability of vehicles at carsharing stations could contribute to more profitable operations. Here, origin-based pricing attempts to minimize empty vehicles miles traveled for relocation by incentivizing trips originating in a cell that has a surplus of vehicles and penalizing trips originating in a cell that has a deficit of vehicles.

Equation 3-6: $Fare_{SAEV} = (\$0.2125 * Distance_{trip})SDMultiplier$

where $SDMultiplier = 0.5,$ when $\left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) < 0.1$

$SDMultiplier = 1,$ when $10 > \left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 0.1$

$SDMultiplier = 2,$ when $\left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 10$

In Equation 3-6, $SAEVSupply_{B,t}$ is the total number of available SAEVs across all blocks B in the current time step, $SAEVSupply_{b,t}$ is the number of vehicles available in the 2-mile by 2-mile block b around the origin cell in the current time step, $TripDemand_{b,t+1}$ is the number of trips (based on average generation rates shown in Table 1) anticipated to originate from the 2-mile by 2-mile block b surrounding the origin cell in the subsequent time step, and $TripDemand_{B,t+1}$ is the total trip demand anticipated for the subsequent time step. Essentially, origin-based pricing compares the proportions of trip demand and available vehicle supply in a 2-mile by 2-mile block out of the entire region. Thus, trips that originate in a block with an excess of vehicles (defined by when the product of vehicle supply and trip demand ratios is less than 1) will be cheaper than trips that originate in a block with a deficit of vehicles (defined by when the product of vehicle supply and trip demand ratios is greater than 1). This ratio of ratios is then normalized by the $SDMultiplier$ term, which halves the SAEV fare when supply is at least 10 times greater than demand and doubles the SAEV fare when demand is at least 10 times greater than supply. By incorporating the $SDMultiplier$ term in place of using absolute ratios, extreme pricing scenarios are avoided.

Destination-Based Pricing

As demonstrated in Chapter 2, up to 5% of a SAEV fleet's VMT can be attributed to unoccupied miles traveled for charging purposes. The destination-based pricing scheme in Equation 3-7 attempts to minimize these empty vehicle miles by incentivizing trips that end in a cell close to a charging station site and penalize trips that end in a cell far away from a charging station site.

Equation 3-7: $Fare_{SAEV} = \$0.2125(Distance_{trip} + Distance_{charge})$

In Equation 3-7, $Distance_{charge}$ represents the distance from the destination cell to the closest charging station site. Thus, the destination-based fare prices both occupied miles traveled during the trip and the unoccupied miles traveled to a charging station after a trip is complete.

Combination Pricing

The last fare structure tested here (Equation 3-8) is simply a combination of origin- and destination-based pricing presented in Equations 3-6 and 3-7.

Equation 3-8: $Fare_{SAEV} = \$0.2125(Distance_{trip} + Distance_{charge})SDMultiplier$

where $SDMultiplier = 0.5,$ when $\left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) < 0.1$

$SDMultiplier = 1,$ when $10 > \left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 0.1$

$SDMultiplier = 2,$ when $\left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 10$

TWO-MODE RESULTS

In order to understand the impact of introducing a new SAEV mode on existing private vehicle and transit modes, it crucial to examine mode choice in the context of only having the latter two modes. In other words, before introducing SAEVs, what mode would the travelers have chosen for their trips? And what mode will they choose once SAEVs are available?

Mode choice results from the two-mode model are shown in Table 3-3. Using the private vehicle and transit utility functions described previously, the model yielded 85.2% private vehicle trips and 14.8% transit trips. For comparison, according to the 2009 American Community Survey, 76.4% of US workers who live and work inside the same metropolitan area commute by drive alone mode and 7.8% commute by public transit (McKenzie and Rapino 2011). While trips with low VOTT are served by both private vehicle and transit modes (both with minimum VOTTs of $0), trips valued at over $21.20 per hour are only served by private vehicles. The long right tail of the VOTT distribution for private vehicle trips (with maximum VOTT at $90.80 per hour) is evident when looking at averages: mean VOTT for a private vehicle trip is 4.5 times the mean VOTT for a transit trip. In a similar manner, short trips are served by both private vehicles and transit, but transit is consistently the preferred mode for longer trips (over 119 miles). In the simplified transit pricing modeled here, longer trips will incur higher operating costs for private vehicles while fare remains flat at $2 for transit, hence the preference for transit mode as trip lengths grow longer. Model results also show that where there are significant parking costs, transit is preferred over private vehicle mode. Hypothetically, trips served by transit would have averaged $1.15 in parking fees per trip had the trips been served by private vehicle. Trips that actually chose private vehicle mode averaged just $0.32 in parking fees per trip. Likewise, when transit access times are significant, private vehicle mode is preferred. Trips that chose transit mode had an average total origin and destination access time of 44 minutes, while trips that chose private vehicle mode would have hypothetically averaged 74 minutes for origin and destination access had transit mode been chosen.

		Private Vehicle Trips	**Transit Trips**
Mode Share		85.19%	14.81%
VOTT ($/hr)	Mean	$16.16	$3.56
	Median	$11.40	$2.75
	Std Dev	$15.04	$3.29
	Max	$90.80	$21.20
	Min	$0.00	$0.00
Trip Distance (mi)	Mean	8.83	17.21
	Median	5.00	10.13
	Std Dev	10.83	19.47
	Max	118.50	146.50
	Min	1.00	1.00
Avg Private Vehicle Parking Cost		$0.32	$1.15
Avg Transit Access Time (min.)		73.70	44.47

Table 3-3: Private Vehicle and Transit Trips in Two-Mode Model

THREE-MODE RESULTS

Simple Distance-Based Pricing

Once SAEVs are introduced into the dynamic mode choice model, there is a significant shift away from private vehicle use. In the results shown in Table 3-4, SAEV fares are structured with simple distance-based pricing at $0.85 per trip mile. The model predicts this pricing scheme will attract 27.1% of all trips generated to the SAEV mode while reducing private vehicle and transit mode shares to 60.8% and 12.1%, respectively.

Comparing these mode shares to the two-mode results in Table 3-3, it is clear that SAEVs are drawing the majority (89.9%) of its market share from trips formerly made in private vehicles. The remaining 10.1% of SAEV trips come from former transit trips.

Mean VOTT for SAEV trips are higher than that for the other two modes, averaging $19.62 per hour compared to $17.97 for private vehicle trips and $3.62 for transit trips. The average trip distance of SAEV trips (10.7 miles) is in between that of private vehicle trips (7.8 miles) and transit trips (19.4 miles). This model result suggests that SAEVs are attracting higher-income (as reflected by higher VOTT) travelers who take advantage of the leisure or productive time during longer trips in a SAEV that would have otherwise been spent driving a private vehicle, echoing results from Childress et al. (2015). For shorter trips, this in-vehicle leisure time advantage is overshadowed by the cost of the SAEV wait time. Note that due to the 80-mile range limitation of SAEVs modeled here, the maximum distance of a SAEV trip is 77 miles, much shorter than the maximum trip distances of private vehicle and transit modes.

Model results also suggest that SAEVs are replacing some former short transit trips: the average transit trip length increases from 17.2 miles (Table 3) to 19.4 miles (Table 4) once SAEVs are introduced. This is likely due to the fact that for shorter trips traveling between zones served sparingly by transit (such as suburban and exurban zones), the long transit access and wait times inflict disproportionately high travel costs (as compared to the cost of IVTT and fare), thus significantly reducing the utility of the mode. In such cases, an SAEV offers relatively short wait times and, for trips less than 3 miles, a competitive fare to the $2 flat transit price. A look at the average transit wait times for each mode's trips confirms this explanation. SAEV trips would have averaged 68 minutes of access and wait time per trip had they hypothetically selected transit, whereas transit trips average 45 minutes of total access and wait times. Results also confirm that trips which incur no or low parking fees prefer private vehicle mode while trips that incur higher parking fees tend to select transit or SAEV mode, enforcing Catalano et al.'s (2008) finding that carsharing activity can increase with a rise in parking fees.

		Private Vehicle Trips	**Transit Trips**	**SAEV**
Mode Share		60.82%	12.08%	27.10%
VOTT ($/hr)	Average	$17.97	$3.62	$19.62
	Median	$12.50	$2.80	$13.30
	Std Dev	$16.54	$3.15	$19.13
	Max	$92.50	$24.20	$92.50
	Min	$0.00	$0.00	$0.00
Trip Distance (mi)	Average	7.78	19.42	10.74
	Median	5.00	12.00	5.25
	Std Dev	8.05	21.37	12.51
	Max	100.00	150.25	77.00
	Min	1.00	1.00	1.00
Avg Private Vehicle Parking Cost		$0.27	$0.88	$0.56
Avg Transit Access Time (min.)		65.82	45.17	68.04

Table 3-4: Private Vehicle, Transit, sand SAEV Trips in Three-Mode Model

Sensitivity Testing

To test how model results vary with parameter changes to the SAEV utility function, sensitivity testing was conducted by looking at higher and lower SAEV fares and valuation of SAEV IVTT (using simple, distance-based pricing). In the base three-mode model, SAEV IVTT was valued at 35% of the cost of private vehicle IVTT, based on evaluation of seated IVTT on transit modes. However, travelers are likely to prefer the privacy and comfort of SAEVs over the often shared and not-always-guaranteed seated space on buses and trains. To reflect this preference, a lower VOTT value (25% of private vehicle VOTT) was assigned in one sensitivity analysis scenario. Alternatively, while being free of driving obligations is a distinct advantage for SAEVs, the type of productive or leisure activity that can be pursued while traveling in a vehicle is still limited. Cyganski et al. (2015) conducted a stated preference survey on AV use and found that only 13% of respondents reported the ability to work as a primary advantage of AVs over manually-driven vehicles. To ensure that the ability to pursue alternative activities while in a SAEV is not overvalued, the sensitivity analysis here also includes a scenario where SAEV VOTT is valued at 50% of private vehicle VOTT. Mode choice model results (shown in Figure 3) reveal that the SAEV VOTT seems to have little impact on transit mode share. As the value of SAEV VOTT approaches that of private vehicle VOTT, SAEV loses market share (almost directly) to private vehicles, with relatively few SAEV trips switching to transit mode. These findings suggest that the relative utility of SAEVs is highly dependent on the individual traveler's choice of in-vehicle activity and valuation of that activity as compared to driving. Cyganski et al. (2015) found that higher income travelers are more likely to work in AVs than lower income travelers, further underscoring SAEVs' attractiveness for high-VOTT travelers on longer, and thus more work-productive, trips.

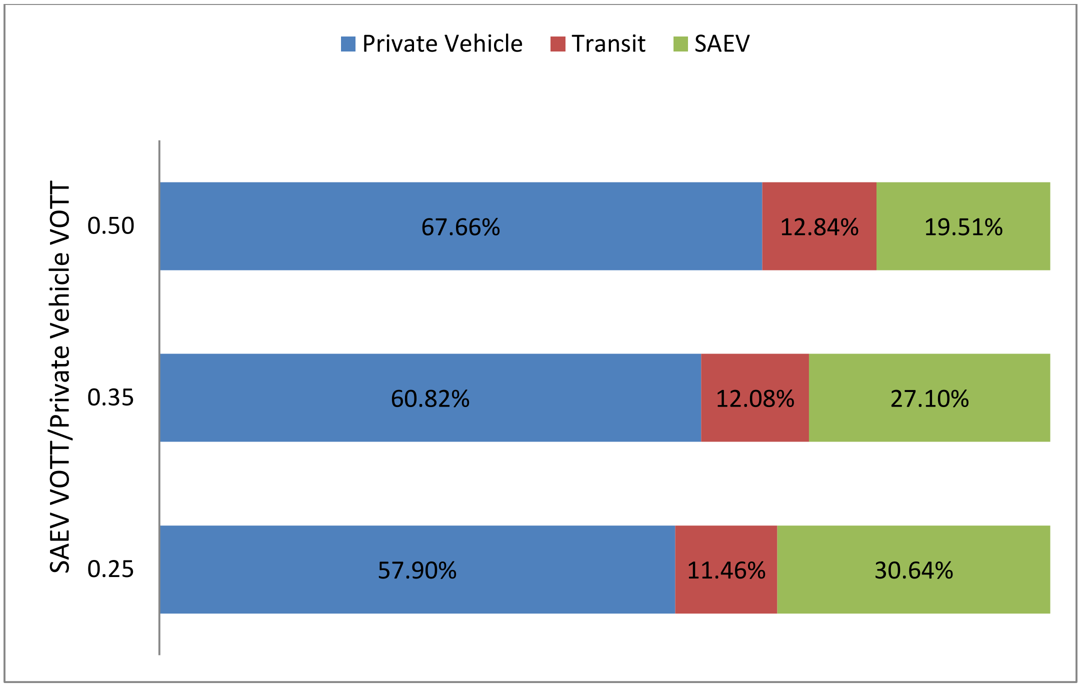


Figure 3-4: Mode Share Sensitivity to SAEV VOTT Assumptions

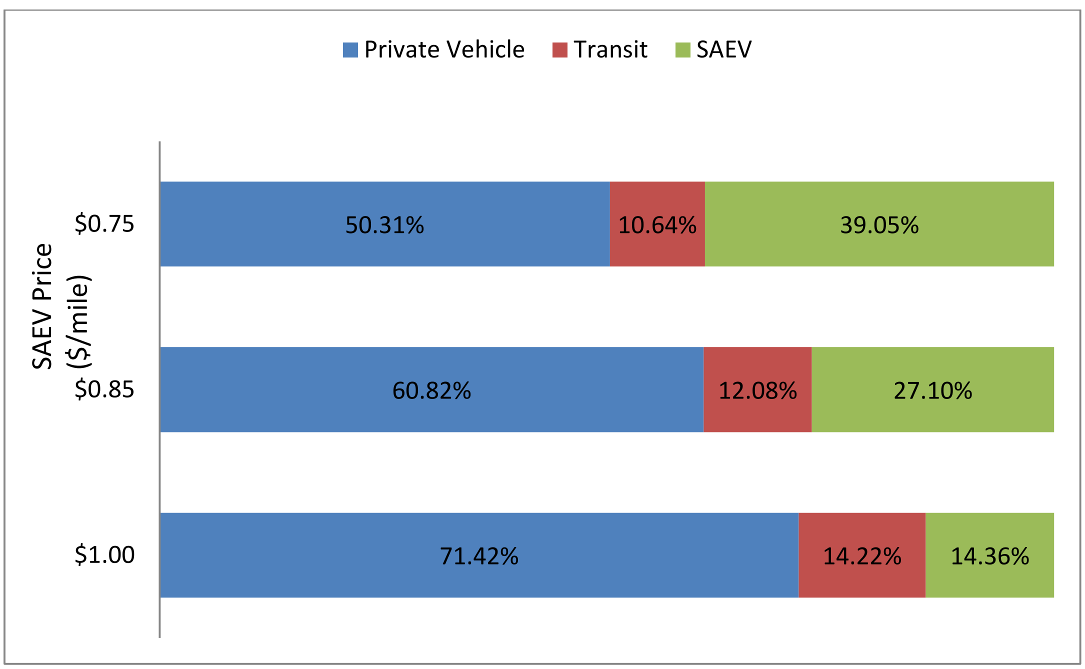


Figure 3-5: Mode Share Sensitivity to SAEV Fare Changes

In the base three-mode model, SAEV fare is set at $0.85 per mile. Depending on the operator's mission (a private operators may seek to maximize profits while public agencies typically strive to ensure basic access to opportunities, while reducing congestion and possibly mobile-source emissions), the price of SAEV service can differ drastically. This sensitivity analysis examines the impact of a higher SAEV fare ($1.00 per mile) and a lower SAEV fare ($0.75 per mile) on mode shares. Mode choice model results (shown in Figure 3-5) suggest that a higher SAEV fare causes SAEV service to lose market share, mostly private vehicles (with some trips switching from SAEVs to transit), further confirming SAEV's substitutability for private vehicles for higher-income travelers. Elasticities show that private vehicle mode is slightly more sensitive to SAEV VOTT valuation than transit mode: For a 1% increase in SAEV VOTT, private vehicle mode share is predicted to increase 0.58% and transit mode share by 0.56%. On the other hand, variation in SAEV pricing demonstrates that transit mode share is more sensitive than private vehicle mode share to SAEV fare. For a 1% increase in SAEV fare, private vehicle mode share is expected to increase by 0.94% and transit mode share by 1.00%.

As SAEV VOTT and fare parameter rise and fall, projected SAEV mode shares, and thus the number (and concentration) of SAEV trips in the gridded region, also change. The agent-based model results (Table 3-5) show the effects of this change in SAEV trip demand on various service metrics, such as SAEV fleet size, average user wait times, and induced (empty) VMT (for vehicle relocation and charging). When SAEV mode share increases under the Low SAEV VOTT and Low Price scenarios, the denser SAEV trip demand lead to shortened user wait times (by 4.8 and 12.2% compared to the base case) and increased vehicle utilization (as measured by the average daily miles per vehicle, which are 7.4 to 19.1% higher than in the base case). More SAEV trips also allows vehicles to travel fewer miles for traveler pickup, decreasing empty VMT in the Low SAEV VOTT and Low Price scenarios by 16.1 and 26.5%, respectively, compared to the base case. Because trip characteristics (such as distance and traveler VOTT) are drawn from the same distributions for all region cells, there are only small decreases in empty VMT for relocation and charging purposes as a result of increased SAEV trip concentration. In other words, because there are no zonal variations in demographic characteristics in this model, the geographic spread of SAEV trip demand is relatively consistent regardless of demand intensity.

	Base	**Low SAEV VOTT**	**High SAEV VOTT**	**Low Price**	**High Price**
SAEV VOTT (as % of Private Vehicle VOTT)	35%	25%	50%	35%	35%
Fare ($/mile)	$0.85	$0.85	$0.85	$0.75	$1.00
Fleet Size	84,945	106,686	54,787	137,323	45,496
Total Trips Served per Day	3.90M	4.03M	3.75M	4.26M	3.62M
Avg Daily Miles per Veh	142.7	153.3	125.0	169.9	105.0
Avg Daily Trips per Veh	45.9	37.7	68.4	31.0	79.6
Avg Trip Distance (mi)	10.6	11.4	8.50	11.9	8.54
Avg Wait Time Per Trip (min)	3.11	2.96	3.36	2.73	3.62
% Total New Induced Travel	7.70%	7.19%	9.06%	6.76%	9.43%
% of VMT for Relocation	2.79%	2.76%	2.87%	2.69%	2.70%
% of VMT for Charging	1.81%	1.83%	1.77%	1.79%	1.82%
% of VMT for Traveler Pickup	3.10%	2.60%	4.43%	2.28%	4.90%
Max % of Concurrent In-Use Vehicles	38.6%	41.5%	34.7%	48.1%	29.1%
Max % of Concurrent Charging Vehicles	53.5%	54.1%	47.99%	58.0%	40.7%
Operational Cost per Equivalent Occupied Mile Traveled	$0.389	$0.383	$0.400	$0.378	$0.409
Daily Revenue	$9.41M	$12.8M	$5.24M	$16.2M	$4.29M
Revenue to Cost Ratio	2.00	2.04	1.92	1.85	2.19

Table 3-5: SAEV Fleet Metrics from Sensitivity Analysis Scenarios

Interestingly, the average trip distance of scenarios with high SAEV trip demand (Low SAEV VOTT and Low Price) are longer than those of scenarios with low SAEV trip demand (High SAEV VOTT and High Price). So while the vehicles in high-demand scenarios are utilized for more miles each day, they actually serve fewer trips per day. However, the households who take these longer trips as SAEV VOTT and fare decrease are different, as reflected by the revenue to cost ratios. Both the Low SAEV VOTT and Low Price scenarios demand a bigger fleet (to serve increased SAEV demand) compared to the base case, but the Low SAEV VOTT scenario registers a bigger profit margin than the base case while the Low Price scenario does the opposite. As discussed previously, travelers who can do productive work while traveling in a SAEV will view their time in a SAEV as less costly, especially as trip distances increase. In the Low SAEV VOTT scenario, more high income travelers' longer trips are captured by SAEV mode. On the other hand, the Low Price scenario captures longer trips from lower income travelers, as the advantage of SAEVs' shorter wait times outweigh the fare advantage of transit in trips that travel between suburban and exurban zones.

Overall, the largest absolute daily revenue is generated by the Low Price scenario, simply due to the significantly increased trip demand. However, when revenue is compared to costs, the High Price scenario yields the most favorable ratio.

Compared to results from Chapter 2, these scenarios exhibit significantly reduced average wait times. This is simply a natural result of pricing, as trips that experience shorter SAEV wait times are more likely to choose SAEV. Trips the waitlist are increasingly more likely to choose another mode with each additional time step they remain on the waitlist.

Origin, Destination, and Combination Pricing

Sensitivity testing results revealed that different assumptions in SAEV VOTT and fare results in a wide range (14 to 39%) for SAEV mode share. These varying trip demands require varying infrastructure to accommodate increasing and decreasing trip densities, and heavily impact revenue and profit margins, as shown in Table 3-5. The next investigation in this dissertation analyzes how various pricing strategies can affect fleet operations (with the same vehicle fleet size, charging infrastructure, and trip demand). Results shown in Table 3-6 employ the charging strategies described in the Mode Choice Methodology section, all assuming SAEV VOTT as 35% of private vehicle VOTT and a base distance pricing of $0.85 per mile.

Pricing Scheme	Distance -Based	Origin-Based	Destination-Based	Combo
Private Vehicle Mode Share	60.8%	63.9%	67.2%	68.6%
Avg Private Vehicle VOTT ($/hr)	$17.97	$17.57	$17.01	$17.57
Avg Private Vehicle Trip Distance (mi)	7.78	8.31	7.67	8.16
Transit Mode Share	12.1%	11.7%	12.0%	13.1%
Avg Transit VOTT ($/hr)	$3.62	$3.58	$3.31	$3.57
Avg Transit Trip Distance (mi)	19.4	19.1	18.2	18.7
SAEV Mode Share	27.1%	24.4%	20.8%	18.3%
Avg SAEV VOTT ($/hr)	$19.62	$18.78	$21.92	$23.17
Avg SAEV Trip Distance (mi)	10.6	10.1	12.6	12.2
Total Trips Served per Day	3.90M	3.85M	3.72M	3.68M
Avg Daily Miles per Veh	142.7	122.6	117.1	101.2
Avg Daily Trips per Veh	45.9	45.3	43.9	43.3
Avg Wait Time Per Trip (min)	3.11	2.51	3.03	2.40
% Total "Empty" Miles Traveled	7.70%	8.11%	7.37%	7.83%
% of VMT for Relocation	2.79%	3.72%	3.11%	4.24%
% of VMT for Charging	1.81%	1.98%	1.80%	2.02%
% of VMT for Traveler Pickup	3.10%	2.41%	2.46%	1.57%
Operational Cost per Equivalent Occupied Mile Traveled	$0.389	$0.398	$0.395	$0.405
Daily Revenue	$9.41M	$8.16M	$8.35M	$7.27M
Revenue to Cost Ratio	2.00	1.97	2.12	2.08

Table 3-6: SAEV Fleet Metrics under Pricing Strategies

Compared to distance-based pricing, the origin-based pricing scheme seems effective in reaching a more balanced vehicle supply and demand. This is reflected by the 22.3% reduction in unoccupied VMT for traveler pickup (compared to distance-based pricing), which then corresponds to a 19.3% reduction in average SAEV wait times. However, this efficiency improvement comes with a 10% reduction in SAEV demand (mode share drops from 27.1% in distance-based pricing to 24.4% in origin-based pricing) and 13.3% decrease in daily revenue. The disproportionate revenue reduction is a result of discounted SAEV trips being more accessible to lower-VOTT households, as witnessed in the 4.3% reduction in average SAEV VOTT between distance- and origin-based pricing.

Destination-based pricing, compared to distance-based pricing, exhibits a negligible (less than 1%) reduction in empty VMT for charging purposes. Due to the coverage-maximizing nature of the charging station site generation discussed in Chapter 2, the distance between the destination cell and the nearest charging station varies little. However, this pricing scheme did have the effect of discouraging shorter trips from choosing SAEV mode, as the charging surcharge of the SAEV fare becomes a larger portion of the overall fare as trip distances decrease. As discussed previously, high-VOTT travelers favor long SAEV trips. Thus, the decrease in short SAEV trips is accompanied by an 11.7% increase in average SAEV VOTT.

The combination pricing scheme results shows some characteristics of both the origin- and destination-based pricing schemes: Average SAEV wait times are reduced by 22.8% and average SAEV VOTT increases 18.1%. The performance metrics of the combination pricing scheme seems to have two aspects which appeal to time-sensitive/high-VOTT travelers: minimized wait times and pricing which favors longer-distance trips. This pricing scheme also resulted in the highest transit mode share and lowest SAEV mode share.

CONCLUSIONS AND LIMITATIONS

Chapter 2 established the combination of 80-mile EVs with Level II Charging infrastructure as the most cost efficient for operations of a SAEV fleet and estimated that such a fleet could be offered at a price of roughly $0.85 per mile. In this Chapter 3, these findings were implemented to explore the impact of pricing strategies on SAEV market shares. The SAEV fleet metrics reported in Chapter 2 are based on an assumption that SAEVs serve roughly 10% of trips in a city (equivalent to some experts' estimates of carsharing's market potential). In this chapter, a dynamic MNL mode choice model was added to the agent-based model to allow 100% of the trips in the city to choose among private vehicle, transit, and SAEV modes. The parameters used in the mode choice model yields an approximate 85/15% split between private vehicles and transit trips before the introduction of SAEVs. When the SAEV mode is priced at $0.85 per mile (and users are assumed to value SAEV IVTT at 35% the cost of private vehicle IVTT), the model estimates 27% of trips will select SAEVs (with 90% of these trips previously choosing private vehicle travel before the introduction of SAEVs).

Sensitivity analysis suggests that SAEV market share can range from 14% to 39% under plausible variations in SAEV VOTT and fare assumptions. Under all scenarios, SAEVs prove to be highly substitutable for private vehicle travel. While private vehicle mode share is most sensitive to an individual's VOTT during SAEV travel, transit mode share is most sensitive to SAEV fare assumptions. These results suggest that once EV and AV technologies gain market maturity and become less costly, low-VOTT trip makers will start to choose SAEVs over transit, particularly in areas with poor transit service (as reflected by longer transit-access and wait times), echoing findings from Levin and Boyles' (2015) center-city, peak-period simulation. Model results also suggest that SAEVs will attract longer trips away from private vehicles, particularly among high-VOTT travelers who find SAEV travel much less burdensome than driving. Vehicle features that encourage and enhance work productivity (such as reliable WiFi, ergonomic work surfaces and seating, and reduced road noise) will likely attract longer trips from high-VOTT travelers willing to pay higher fares. Like airlines, public SAEV operators may find the best balance of profitability and service completeness by offering a refined, work-enhancing vehicle environment at higher fares to serve high-VOTT travelers (similar to the first- and business-class airplane cabins) and a discounted, sufficiently basic service to serve low-VOTT travelers (similar to economy-class airplane cabins).

Model outputs from various SAEV pricing schemes show that specific fleet metrics can be improved via targeted strategies. For example, fares that seek to balance available SAEV supply with anticipated trip demand (over space and time) can decrease average wait times by 19 to 23%, demonstrating the effectiveness of congestion pricing in a vehicle-balancing framework. However, trade-offs are evident in these pricing schemes: fare structures that favor higher revenue-to-cost ratios (by targeting higher-VOTT travelers) inevitably reduce SAEV mode shares, while those that favor greater market share (by appealing to a wider range of travelers and VOTTs) inevitably produce lower revenue-to-cost ratios. These pricing outputs emphasize the role of the SAEV operators' goals when selecting a fare structure. For private SAEV operators, whose goal typically is to maximize profits, a combination pricing scheme that minimizes user wait times while discouraging shorter trips (which tend to incur a higher level of empty VMT-to-occupied VMT) are most suitable. For a public SAEV operator, whose goal presumably is to maximize equitable access to SAEVs while still reducing wait times, a supply-and-demand (origin-based) pricing scheme may be most suitable.

The model outputs also reinforce the importance of efficient parking prices, since SAEVs will be more competitive against private vehicles in areas which prices parking marginally according to usage rather than subsidies through development policies (e.g. requiring developers to provide specific numbers of parking spaces per retail square footage) or employer-provided benefits. Under-priced and inefficiently-priced parking spaces in most U.S. and non-U.S. cities play a direct role in increasing traffic congestion, housing inaffordability, sprawl, and mobile-source emissions (Litman 2011). Inefficient parking prices also cause undervaluation of one of SAEVs' key benefits: reduced parking demand (and out-of-pocket parking costs), decreasing their competitive advantage relative to private vehicles.

The pricing strategies and sensitivity analysis explored here offer insights on the many factors that influence SAEV mode shares and fleet performance. However, this agent-base model and application can be improved in various ways. For example, more than three modes are possible, including privately held AVs, which may become very popular, so a vehicle-ownership model (upstream) is needed, along with non-motorized modes and trip distances below 1 mile. Nevertheless, while autonomous driving technology is in its infancy (and expensive), SAEVs offer users access to AV technology without significant up-front investment. Additionally, as mentioned in the results discussion, the lack of more individual trip-maker and trip-type attributes over space and time (by time of day and day of year) oversimplifies the mode (and destination) choice process. In reality, urban geography is highly heterogeneous in terms of trip generation and attraction rates, by time of day and across demographic characteristics. Moreover, trips are segments of complex tours with a variety of constraints on them. More clustered origins and destinations, and routing opportunities may make the systems more efficient, but variations over the days of week and months of year may make fixed fleets less able to serve all comers. Fortunately, pricing can be made flexible, and vehicles can hold more than one travelers, so operators have a variety of price-setting strategies to explore. The future is uncertain, but interesting and full of opportunity for those who make use of these new technologies in socially meaningful ways.

CONCLUDING REMARKS AND FUTURE WORK

This dissertation presents a cohesive argument for the possibility of a new mode which will revolutionize urban transportation through the simulation of a fleet of SAEVs in an agent-based model framework. A SAEV fleet will allow carsharing without costly manual relocation, lowered mobile emissions from EVs without worry about range management, and user access to AV technology without the personal large financial investment.

To understand the full impacts and challenges of implementing a SAEV service, this dissertation turns to existing literature on carsharing, EV infrastructure planning, and AV technology development. The recent rapid growth in carsharing membership points to an even faster market growth for SAEV service once it is available, which can be as early as 2020 based on autonomous driving technology development. Upon initial launch of SAEVs, travelers with characteristics similar to current carsharing members (educated households with lower vehicle ownership rates and good access to alternative modes) will likely be the early adopters.

Over time, as modeled in Chapter 3, the overall mode share of SAEVs in a mid-sized US city is predicted to be anywhere between 14 and 39%, when competing against privately-owned manually-driven vehicles and city bus service. This assumes SAEVs will be priced between \$0.75 and \$1.00 per mile, which translates into roughly 2-to-1 revenue-to-cost ratio in all modeled scenarios with 80-mile range vehicles and wireless Level II charging infrastructure.

Model results also suggest many trade-offs between investment and fleet performance. Results from Chapter 2 show that with additional investment into longer-range EVs and Level III fast charging infrastructure, the required size for a SAEV fleet shrinks to almost the same as non-electric SAVs, with each SAEV roughly replacing 6.8 privately owned vehicles. Average wait times, percent of trips unserved, and induced "empty" VMT also decrease with longer-range EVs and fast charging infrastructure. However, despite these improvements in fleet metrics, on a per-mile cost basis, a fleet of LR SAEVs with fast charging infrastructure is 15% more expensive to operate than a fleet of 80-mile range SAEVs with Level II charging infrastructure. Model outputs from Chapter 3's various pricing schemes for SAEV fare show that specific fleet metrics can be improved with targeted strategies. For example, pricing strategies that attempt to balance available SAEV supply with anticipated trip demand can decrease average wait times by 19-23%. However, tradeoffs also exist within price-setting: fare structure which favors higher revenue-to-cost ratio (by targeting high-VOTT travelers) reduce SAEV mode share while fare structures which favor larger mode shares (by appealing to a wide range of VOTTs) produce lower revenue-to-cost ratios.

The competitiveness of SAEVs compared to non-electric SAVs hinges almost singly on the availability of automated wireless charging. With wireless automated charging, SAEVs can be price-competitive with SAVs when gasoline is priced at $3.50 per gallon or less. But with attendant serviced charging, SAEVs are only price competitive with SAVs when gasoline reaches $4.35 to $5.70 per gallon.

To examine the sensitivity of model outputs to trip generation patterns, a case study using Austin-region trip tables was also modeled here. With much shorter average trip distances, a SAEV fleet serving Austin trips gridded onto the 100-mile by 100-mile region can serve 99% of all trip requests with average wait times between 2 and 4 minutes in each SAEV scenario. The shorter trips also correspond to higher vehicle usage rates, which translates to private vehicle replacement rates between 5.0 and 9.0 for each SAEV scenario.

On the other hand, the competitiveness of SAEVs to non-autonomous private vehicles depends on many internal and external factors. First, to maximize SAEVs' appeal to users, operators must focus on increasing traditional measures of transportation service quality such as decreased wait times and increased reliability. Model results and previous literature suggest this can be accomplished through strategic vehicle relocation, a dynamic supply-and-demand based fare structure, and penalties for adding uncertainty to the system (such as a nonrefundable reservation fee). To increase market share, particularly amongst high-VOTT travelers, SAEV operators should focus on tailoring the in-vehicle travel experience to optimize work productivity, leisure, or any other activities which the traveler would value more than driving. As suggested in Chapter 3, SAEV operators may find a good balance between maximizing revenue-to-cost ratio and mode share by offering segmented service levels: a first-class segment which caters to high-VOTT travelers (and maximizes revenue capture) and an economy-class segment which appeals to a larger proportion of travelers (and allows more efficient fleet operations with higher densities of trip demand). Externally, the competitiveness of SAEVs against other modes depends heavily on efficient parking pricing (without which the true value of SAEVs cannot be realized), policy frameworks for licensing and insurance, and public perception.

Each chapter of this dissertation has addressed specific limitations of each model component and its assumptions, but there are also prescriptive changes to the overall model design which would better capture real-world travel. First, this model uses simple average travel speeds (albeit zone-based and disaggregated by peak and off-peak periods) which are not responsive to actual roadway network characteristics. Furthermore, the mode choice step in this agent-based framework only tracks the choice of the mode, but not the route choices of trips that chose non-SAEV modes. Integrating the agent-based model into a real traffic network with a comprehensive mode choice step means the SAEV operations will be reflective of the congestion-dependent link travel times as SAEVs, private vehicles, buses, and even other modes chooses specific routes to complete their trips. Second, while the temporal and distance distribution of the population density-based trip generation rates used here follow real national data, these trip generation and attraction rates are not based on real land use and demographic characteristics.

Nonetheless, this model remains a solid base for exploration into the operations of a SAEV fleet, and there are also many extensions and opportunities for future research. First, the trip matching algorithm in this agent-based framework is done via a greedy search algorithm. In a setting with many simultaneous trip requests and available vehicles, a matching algorithm employing graph theory will likely be more efficient. Moreover, introducing a recharging strategy with battery swap stations would likely significantly decrease fleet size and charging infrastructure needs. However, this scenario would hinge on the ease of automated battery swapping, as the analysis in Chapter 2 shows that adding any manual component into the system can significantly increase per-mile costs. The scenarios modeled here all assume single-occupant SAEVs, and introducing a ride-sharing methodology would likely allow SAEVs to compete more efficiently against transit mode in short trips and against private vehicles amongst mid- and low-VOTT travelers. Ride-sharing can also be used as a strategy in the dynamic pricing of SAEV trips, incentivizing carpooling to decrease the shift of vehicles from low-supply blocks to high-supply blocks. Along the same line as ride-sharing, modeling a heterogeneous fleet of SAEVs of varying seating capacity (cars, vans, mini-buses) can shed insight into where the benefits of on-demand transportation start to blur into the capacity efficiency of mass transit.

Appendix A: Sample Source Code

This is a select representation of the C++ code used for the gridded agent-based model.

```
int main(int argc, char* argv[])
{
//	cout << "main begins"<<endl;
	randomSeed = -1;
	if (argc > 1)
		randomSeed = atoi(argv[1]);

strcpy(zName, "Warm Zones.txt");
clock_t t1,t2,tot1,tot2;
float time_diff, seconds;
tot1 = clock();
// Generate stations until convergence
int prevMaxAvailStations = 1000;
maxAvailStations = 0;
int iter = 1;
cout << abs(prevMaxAvailStations - maxAvailStations)/(1.0*prevMaxAvailStations) <<
endl;
while ((abs(prevMaxAvailStations - maxAvailStations)/(1.0*prevMaxAvailStations) >
0.01) && iter < 100){
```

```
        prevMaxAvailStations = maxAvailStations;
//      cout << "initVars" << endl;
        initVars(iter, true, false);
//      cout << "findDistWeight" << endl;
        findDistWeight();
        if (!error)
        {
                if (!readFile){
                generateTrips(true);
                }
                if (!readFile || wStart) {
                        cout << "Run " << iter + 1 << endl;
                        runSharedAV(timeTripCounts, CarMx, maxTrav, maxTravC,
                        dwLookup, zoneSharesL, zoneSharesS, maxCarUse, maxCarOcc,
                        totDist, unoccDist, waitT, reportProcs, saveRate, true, false,
                        maxAvailCars, readFile, startIter, unservedT, waitCount, hotStarts,
                        coldStarts, numRuns, iter, false);
                        placeInitCars(CarMx, timeTripCounts, maxCarUse, maxCarOcc,
                        totDist, unoccDist, waitT, dwLookup, reportProcs, hotStarts,
                        coldStarts);

                        cout << "Run " << iter + 1 << endl;
                        cout << "Cars: " << maxAvailCars << endl;
                        cout << "Stations: " << maxAvailStations << endl;
                        cout << "Prev Stations: " << prevMaxAvailStations << endl;
```

```
        }
    }
    iter++;

}



// warm start to determine fleet size
for (int i = 1; i <= numWarmRuns; i++)
{
    cout << "initVars" << endl;
    initVars(i,true,true);
    cout << "findDistWeigh" << endl;
    findDistWeight();

    if (!error)
    {

    if (!readFile)
    {
    generateTrips (true);
    }
    if (!readFile || wStart)
    {
        cout << "About to run program: "<< i << endl;
```

```
	t1 = clock();
		runSharedAV (timeTripCounts, CarMx, maxTrav, maxTravC,  dwLookup,
		zoneSharesL, zoneSharesS, maxCarUse, maxCarOcc, totDist, unoccDist,
		waitT, reportProcs, saveRate, true, false, maxAvailCars, readFile, startIter,
		unservedT, waitCount, hotStarts, coldStarts, numRuns, i, true);

		placeInitCars (CarMx,   timeTripCounts, maxCarUse, maxCarOcc, totDist,
		unoccDist, waitT, dwLookup, reportProcs, hotStarts, coldStarts);
		t2 = clock();
	}
		time_diff = ((float)t2 - (float)t1);
		seconds = time_diff / CLOCKS_PER_SEC;
	cout << "Warm Run " << i << " completed. Time: " << seconds << endl;
	nCars = 0; nStations = 0;
	for(int x=0; x<xMax; x++){
		for(int y=0; y<yMax; y++){
			nCars += CarMx[x][y].size();
			nStations += ChStMx[x][y].size();
			if(ChStMx[x][y].size() > 1)
				cout << "problem w/ num charge stations"<<endl;
		}
	}
	cout << "nCars is "<<nCars <<"\nnStations is "<<nStations<<endl;
	}
}
```

```
distWt = netDistWt / numWarmRuns;
maxAvailCars = maxAvailCars / numWarmRuns;
maxAvailStations = maxAvailStations / numWarmRuns;
nCars = 0;
nStations = 0;
for (int i = 2; i < 100 && nCars < maxAvailCars; i++)
{
	initVars (i,true,true);
	cout << "Max avail cars is " << maxAvailCars << endl << endl;

	cout << "Possible last warm start before running scenario" << endl;

	generateTrips (true);
	runSharedAV ( timeTripCounts, CarMx, maxTrav, maxTravC, dwLookup,
	zoneSharesL, zoneSharesS, maxCarUse, maxCarOcc, totDist, unoccDist,
		waitT, reportProcs, saveRate, true, true, maxAvailCars, readFile, startIter,
		unservedT, waitCount, hotStarts, coldStarts, numRuns, i, true);
	placeInitCars (CarMx, timeTripCounts, maxCarUse, maxCarOcc, totDist,
	unoccDist, waitT, dwLookup, reportProcs, hotStarts, coldStarts);

	nCars = 0;
	nStations = 0;
	for (int x = 0; x < xMax; x++)
	{
	for (int y = 0; y < yMax; y++)
```

```
        {
        nCars = nCars + CarMx[x][y].size();
                nStations = nStations + ChStMx[x][y].size();
        }
        }

}

cout << "nCars is " << nCars << endl;
cout<< "nStations is "<<nStations << endl;
strcpy(zName, "Zones.txt");

// Run Full Program
for (int i = 1; i <= numRuns; i++)
{
        initVars(i,false,true);
        if (randomSeed == -1)
                cout << "Run: "<<i<<" seed: "<< random_seeds[i-1] <<endl;
        else
                cout << "Run: "<<i<<" seed: "<< randomSeed <<endl;

        placeInitCars (CarMx,    timeTripCounts, maxCarUse, maxCarOcc, totDist,
        unoccDist, waitT, dwLookup, reportProcs, hotStarts, coldStarts);
        generateTrips (true);
        t1 = clock();
```

```
        runSharedAV ( timeTripCounts, CarMx, maxTrav, maxTravC,  dwLookup,
        zoneSharesL, zoneSharesS, maxCarUse, maxCarOcc, totDist, unoccDist, waitT,
                reportProcs, saveRate, false, false, maxAvailCars, readFile, startIter,
                unservedT, waitCount, hotStarts, coldStarts, numRuns, i, true);
        t2 = clock();
        time_diff = ((float)t2 - (float)t1);
        seconds = time_diff / CLOCKS_PER_SEC;
//      reportMatchingResults();
        reportResults ( timeTripCounts, CarMx,  maxCarUse, maxCarOcc, totDist,
        unoccDist, waitT, unservedT, waitCount, hotStarts, coldStarts,
                totDistRun, totUnoccDistRun, totCarsRun, totTripsRun, totHSRun,
                totCSRun, totWaitTRun, totUnservedTRun, totWaitCountRun,
                totUnusedRun,     totUnoccRun,     totAvgWait,     totAvgTripDist,
                totDistRunCOV,          totUnoccDistRunCOV,          totCarsRunCOV,
                totTripsRunCOV,
                totHSRunCOV,              totCSRunCOV,              totWaitTRunCOV,
                totUnservedTRunCOV,   totWaitCountRunCOV,   totUnusedRunCOV,
                totUnoccRunCOV,
                totAvgWaitCOV,        totAvgTripDistCOV,        totStartsPerTripCOV,
                totAvgTripsPerCarCOV, totWaitCOV, totTripDistCOV, totCarTripsCOV,
                totPctMaxWaitFiveCOV,   totPctInducedTCOV,   totPctMaxInUseCOV,
                totPctMaxOccCOV, totPctColdShareCOV, numRuns, i);
        cout << "Completion time: " <<seconds << endl;
//      if (numRuns > 1)
//      {
```

```
//        cout << "Run " << i << " completed. Time: " << seconds << endl;
//              cout << "Random Seed: " << random_seeds[i] << endl;
//      }
}

if (numRuns > 1)
{
        reportFinalResults(totDistRun, totUnoccDistRun, totCarsRun, totTripsRun,
        totHSRun, totCSRun, totWaitTRun, totUnservedTRun, totWaitCountRun,
                totUnusedRun, totUnoccRun, totAvgWait, totAvgTripDist,
                totDistRunCOV, totUnoccDistRunCOV, totCarsRunCOV,
                totTripsRunCOV,
                totHSRunCOV, totCSRunCOV, totWaitTRunCOV,
                totUnservedTRunCOV, totWaitCountRunCOV, totUnusedRunCOV,
                totUnoccRunCOV,
                totAvgWaitCOV, totAvgTripDistCOV, totStartsPerTripCOV,
                totAvgTripsPerCarCOV, totWaitCOV, totTripDistCOV, totCarTripsCOV,
                totPctMaxWaitFiveCOV, totPctInducedTCOV, totPctMaxInUseCOV,
                totPctMaxOccCOV, totPctColdShareCOV, numRuns);
}
if (! CHARGE_IN_PLACE){
//      cout << "Cell Charge Counts "<<endl;
//      writeChargeStats(0);
//      cout << "Cell Charge Time " <<endl;
//      writeChargeStats(1);
```

```
//     cout << "Cell Congestion Counts" <<endl;
//     writeChargeStats(2);
//      writeStationLocation();
}

tot2 = clock();
time_diff = ((float)tot2 - (float)tot1);
seconds = time_diff / CLOCKS_PER_SEC;
cout << "Total time: " << seconds;
return 0;
}
```

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