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THE FUTURE OF FULLY AUTOMATED VEHICLES: OPPORTUNITIES FOR VEHICLE- AND RIDE-SHARING, WITH COST AND EMISSION SAVINGS

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by

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Dedication

This doctoral dissertation is dedicated to my loving, brilliant and steadfast wife, Amy, and to my two delightful children, Sam and Abby. These three persons never cease to bring a smile to my face, a lift in my step, and sunshine to my day.

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THE FUTURE OF FULLY AUTOMATED VEHICLES: OPPORTUNITIES FOR VEHICLE- AND RIDE-SHARING, WITH COST AND EMISSION SAVINGS

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Fully automated or autonomous vehicles (AVs) hold great promise for the future of transportation, with Google and other auto manufacturers intending on introducing self-driving cars to the public by 2020. New automation functionalities will produce dramatic transportation system changes, in safety, mobility, travel behavior, and the built environment.

This work's results indicate that AVs may save the U.S. economy up to $37.7 billion from safety, mobility and parking improvements at the 10% market penetration level (in terms of system-wide vehicle-miles traveled [VMT]), and up to $447.1 billion with 90% market penetration. With only 10% market share, over 1,000 lives could be saved annually. However, realizing these potential benefits while avoiding pitfalls requires overcoming significant barriers including AV costs, liability, security, privacy, and missing research.

Additionally, once fully self-driving vehicles can safely and legally drive unoccupied, a new personal travel transportation mode looks set to arrive. This new mode is the shared automated vehicle (SAV), combining on-demand service features with self-driving capabilities. This work simulates a fleet of SAVs operating within Austin, Texas, first using an idealized grid-based representation, and next using Austin's actual transportation network and travel demand flows. This second model incorporates dynamic ride-sharing (DRS), allowing two or more travelers with similar origins, destinations and departure times to share a ride.

Model results indicate that each SAV could replace around 10 conventionally-owned household vehicles, with a fleet of 1715 SAVs serving over 56,000 person-trips. SAVs' ability to relocate unoccupied between serving one traveler and the next may cause an increase of 7-10% more travel; however, DRS can result in reduced overall VMT, given enough SAV-using travelers willing to ride-share. Furthermore, using DRS results in overall lower wait and service times for travelers, particularly from pooling rides during peak demand. SAVs should produce favorable emissions outcomes, with an estimated 16% less energy use and 48% lower volatile organic compound emissions, per person-trip compared to conventional vehicles. Finally, assuming SAVs cost $70,000 each, an SAV fleet in Austin could provide a 19% return on investment, when charging $1 per trip-mile served. In closing, this new paradigm holds much promise in helping to create a more efficient and sustainable transport system.

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INTRODUCTION

More and more, personal vehicles are assuming operational tasks that were previously managed by their human drivers. Over the past 30 years, their new features have transitioned from luxury models, to options on common models, and then become standard on all vehicles, with applications ranging from simple, powered-window openers and automated transmissions to new features still on this path, like self-parking and anticipatory forward collision braking. Automotive manufacturers and technology suppliers are now working to equip vehicles with sensors and controls that allow the vehicles to take over full operation from the driver. These capabilities may first become commercialized in limited circumstances like low-speed settings or freeway driving only, but may eventually become viable for all settings, even without a human on board. Vehicles with these limited or full self-driving capabilities are commonly referred to as automated or autonomous vehicles (AVs) and will transform transportation systems as they exist today.

This dissertation research examines the likely implications of AVs through a three-part investigation, as follows:

- Part 1: Overview and Potential Impacts of Road Vehicle Automation,
- Part 2: An Agent-Based Shared Autonomous Vehicle Model, and
- Part 3: Shared Autonomous Vehicle Fleet Simulations in a Network Setting

Part 1 examines the current state and potential outlook for vehicle automation technologies. In addition to a qualitative overview discussion of potential impacts, this set of chapters conducts an economic evaluation of potential impacts (particularly focusing on potential safety and mobility impacts) and discusses barriers to implementation and mass-market penetration (including vehicle costs and registration, liability and security questions, privacy concerns, and missing research). A version of this section (Fagnant and Kockelman 2013) has been published by the Eno Center for Transportation and is under review for publication in *Transportation Research Part A*.

Part 2 offers a detailed look at a potential application for AVs. This investigation combines a shared-vehicle system with the capabilities of fully automated vehicles to investigate the potential travel and environmental implications for shared autonomous vehicles (SAVs, also known as driverless taxis or autonomous taxis). This work assumes an idealized grid-based urban area with perfect connectivity and uniform travel times, with congestion experienced during peak hours. The work tests four relocation strategies and varies base-parameter settings many times to understand how they impact performance outcomes. A version of this section (Fagnant and Kockelman 2014) has been published in *Transportation Research Part C*.

Part 3 expands on Part 2's contributions. In lieu of an idealized grid-based urban area, the City of Austin's network and travel data are used, providing a much more realistic setting. An interface of the fleet assignment, route-selection, and trip reservation C++ codes with existing network-simulation model MATSim allows for the continual updating of hourly link-level travel times throughout the day. Part 2's most effective vehicle-relocation strategy is applied, with some variations, to improve its effectiveness in the network setting. Dynamic (real-time) ride-sharing is also permitted and applied under various parameter settings to test its travel implications across various demand and user acceptance scenarios. Materials from this section have not yet been published, though two papers are under review in *Transportation* and *Transportation Research Record*.

PART 1: OVERVIEW AND POTENTIAL IMPACTS OF ROAD VEHICLE AUTOMATION

Chapter 1.1: The Current State of Road Vehicle Automation

In 2004, DARPA's Grand Challenge was launched with the goal of demonstrating AV technical feasibility by navigating a 150-mile route. While the best team completed just over seven miles, one year later five driverless cars successfully navigated the route. In 2007, six teams finished the new Urban Challenge, with AVs required to obey traffic rules, deal with blocked routes, and maneuver around fixed and moving obstacles, together providing realistic, every-day-driving scenarios (DARPA 2012). AV technology continues to progress and is entering the public domain. As of September 2013, Google's self-driving cars have driven over 700,000 miles on public roads (Etherington 2014), and numerous manufacturers – including Audi, BMW, Cadillac, Ford, GM, Mercedes-Benz, Nissan, Toyota, Volkswagen, and Volvo – have begun testing driverless systems (Wikipedia 2013).

Moreover, AVs appear set to soon become commercially available. At the September 2012 signing of California's law enabling AV licensure (SB 1298), Google founder Sergey Brin predicted that Americans could experience AVs within five years (O'Brien 2012). More recently, Google announced its intent to deploy 100 fully automated, low-speed, two-passenger vehicles, without steering wheels and other devices that could cede driving control to a human driver (Markoff 2014). Nissan (Nissan Motor Company 2013), Volvo (Carter 2012), Mercedes Benz (Andersson 2013), and GM (LeBeau 2013) have all announced their intentions to have commercially viable autonomous-driving capabilities by 2020 in multiple vehicle models. Assuming an additional five years for prices to drop to allow for some degree of mass-market penetration, AVs may be available on the mass market by 2022 or 2025, approximately two decades after the DARPA (Defense Advanced Research Projects Agency) Grand Challenge's first successful tests.

Semi-automated features are now commercially available, including adaptive cruise control (ACC), lane departure warnings, collision avoidance, parking assist systems, and on-board navigation. Europe's CityMobile2 project is currently demonstrating low-speed fully autonomous transit applications in five cities. Additionally, AVs are becoming increasingly common in other sectors including military, mining, and agricultural (ETQ 2012). While urban environments pose much greater challenges, these environments can be helpful testing grounds for AV innovation.

States are proceeding with AV-enabling legislation: California, Florida, Nevada and Michigan have enacted bills to regulate AV licensing and operation, with instructions to their respective Department of Motor Vehicles (DMV) for fleshing out details, and another ten states have legislation pending under consideration. Yet some of these efforts are in direct conflict with federal guidance. NHTSA (The National Highway and Traffic Safety Administration) has issued a statement advocating that states should begin establishing procedures for allowing testing on public roads, though should not yet begin licensing AV sales to the general public (NHTSA 2013a). In contrast, California has directed its DMV to provide AV licensing requirements by 2015 (CIS 2012).

1.1.1 LEVELS OF AUTOMATION

In May 2013, the National Highway Traffic Safety Administration (NHTSA) issued a policy statement (NHTSA 2013a) regarding automated vehicles, focused on three main areas: definitions of automation levels, a national research plan, and recommendations for states regarding AV adoption.

The following automation levels summarize the NHTSA definitions.

Level 0: No automation. The driver is in complete and sole control of the primary vehicle controls (brake, steering, throttle, and motive power) at all times, and is solely responsible for monitoring the roadway and for safe operation of all vehicle controls. (Vehicles with V2V warning systems only would fit into this category)

Level 1: Functional-specific automation. One or more specific control functions (e.g., adaptive cruise control, electronic stability control, dynamic brake support in emergencies) are present in the vehicle, but do not work in unison. Most new vehicles today operate under some degree of Level 1 automation.

Level 2: Combined function automation. At least two control functions work in unison. The system can relinquish control with no advance warning and the driver must be ready to control the vehicle safely. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering.

Level 3: Such vehicles allow drivers to cede full control of all safety-critical functions under certain traffic and/or environmental conditions, and, in those conditions, to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control.

Level 4: Full Self-Driving Automation. The vehicle is can perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Drivers are not expected to continually monitor the roadway.

These levels of automation provide consistent terminology for use by transportation professionals, policymakers and researchers. While the Society of Automotive Engineers (SAE) has developed an alternative 6-level (0-5) framework on driving automation for on-road vehicles (Smith 2013b), all discussions used in this document will refer to NHTSA's definitions, particularly focusing on Level 3 and 4 (limited or full self-driving automation). For the following discussion on overall impacts, AVs are assumed to possess Level 4 automation capabilities, though some of the benefits discussed herein may also be realized with Level 3 automation, and to a lesser extent with Level 2 automation.

Chapter 1.2: Potential Impacts of Automation

AV operations are inherently different from human-driven vehicles. AVs can be programmed to not break traffic laws. They do not drink and drive. Their reaction times are quicker and they can be optimized to smooth traffic flows, improve fuel economy, and reduce emissions. They can deliver freight and unlicensed travelers to their destinations. This section examines some of the largest potential benefits that have been identified in existing research. The exact extent of these benefits is not yet known, but this paper attempts to place estimates on these benefits to gauge the magnitude of their impact assuming varying levels of market penetration.

1.2.1 Safety

Autonomous vehicles have the potential to dramatically reduce crashes. Table 1-1 highlights the magnitude of automobile crashes in the United States, and indicates sources of driver error that may disappear as vehicles become increasingly automated.

Total Crashes per Year in U.S.[1]	5.5 million
% human cause as primary factor[2]	93%
Economic Costs of U.S. Crashes[1]	$300 billion
% of U.S. GDP[3]	2%
Total Fatal & Injurious Crashes per Year in U.S.	2.22 million
Fatal Crashes per Year in U.S.[4]	32,367
% of fatal crashes involving alcohol	31%
% involving speeding	30%
% involving distracted driver	21%
% involving failure to keep in proper lane	14%
% involving failure to yield right-of-way	11%
% involving wet road surface	11%
% involving erratic vehicle operation	9%
% involving inexperience or overcorrecting	8%
% involving drugs	7%
% involving ice, snow, debris, or other slippery surface	3.7%
% involving fatigued or sleeping driver	2.5%
% involving other prohibited driver errors (e.g. improper following, driving on shoulder, wrong side of road, improper turn, improper passing, etc.)	21%

Table 1-1: U.S. Crash Motor Vehicle Scope and Selected Human and Environmental Factor Involvement

Over 40 percent of these fatal crashes involve alcohol, distraction, drug involvement and/or fatigue[5]. Self-driven vehicles would not fall prey to human failings, suggesting the potential for at least a 40 percent fatal crash-rate reduction, assuming automated malfunctions are minimal and everything else remains constant (such as the levels of long-distance, night-time and poor-weather driving). Such reductions do not

1 Cambridge Systematics (2011)
2 NHTSA (2008)
3 Cambridge Systematics (2011), CIA (2012)
4 NHTSA (2012a)
5 Table 1-1's factors contributing to fatal crashes are not mutually exclusive. For example, alcohol, drugs, inexperience, speeding, and ice can all contribute to a single crash. As a result, Table 1 percentages sum to more than 100 percent.

reflect crashes due to speeding, aggressive driving, over-compensation, inexperience, slow reaction times, inattention and various other driver shortcomings. Driver error is believed to be the main reason behind over 90 percent of all crashes (NHTSA 2008). Even when the critical reason behind a crash is attributed to the vehicle, roadway or environment, additional human factors such as inattention, distraction, or speeding are regularly found to have contributed to the crash occurrence and/or injury severity.

The scope of potential benefits is substantial, both economically and politically. Over 30,000 persons die each year in the U.S. in automobile collisions, with 2.2 million crashes resulting in injury (NHTSA 2012a). At $300 billion, the annual economic cost of crashes is three times higher than that of congestion (Cambridge Systematics 2011) and is highlighted as the number-one transportation goal (U.S. House of Representatives and Senate 2012) in the nation's federal legislation, Moving Ahead for Progress in the 21st Century (MAP-21) (Section 1203§150.b.1). These issues have long been the top priorities of the U.S. Department of Transportation's Strategic Plan. Traffic crashes remain the primary reason for the death of Americans between 15 and 24 years of age (CDC 2011).

While many driving situations are relatively easy for an autonomous vehicle to handle, designing a system that can perform safely in nearly every situation is challenging (Campbell et al. 2010). For example, recognition of humans and other objects in the roadway is both critical and more difficult for AVs than human drivers (e.g., Dalal and Trigs 2005, ETQ 2012, Farhadi et al 2009). A person in a roadway may be small or large, standing, walking, sitting, lying down, riding a bike, and/or partly obscured – all of which complicate AV sensor recognition. Poor weather, such as fog and snow, and reflective road surfaces from rain and ice create other challenges for sensors and driving operations. Additionally, evasive decisions should depend on whether an object in the vehicle's path is a large cardboard box or a large concrete block. When a crash is unavoidable, it is crucial that AVs recognize the objects in their path so they may act accordingly. Liability for these incidents is a major concern and could be a substantial impediment to implementation.

Ultimately, some analysts predict that AVs will overcome many of the obstacles that inhibit them from accurately responding in complex environments. Hayes (2011) suggests that motor-vehicle fatality rates (per person-mile traveled) could eventually approach those seen in aviation and rail, about 1 percent of current rates; and KPMG and CAR (2012) advocate an end goal of "crash-less cars." However there is the possibility that drivers will take their vehicles out of self-driving mode and take control. Google's only reported AV crash occurred when a human driver was operating the vehicle. The rate at which human control is needed will be a substantial factor in the safety of these vehicles.

1.2.2 Congestion and Traffic Operations

Aside from making automobiles safer, researchers are also developing ways for AV technology to reduce congestion and fuel consumption. For example, AVs can sense and possibly anticipate lead vehicles' braking and acceleration decisions. Such technology allows for smoother braking and fine speed adjustments of following vehicles, leading to fuel savings, less brake wear, and reductions in traffic-destabilizing shockwave propagation. AVs are also expected to use existing lanes and intersections more efficiently through shorter headways, coordinated platoons, and more efficient route choices. Many of these features, such as adaptive cruise control (ACC), are already being integrated into automobiles and some of the benefits will be realized before AVs are fully operational.

As the research shows, these benefits will not happen automatically. Many of these congestion-saving improvements depend not only on automated driving capabilities, but also on cooperative abilities through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. But significant congestion reduction could occur if the safety benefits alone are realized. FHWA estimates that 25 percent of congestion is attributable to traffic incidents, around half of which are crashes (FHWA 2005).

Multiple studies have investigated the potential for AVs to reduce congestion under differing scenarios. Under various levels of AV adoption congestion savings due to ACC measures and traffic monitoring systems could smooth traffic flows by seeking to minimize accelerations and braking in freeway traffic. This could increase fuel economy and congested traffic speeds by 23 percent to 39 percent and 8 percent to 13 percent, respectively, for all vehicles in the freeway travel stream, depending on V2V communication and how traffic-smoothing algorithms are implemented (Atiyeh 2012). If vehicles are enabled to travel closer together, the system's fuel and congestion savings rise further, and some expect a significant increase in highway capacity on existing lanes (Tientrakool 2011). Shladover et al. (2012) estimate that cooperative adaptive cruise control (CACC) deployed at 10 percent, 50 percent, and 90 percent market-penetration levels will increase lanes' effective capacities by around 1 percent, 21 percent and 80 percent, respectively. Headway reductions coupled with near-constant velocities produce more reliable travel times – an important factor in trip generation, timing, and routing decisions. Similarly, shorter headways between vehicles at traffic signals (and shorter start-up times) mean that more AVs could more effectively utilize green time at signals, considerably improving intersection capacities.

Over the long term, new paradigms for signal control such as autonomous intersection management could use AVs' powerful capabilities. Some evidence shows that advanced systems could nearly eliminate intersection delay while reducing fuel consumption, though this concept is only theoretical and certainly a long way off. In order to achieve substantial benefits from such technologies, Dresner and Stone (2008) estimate that an AV-market penetration rate of 95 percent or more may be required, leaving many years before deployment. However, full autonomy may not be required for such applications: a semi-automated "intersection assist" (where the vehicle takes temporary driving control to navigate through the intersection) with V2I communication may be all that is needed.

Of course, many such benefits may not be realized until high AV shares are present. For example, if 10 percent of all vehicles on a given freeway segment are AVs, there will likely be an AV in every lane at regular spacing during congested times, which could smooth traffic for all travelers (Bose and Ionnou 2003, Atiyeh 2012). However, if just one out of two hundred vehicles are AVs, the impact would be non-existent or greatly lessened. Also, if one AV is following another, the following AV can reduce the headway between the two vehicles, increasing effective roadway capacity. This efficiency benefit is also contingent upon higher AV shares. Technical and implementation challenges also loom in order to realize the full potential of high adoption shares, including the implementation of cloud-based systems and city or region-wide coordinated vehicle-routing paradigms and protocols. While AVs have a potential to increase roadway capacity with higher market penetration, the induced demand resulting from more automobile use might require additional capacity needs.

1.2.3 TRAVEL-BEHAVIOR IMPACTS

The safety and congestion-reducing impacts of AVs have potential to create significant changes in travel behavior. For example, AVs may provide mobility for those too young to drive, the elderly and the disabled, thus generating new roadway capacity demands. Parking patterns could change as AVs self-park in less-expensive areas. Car- and ride-sharing programs could expand, as AVs serve multiple persons on demand. Most of these ideas point toward more vehicle-miles traveled (VMT) and automobile-oriented development, though perhaps with fewer vehicles and parking spaces. Added VMT may bring other problems related to high automobile use such as increased emissions, greater gasoline consumption and oil dependence, and higher obesity rates.

As of January 2013, state legislation in California, Florida and Nevada mandates that all drivers pursuing AV testing on public roadways be licensed and prepared to take over vehicle operation, if required. As AV experience increases, this requirement could be relaxed and AVs may be permitted to legally chauffeur children and persons that otherwise would be unable to safely drive. Such mobility may be increasingly beneficial, as the U.S. population ages, with 40 million Americans presently over the age of 65 and this demographic growing at a 50 percent faster rate than the nation's overall population (U.S. Census Bureau 2011). Wood (2002) observes that many drivers attempt to cope with such physical limitations through self-regulation, avoiding heavy traffic, unfamiliar roads, night-time driving, and poor weather, while others stop driving altogether. AVs could facilitate personal independence and mobility, while enhancing safety, thus further increasing the demand for automobile travel.

Research cites that with increased mobility among the elderly and others, as well as lowered travel effort and congestion delays, the U.S. can expect VMT increases, along with associated congestion, emissions, and crash rates, unless demand-management strategies are thoughtfully implemented (e.g., Kockelmand and Kalmanje 2006, Litman 2013a). However, AV benefits could exceed the negative impacts of added VMT. For example, if VMT were to double, a reduction in crash rates per mile-traveled by 90 percent yields a reduction in the total number of crashes and their associated injuries and traffic delays by 80 percent. Likewise, unless new travel from AV use is significantly underestimated, research cites that existing infrastructure capacity on roadways should be adequate to accommodate the new/induced demand. AVs' congestion-mitigating features (like traffic smoothing algorithms [Atiyeh 2012]) and effective capacity-increases (through CACC [Shladover et al. 2012]), as well as public-infrastructure investments (like V2I communication systems with traffics signals [KPMG and CAR 2012]) may be designed to support these capabilities. However, other negative impacts, such as sprawl, emissions and health concerns, may not be readily mitigated.

It is possible that already-congested traffic patterns and other roadway infrastructure will be negatively affected, due to increased trip-making. Indeed, Smith (2013a) argues the possibility that "Highways may carry significantly more vehicles, but average delay during the peak period may not decrease appreciably. Similarly, emissions per vehicle mile traveled may decrease, but total emissions (throughout the day) may actually increase." However, AVs could enable smarter routing in coordination with intelligent infrastructure, quicker reaction times, and closer spacing between vehicles to counteract increased demand. Whether arterial congestion improves or degrades ultimately depends on how much induced VMT is realized, the relative magnitude of AV benefits, and use of demand management strategies, such as road pricing. Emissions have been estimated to fall when travel is smooth, rather than forced, with Berry (2010) estimating that a 20- percent reduction in accelerations and decelerations should lead to 5 percent reductions in fuel consumption and associated emissions. Thus, while AVs may increase VMT, emissions per mile could be reduced.

Additional fuel savings may accrue through AVs' smart parking decisions (Bullis 2011, Shoup 2007), helping avoid "cruising for parking." For example, in-vehicle systems could communicate with parking infrastructure to enable driverless drop-offs and pick-ups. This same technology could improve and expand car-sharing and dynamic ride-sharing by allowing for nearby, real-time rentals on a per-minute or per-mile basis. If successful, this offers great promise for program expansions since users could simply order a vehicle online or using mobile devices, much like an on-demand taxi, to take them to their destinations. Preliminary results in Parts 2 and 3 of this investigation using an agent-based model for assigning vehicles around a region in combination with NHTS data (FHWA 2009b) indicate that a single shared AV (SAV) could replace between nine and thirteen privately owned or household-owned vehicles, without compromising current travel patterns. As shown in Figure 1-1, even in Seattle where vehicle use is more intense than national averages (PSRC 2006), just less than 11 percent of vehicles are "in use" throughout the day, even at peak times, though usage rises to 16 percent if only including newer vehicles are monitored.

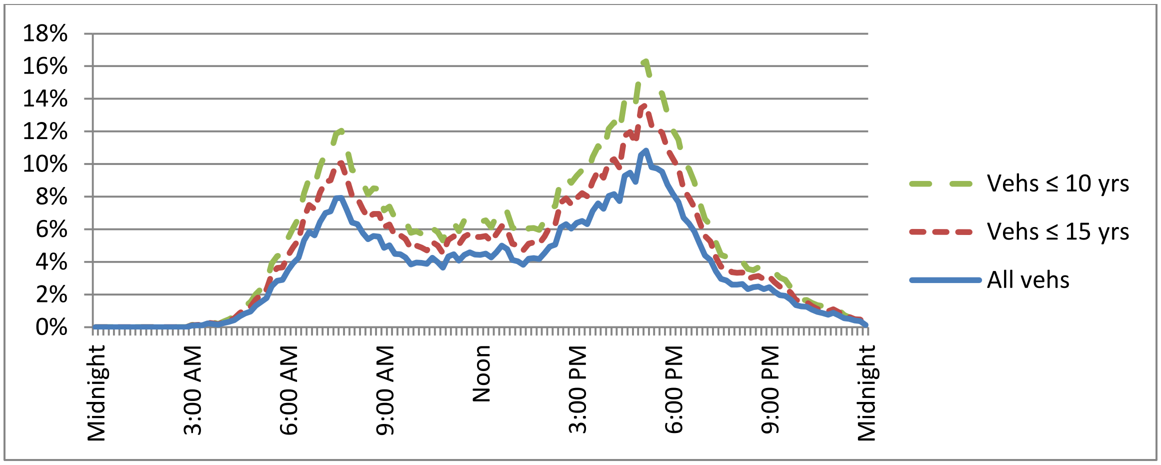


Figure 1-1: Vehicle Use by Time of Day and by Vehicle Age

1.2.4 FREIGHT TRANSPORTATION

Freight transport on and off the road will also be impacted. The mining company Rio Tinto is already using 10 self-driving ore trucks, with plans to expand to 150 vehicles within four years (ETQ 2012). The same technologies that apply to autonomous cars can also apply to the trucking industry, increasing fuel economy and lowering the need for truck drivers. While workers would likely still need to load and unload cargo, long-distance journeys may be made without drivers, with warehousing employees handling container contents at either end. Autonomously operated trucks may face significant resistance from labor groups, like the Teamsters, and competing industries, such as the freight railroad industry.

Additional benefits can emerge through higher fuel economies when using tightly coupled road-train platoons, thanks to reduced air resistance of shared slipstreams, not to mention lowered travel times from higher capacity networks (a result of shorter headways and less incident-prone traffic conditions). Bullis (2011) estimates that four-meter inter-truck spacings could reduce fuel consumption by 10 to 15 percent, and road-train platoons facilitate adaptive braking, potentially enabling further fuel savings. Kunze et al.

(2009) successfully demonstrated a trial run using 10-meter headways between multiple trucks on public German motorways, and a variety of autonomously platooned Volvo trucks recently logged approximately 10,000 km along Spanish highways (Newcomb 2012). However, tight vehicle spacing on roads could cause problems for other motorists trying to exit or enter highways, possibly resulting in the need for new or modified infrastructure with dedicated platoon lanes and thicker pavements to handle high truck volumes.

1.2.5 ANTICIPATING AV IMPACTS

Since AVs are only in the testing phase, it is difficult to precisely anticipate actual outcomes. Nevertheless, it can be useful to roughly estimate likely magnitudes of impact. Based on research estimates for the potential impacts discussed above, this paper quantifies crash, congestion and other impacts for the U.S. transportation system (including changes in parking provision, VMT, and vehicle counts). To understand how AVs' assimilation into the road network might work, multiple assumptions are needed and are explained below. To further understand the impact, the analysis assumes three AV market-penetration shares: 10 percent, 50 percent and 90 percent. These are assumed to represent not only market shares, but technological improvements over time, since it could take many years for the U.S. to see high penetration rates. This analysis is inherently imprecise, it provides an order-of-magnitude estimate of the broad economic and safety impacts this technology may have.

This analysis assumes that primary benefits for AV use will include safety benefits, congestion reduction (comprised of travel time savings and fuel savings), and savings realized from reduced parking demands, particularly in areas with high parking costs. Assumptions that drive these estimated impacts are discussed in this section, as well as assumptions that are used to estimate changes in Vehicle Miles Traveled (VMT), to estimate AV technology costs, and to select an appropriate discount rate for net present value (NPV) calculations.

1.2.6 CHANGES IN VMT

VMT per AV is assumed to be 20 percent higher than that of non-AV vehicles at the 10 percent market penetration rate, and 10 percent higher at the 90 percent market penetration rate. This reflects that early adopters will have more pent-up demand for such vehicles than later buyers. Preliminary agent-based simulations described in Parts 2 and 3 of this work underscore this idea, finding that a fleet of shared AVs serving over 60,000 trips (across a simulated city grid) cover 11 percent of their daily travel unoccupied, with this figure falling to 7 percent as the number of trips served doubles (thanks to a higher intensity of nearby pick-ups and drop-offs).

Additional VMT increases may be realized from induced demand, as travel costs and congestion fall. In his review of literature spanning 30 years across California and the U.S., Cervero (2001) showed that the long-term (six years or more) urban area elasticity of VMT demand with respect to the number of highway lane-miles supplied ranges from around 0.47 to 1.0, averaging 0.74. This suggests that if a region's lane-miles increase by 1 percent, regional VMT is expected to increase by around 0.74 percent over the long term, after controlling for population, income and other factors. While the congestion-relieving impact of AVs is similar to that of adding lane-miles, it differs in two crucial respects. First, AVs' effective capacity expansion is uniform, rather than targeted. Many road segments in a region are not currently congested, and do not have pent-up or elastic demand. Second, personal values of travel time may also fall, due to drivers' increased productivity gains which may be freed for purposes other than driving. This report does not account for induced travel due to latent demand, which may be stemmed if policies like congestion pricing are enacted in concert with the introduction of AVs. However, if a demand elasticity of just 0.37 is applied, system-wide VMT may be expected to rise 26 percent under the 90 percent AV market-penetration assumptions, due to an increase in effective capacity.

1.2.7 Discount Rate and Technology Costs

For net-present-value calculations, a 10-percent discount rate was assumed, which is higher than the 7-percent rate required by the federal Office of Management and Budget (OMB) for federal projects and TIGER grant applications (LaHood 2011), in order to reflect the greater uncertainty of this emerging technology. Early-introduction costs (five to seven years after initial rollout) at the 10-percent market penetration level were assumed to add $10,000 to the purchase price of a new vehicle, falling to $3,000 by the 90 percent market-penetration share, consistent with the findings noted in the Vehicle Cost section of this paper (e.g., see Dellenback [2013] and ETQ [2012]). Discussion of internal rates of return for initial costs are also included at the $37,500 level, which may be closer to the added price of AV technologies, when these are first introduced.

1.2.8 Safety Impacts

The analysis assumes that 10 percent of AVs are shared (at all levels of penetration), and that a single shared AV serves five times as many trips as a non-shared vehicle. U.S. crash rates for non-AVs are assumed constant, based on NHTSA's 2011 values, and the severity distribution of all crashes remains unchanged from present. As noted previously, over 90 percent of the primary factors behind crashes are due to human errors (NHTSA 2008), and 40 percent of fatal crashes involve driver alcohol or drug use, driver distraction and/or fatigue (NHTSA 2012a). Therefore, AVs may be assumed to reduce crash and injury rates by 50 percent, versus non-AVs at the early, 10-percent market penetration rate (reflecting savings due to eliminating the aforementioned factors, as well as reductions due to fewer legal violations like running red lights), and 90 percent safer at the 90 percent market penetration rate (reflecting the near-elimination of human error as a primary crash cause, thanks to greater use of V2V communications and improving AV technologies). Pedestrian and bicycle crashes (with motor vehicles) are assumed to enjoy half of the AV safety benefits, since just one of the two crash parties (the driver) relies on the AV technology. Similarly, motorcycles may not enjoy autonomous status for a long time (and their riders may be reluctant to relinquish control), and around half of all fatal motorcycle crashes do not involve another vehicle. Therefore, motorcycles are assumed to experience just a 25 percent decline in their crash rates, relative to the declines experienced by other motor vehicles. Crash costs were estimated first based on their economic consequences, using National Safety Council (2012) guidance, and then on higher comprehensive costs, as recommended by the USDOT (Trottenberg 2011), to reflect pain and suffering and the full value of a statistical life.

While this analysis estimates that safety improvements will be greater than new safety risks due to automation, it is possible that new risks will be greater for some system users under certain circumstances, particularly at early technology stages. Lin argues that increased safety to some users at the expense of others is not necessarily a clear-cut benefit, even if net safety risks to the whole population is lower (Lin 2013). Readers should note that this analysis acknowledges such dilemmas are present, even though it assesses net safety improvements, rather than potential improvements for some types of crashes and added complications for other crash types.

1.2.9 CONGESTION REDUCTION

Shrank and Lomax's (2011) congestion impact projections for 2020 are used here as a baseline. They assumed a $17 per person-hour value of travel time, $87 per truck-hour value of travel time, and statewide average gas prices in 2010. They estimated that 40 percent of the nation's roadway congestion occurs on freeway facilities (with the remainder on other streets), and that by 2020, U.S. travelers will experience around 8.4 billion hours of delay while wasting 4.5 billion gallons fuel (due to congestion), for an annual economic cost of $199 billion.

Here, it is assumed that AVs are equipped with CACC and traffic-flow-smoothing capabilities. At the 10 percent AV-market penetration level, freeway congestion delays for all vehicles are estimated to fall 15 percent, mostly due to smoothed flow and bottleneck reductions. This is lower than Atiyeh (2012) suggests, in order to reflect induced travel, though additional congestion benefits may be realized (due to fewer crashes, a small degree of increased capacity from CACC, and smarter vehicle routings). At the 50 percent market penetration level, a cloud-based system is assumed to be active (Atiyeh suggests 39 percent congestion improvements from smoothed flow), and further capacity enhancements of 20 percent may be realized. Furthermore, with crashes falling due to safety improvements, another 4.5 percent in congestion reduction may be obtained. Again, induced travel will counteract some of these benefits, and a 35 percent delay reduction on freeways is estimated in this analysis. Finally, at the 90 percent level, freeway congestion is assumed to fall by 60 percent, with the near doubling of roadway capacity (Shladover et al. 2012) and dramatic crash reductions. However, readers should note that capacity and delay are not linearly related and congestion abatement may be even greater than these predictions at the with 90 percent market penetration.

At the arterial-roadway level, congestion is assumed to experience much lower benefits from AVs (without near-complete market penetration and automated intersection management [Dresner and Stone 2008]), since delays emerge largely from conflicting turning movements, pedestrians, and other transportation features that AV technologies cannot address as easily. Therefore, arterial congestion benefits are assumed to be just 5 percent at the 10 percent market-penetration level, 10 percent at the 50 percent penetration rate, and 15 percent at 90 percent market penetration. AV fuel efficiency benefits are assumed to begin at 13 percent, increasing to 25 percent with 90 percent market penetration, due to better route choices, less congestion, road-train drag reductions (from drafting), and more optimal drive cycles. Non-AVs on freeways are assumed to experience 8 percent fuel economy benefits during congested times of day under a 10 percent market penetration, and 13 percent at the 50 percent and 90 percent penetration levels. For simplicity, this analysis assumes that all induced travel's added fuel consumption will be fully offset by AVs' fuel savings benefits during non-congested times of day.

1.2.10 PARKING

Parking savings comprise the final monetized component of this analysis. Litman (2012) estimates that comprehensive (land, construction, maintenance and operation) annual parking costs are roughly $3,300 to $5,600 per parking space in central business districts (CBDs), $1,400 to $3,700 per parking space in other central/urban areas, and $680 to $2,400 per space in suburban locations. So simply moving a parking space outside of the CBD may save nearly $2,000 in annualized costs, while moving one to a suburban location may save another $1,000. In addition to self-parking AVs allowing for moved spaces, fewer overall spaces should be needed thanks to car-sharing. Therefore, while not every AV will result in a moved or eliminated parking space, this analysis assumes that $250 in parking savings will be realized per new AV (thanks in part to the earlier assumption of 10 percent of AVs being publicly shared).

1.2.11 Privately Realized Benefits

Privately realized benefits were estimated using Table 1-2's assumptions for the $10,000 purchase price. These were first compared to 50 percent insurance cost savings from a base of $1,000 per year and 13 percent fuel savings from a base of $2,400 per year (AAA 2012) over a 15-year vehicle life. Parking costs of $250 were added next, which represents about $1 per work day. Finally, driven time under autonomous operation was added under $1 per hour and $5 per hour assumptions, with total annual vehicle hours traveled estimated based on U.S. average vehicle-miles traveled (10,600 miles per year) divided by an assumed average speed of 30 mph (FHWA 2013). Privately realized internal rates of return were also compared to a higher added-technology price, of $37,500.

1.2.12 Summary of Anticipated AV Impacts

Table 1-2 summarizes all of these estimated impacts, suggesting economic benefits reaching $196 billion ($442 billion, comprehensive) with a 90 percent AV market penetration rate. Meaningful congestion benefits are estimated to accrue to all travelers early on, while the magnitude of crash benefits grows over time (and accrues largely to AV owners/users). For example, congestion savings represent 66 percent of benefits, and crash savings represent 21 percent of benefits – at the 10-percent market penetration level (in terms of system-wide VMT), versus 31 percent and 54 percent of benefits, respectively, at the 90-percent penetration rate. When comprehensive crash costs are included, overall crash savings jump by more than a factor of three[6].

[6] Comprehensive crash costs include indirect economic factors, like the statistical value of life and willingness-to-pay to avoid pain and suffering, with values recommended by the USDOT (Trottenberg 2011).

	Assumed Market Shares		
	10%	**50%**	**90%**
Crash Cost Savings from AVs			
Lives Saved (per year)	1,100	9,600	21,700
Fewer Crashes	211,000	1,880,000	4,220,000
Economic Cost Savings	$5.5 B	$48.8 B	$109.7 B
Comprehensive Cost Savings	$17.7 B	$158.1 B	$355.4 B
Economic Cost Savings per AV	$430	$770	$960
Comprehensive Cost Savings per AV	$1,390	$2,480	$3,100
Congestion Benefits			
Travel Time Savings (M Hours)	756	1680	2772
Fuel Savings (M Gallons)	102	224	724
Total Savings	$16.8	$37.4	$63.0
Savings per AV	$1,320	$590	$550
Other AV Impacts			
Parking Savings	$3.2	$15.9	$28.7
Savings per AV	$250	$250	$250
VMT Increase	2.0%	7.5%	9.0%
Change in Total # Vehicles	-4.7%	-23.7%	-42.6%
Annual Savings: Economic Costs Only	**$25.5 B**	**$102.2 B**	**$201.4 B**
Annual Savings: Comprehensive Costs	**$37.7 B**	**$211.5 B**	**$447.1 B**
Annual Savings Per AV: Economic Costs Only	**$2,000**	**$1,610**	**$1,760**
Annual Savings Per AV: Comprehensive Costs	**$2,960**	**$3,320**	**$3,900**
Net Present Value of AV Benefits minus Added Purchase Price: Economic Costs Only	**$5,210**	**$7,250**	**$10,390**
Net Present Value of AV Benefits minus Added Purchase Price: Comprehensive Costs	**$12,510**	**$20,250**	**$26,660**
Assumptions			
Number of AVs Operating in U.S.	12.0 M	45.1 M	65.1 M
Crash Reduction Fraction per AV	0.5	0.75	0.9
Freeway Congestion Benefit (delay reduction)	15%	35%	60%
Arterial Congestion Benefit	5%	10%	15%
Fuel Savings	13%	18%	25%
Non-AV Fuel Efficiency Benefit (Freeway)	8%	13%	13%
VMT Increase per AV	20%	15%	10%
% of AVs Shared Across Users	10%	10%	10%
Added Purchase Price for AV Capabilities	$10,000	$5,000	$3,000
Discount Rate	10%	10%	10%
Vehicle Lifetime (years)	15	15	15

Table 1-2: Estimates of Annual Economic Benefits from AVs in the United States

Additional monetized congestion benefits may be realized beyond the values shown in Table 1-2, due to falling values of travel time. For example, an hour stuck driving in traffic may be perceived as more onerous than an hour spent being driven by an AV. While Table 1-2 illuminates AVs' social benefits, it is also important to anticipate the privately realized benefits of AV ownership and use. These benefits are assessed using Table 1-2's assumptions at the 10-percent market penetration, taking into account monetary savings from reduced fuel use and insurance, along with several levels of daily parking savings and (hourly) travel time savings. This results in the ranges of benefits shown in Table 1-3, across various purchase prices, values of time and parking costs:

Development Stage	**Estimated Added Costs**	**Benefits (Daily Parking & Hourly Value of Travel Time Savings)**							
		$0 & $0	**$0 & $1**	**$1 & $1**	**$5 & $1**	**$1 & $5**	**$5 & $5**	**$5 & $10**	**$10 & $10**
Current	$100k+	-19%	-17%	-15%	-11%	-9%	-6%	-2%	0%
Initial Price	$37.5k	-12%	-8%	-6%	0%	2%	6%	12%	16%
Mass Production	$10k	3%	8%	11%	23%	28%	38%	56%	68%

Table 1-3: AV Owners' Privately Realized Internal Rates of Return (from 0% [Current] to 10% [Mass Production] Market Shares)

At current high technology costs of $100,000 or more, benefits are mostly small compared to purchase prices, except for individuals with very high values of time. Once prices come down to $37,500, persons with high values of travel time and/or parking costs may find the technology a worthwhile investment. Only at the $10,000 added price does the technology become a realistic investment for many, with even the $1 per hour time value savings and $1 daily parking cost savings generating an 11-percent rate of return for AV owners.

Additionally, the net present value of benefits accrued to *shared* AV (SAV) owners and operators will likely be significantly higher than privately-held household AVs, perhaps on the order of twice as great. Higher net benefits and returns on investment are expected since SAVs will travel many more miles per year than household-owned AVs (but also wear out in just a few years). As such, SAV benefits will be compressed into a much shorter timeframe, resulting in less discounting. (For example, assuming a 7% discount rate, year-three's benefits from a present-worth perspective are valued at 87%, while year-fifteen's benefits are valued at just 39%). Moreover, with technology evolving rapidly, quick turnovers should result in better equipped SAVs than household-owned AVs (and, presumably, safer SAVs with potentially more nimble mobility operations).

This report does not attempt to quantify or monetize several of the impacts discussed earlier. For example, the potential benefits to the newly mobile are not forecasted, nor are the health impacts of potentially diminished walk distances, thanks to self-park, door-to-door services. Many of the nation's 240,000 taxi drivers and 1.6 million truck drivers (BLS 2012) could be displaced by AV technologies, while greenhouse gas emissions, infrastructure needs, and rates of walking may fall or rise, depending on the induced VMT. Increased sprawl or automobile-style development could also result. Such impacts are not included in the analysis.

While exact magnitudes of all impacts remain uncertain, this analysis illustrates the potential for AVs to deliver substantial benefits to many, if not all, Americans, thanks to sizable safety and congestion savings. Even at 10-percent market penetration, this technology has the potential to save over 1,000 lives per year and offer tens of billions of dollars in economic gains, once added vehicle costs and possible roadside hardware and system administration costs are covered.

Chapter 1.3: Barriers to Implementation

AVs present many opportunities, benefits and challenges, while ushering in behavioral changes that effect how travelers interact with transportation systems. The speed and nature of any transition to a largely AV system are far from guaranteed; they will depend heavily on AV purchase costs, as well as state and federal licensing and liability requirements. Moreover, AVs present some unusual risks, particularly from security and privacy standpoints. Even with a smooth and relatively rapid deployment that addresses security and privacy concerns, a system that optimally exploits AV capabilities requires special research efforts. The following discussion outlines several barriers that AVs face.

1.3.1 Vehicle Costs

One barrier to large-scale market adoption is the cost of AV platforms. The technology needed for an AV includes the addition of new sensors, communication and guidance technology, and software for each automobile. KPMG and CAR (2012) note that the Light Detection and Ranging (LIDAR) systems on top of Google's AVs cost \$70,000, and additional costs will accrue from other sensors, software, engineering, and added power and computing requirements. To be reasonably affordable, future AVs may need to use non-LIDAR sensors, or LIDAR prices must fall dramatically. Dellenback (2013) estimates that most current civilian and military AV applications cost over \$100,000. This is unaffordable for most Americans, with 2012 sticker prices for the top 27 selling vehicles in America (Boesler 2012) ranging from \$16,000 to \$27,000. More cost-effective approaches are possible, with Chengalva et al. (2009) paying less than

$20K in total hardware costs to build an AV reaching the semi-final rounds of DARPA's 2007 Urban Challenge.

As with electric vehicles, technological advances and large-scale production promise greater affordability over time. Dellenback (2013) estimates that added costs may fall to between $25,000 and $50,000 (per AV) with mass production, and likely will not fall to $10,000 for at least ten years. Insurance, fuel, and parking-cost savings may cover much of the added investment. Typical annual ownership and operating costs ranged from $6,000 to $13,000, depending on vehicle model and mileage (AAA 2012), with insurance and fuel costs around $900 to $1,000 and $1,100 to $3,700, respectively. These costs may fall by 50 percent for insurance and 13 percent for fuel costs and substantial further savings may be realized in expensive parking environments.

If AV prices come close to conventional vehicle prices, research suggests a ready and willing market for AVs. J.D. Power and Associates' (2012) recent survey found that 37 percent of persons would "definitely" or "probably" purchase a vehicle equipped with autonomous driving capabilities in their next vehicle, though the share dropped to 20 percent after being asked to assume an additional $3,000 purchase price. This is the eventual price increase estimated by Volvo senior engineer Erik Coelingh (ETQ 2012) for AV capabilities, though early-sales' costs will likely be much higher for early adopters, as noted above. Hensley et al. (2009) noted that electric vehicle costs have been declining by 6 percent to 8 percent annually, suggesting that it may be 15 years at 8 percent annual cost reduction to go from a $10,000 AV mark-up (perhaps possible in five to seven years' time after initial introduction) to a $3,000 mark-up (20 to 22 years after introduction). For comparison, as of February 2013, adding all available driver-assist features, adaptive cruise control, safety options (including night vision with pedestrian detection), and the full "technology package" increases a BMW 528i sedan's purchase price by $12,450, from a base MSRP of $47,800 (BMW of North America 2013). While these features provide guidance and a degree of automation for certain functions, full control remains with the human driver.

As AVs migrate from custom retrofits to mass-produced designs, it is possible that these costs could fall somewhere close to Coelingh and J.D. and Associates' $3,000 mark, and eventually just $1,000 to $1,500 more per vehicle (KPMG and CAR 2012). Nevertheless, cost remains high and is therefore a key implementation challenge, due to the current unaffordability of even some of the more basic technologies.

1.3.2 AV LICENSING AND REGISTRATION

As of February 2014, California (SB 1298) and Nevada (AB 511) have enacted legislation seeking to establish a framework that would allow AV operation on public roads. Meanwhile Florida's CS/HB 1207, Washington, D.C.'s B19-0931, and Michigan's (SB 0169) have passed legislation enabling AV testing on public roads, among other AV-related regulatory action. Related legislation is pending in Georgia, Hawaii, Maryland, Massachusetts, Minnesota, New Jersey, New York, South Carolina, South Dakota, Washington, and Wisconsin. States have thus far declined to set many specific restrictions, directing their state DMVs to establish regulatory licensing and provisional testing standards. This legislative guidance has varied significantly, from state to state. For example, Nevada's original legislation (since amended) contained just 23 lines of definitions and broad guidance to its DMV, while California's is a more detailed six pages and similar direction to its DMV (to establish safety and testing specifications and requirements). Without a consistent licensing framework and standardized set of safety for acceptance, AV manufacturers may be faced with regulatory uncertainty and unnecessary overlap, among other issues.

California's more detailed legislative content provides concrete requirements for AVs. SB 1298 states specific requirements for AV testing on public roads, including insurance bonding, the ability to quickly engage manual driving, fail-safe systems in case of autonomous technology failure, and sensor data storage prior to any collision. This legislation calls upon the California DMV to consider possible regulations for a broad array of issues, including the total number of AVs using California's public roadway system, AV registration numbers, AV operator licensing and requirements, possible revocation of AV licenses, and the denial of licensing. California's legislation contains a subsection requiring public hearings on driverless AVs and directs the DMV to enact stricter oversight for such AVs. Moreover, it is instructive that California's DMV has clarified definitions of AV licensing and endorsements (attached to a person licensed to operate an AV) and AV registration (attached to an AV). As such, this framework implicitly continues the current human-driver operating the vehicle perspective, even though the vehicle may control either some or even all of the driving operation.

While California's DMV rulemaking is expected by 2015, Nevada has already processed AV licenses for Google, Continental, and Audi, for testing on Nevada's public roads. These licensing requirements include a minimum of 10,000 autonomously driven miles and documentation of vehicle operations in complex situations. Such situations reflect use of various traffic control devices (including roundabouts, traffic signals, signs, school zones, crosswalks and construction zones); the presence of pedestrians, cyclists, animals, and rocks, and recognition of speed limit variations, including temporary restrictions and variable school-zone speed limits. Furthermore, Nevada can grant testing licenses subject to certain geographic and/or environmental limitations (e.g., autonomous operation only on the state's interstates, for daytime driving free of snow and ice). While the proactive strategies pursued by these states is commendable, if many disparate versions of these crucial regulatory issues emerge (across distinct states), AV manufacturers will incur delays and increased production and testing costs.

Drivers licensed in one U.S. state are able to legally operate a vehicle in other states through reciprocity agreements, as outlined in the state Driver License Compact, constituting agreements between all but five U.S. states (Georgia, Wisconsin, Massachusetts, Michigan, and Tennessee). The language states: “It is the policy of each of the party states to… make the reciprocal recognition of licenses to drive… in any of the party states” (State of Montana 2011). Smith (2013a) notes that current law probably does not prohibit automated vehicles in states without explicit AV licensing, though failure to clarify regulations may “discourage their introduction or complicate their operation.”

1.3.3 Litigation, Liability and Perception

A car or truck driven by a computer on public roads opens up the possibility of many insurance and liability issues. Even with near-perfect autonomous driving, there may be instances where a crash is unavoidable. For example, if a deer jumps in front of the car, does the AV hit the deer or run off the road? How do actions change if the deer is another car, a heavy-duty truck, a motorcyclist, bicyclist, or pedestrian? Does the roadside environment and/or pavement wetness factor into the decision? What if the lane departure means striking another vehicle? With a split second for decision-making, human drivers typically are not held at fault when responding to circumstances beyond their control, regardless of whether their decision was the best. In contrast, AVs have sensors, visual interpretation software, and algorithms that enable them to potentially make more informed decisions. Such decisions may be questioned in a court of law, even if the AV is technically not “at fault.” Other philosophical questions also arise, like to what degree should AVs prioritize minimizing injuries to their occupants, versus other crash-involved parties? And should owners be allowed to adjust such settings?

Regardless of how safe AVs eventually become, there is likely to be an initial perception that they are potentially unsafe because the lack of a human driver. Perception issues have often been known to drive policy and could delay implementation. Moreover, if AVs are held to a much higher standard that human drivers, which is likely given perception issues, AV costs will rise and fewer people will be able to purchase them. Some steps have been made to account for liability concerns. California law (CIS 2012) requires 30 seconds of sensor data storage prior to a collision to help establish fault, assuming that the AV has been programmed and tested properly. Other semi-autonomous technologies, such as parking assist and adaptive cruise control, will likely provide initial test cases that will guide how fully autonomous technologies will be held liable.

1.3.4 Security

Transportation policymakers, auto manufacturers, and future AV drivers often worry about electronic security. Computer hackers, disgruntled employees, terrorist organizations, and/or hostile nations may target AVs and intelligent transportation systems more generally, causing collisions and traffic disruptions. As one worst-case scenario, a two-stage computer virus could be programmed to first disseminate a dormant program across vehicles over a week-long period, infecting virtually the entire U.S. fleet, and then cause all in-use AVs to simultaneously speed up to 70 mph and veer left. Since each AV in the fleet represents an access point into such systems, it may be infeasible to create a system that is completely secure.

To understand the extent of this threat, it is important to view the problem from an effort-and-impact perspective and to recognize mitigation techniques commonly used in comparable critical infrastructure systems of national importance. According to Jason Hickey (2012), vice president of software security firm Vínsula, current cyber-attacks are more commonly acts of espionage (gaining unauthorized access to a system for the purpose of information gathering) rather than sabotage (actively compromising a system's normal operation). Disrupting a vehicle's communication or sensors, for example, would require a more complex and sophisticated attack than one designed to simply gather information, and disrupting the vehicle's control commands would be harder still. Engineering an attack to simultaneously compromise a fleet of vehicles, whether from a point source (for example, compromising all vehicles near an infected AV) or from a system-wide broadcast over infected infrastructure would likely pose even greater challenges for a would-be attacker. Regardless, the threat is real and a security breach could have lasting repercussions.

Fortunately, robust defenses should make attacks even more difficult to stage. The U.S. has demonstrated that it is possible to maintain and secure large, critical, national infrastructure systems, including power grids and air traffic control systems. The National Institute of Standards and Technology (NIST) is currently developing a framework to improve critical infrastructure cyber security, and recommendations that stem from this framework may be incorporated into automated and connected vehicle technologies. While security measures for personal computers and Internet communication were implemented largely as an afterthought, and in an ad-hoc manner (Hickey 2012), V2V and V2I protocols have been developed with security implemented in the initial development phase (NHTSA 2011). These and other security measures (like the separation of mission-critical and communication systems) should make large-scale attacks on AVs and related infrastructure particularly difficult (Hickey 2012). Though Grau (2012) and Hickey (2012) both acknowledge that there is no "silver bullet," such measures make attacks much harder to pull off while limiting the damage that can be done.

1.3.5 PRIVACY

California-based consumer education and advocacy organization Consumer Watchdog raised privacy concerns during a recent round of AV-enabling legislation (Brandon 2012). Such concerns are likely to grow as AVs and non-autonomous connected vehicles become more mainstream and data sharing becomes commonplace. This gives rise to five data-related questions: Who should own or control the vehicle's data? What types of data will be stored? With whom will these data sets be shared? In what ways will such data be made available? And, for what ends will they be used?

It is likely that crash data will be owned or made available to AV technology suppliers, since they will likely be responsible for damages in the event of a crash, provided that the AV was at fault. If a human is driving a vehicle with autonomous capabilities when the crash occurs, however, privacy concerns arise. No one wants his/her vehicle's data recorder being used against them in court, though this is merely an extension of an existing issue: around 96 percent of new passenger vehicles sold in the U.S. today have similar (but less detailed) event data recorders that describe vehicle actions taken in the seconds prior to and following a crash, and NHTSA is considering mandating event data recorders on all new vehicles under 8,500 lbs. by late 2014 (NHTSA 2012b). While some states restrict insurance company access to such data (and require a warrant for access), in much of the U.S. data ownership and control remain undefined (Kaste 2013).

Providing AV travel data, such as routes, destinations, and times of day, to centralized and governmentally controlled systems is likely more controversial, particularly if the data is recorded and stored. While movement tracking of individuals already occurs to some degree through roadside Bluetooth sensors and cell phone tower triangulation, continual monitoring could take this phenomenon to a whole new level. Without proper safeguards, this data could be misused by government employees for tracking individuals, or provided to law enforcement agencies for unchecked monitoring and surveillance. Vehicle travel data has wide-ranging commercial applications that may be disconcerting to individuals, such as targeted advertising.

At the same time, responsible dissemination and use of AV data can help transportation network managers and designers. This data could be used to facilitate a shift from a gas tax to a VMT fee, or potentially implement congestion pricing schemes by location and time of day. Those who program traffic signal systems, for example, could use such data to improve system efficiency and trip quality for travelers. In contrast, continuously connected AVs or connected conventional vehicles could illuminate continuous vehicle paths and speed changes, and so inform signal systems operational changes. Moreover, such data could be used to assist transportation planners evaluating future improvements, leading to more effective investment choices and transportation policies. Law enforcement could also benefit from such data, and commercial profits from advertising may drive down AV prices. Sharing of this data has tradeoffs, and any decisions to enhance traveler privacy should be balanced against the benefits of shared data.

1.3.6 MISSING RESEARCH

While AVs may be commercially available within five years, related research lags in many regards. Much of this is due to the uncertainty inherent in new contexts: with the exception of a few test vehicles, AVs are not yet present in traffic streams and it is difficult to reliably predict the future following such disruptive paradigm shifts. Moreover, technical developments along with relevant policy actions, will effect outcomes and create greater uncertainty. With these caveats in mind, it is useful to identify the critical gaps in existing investigations to better prepare for AVs' arrival.

One of the most pressing needs is a comprehensive market penetration evaluation. As KPMG and CAR (2012), Google (O'Brien 2012), Nissan (Nissan Motor Company 2013) and Volvo (Carter 2012) make clear, AVs probably will be driving on our streets and highways within the next decade, but it is uncertain when they will comprise a substantial share of the U.S. fleet. More meaningful market penetration estimates should attach dates and percentages to aggressive, likely, and conservative AV-adoption scenarios. This would provide transportation planners and policy-makers with a reasonable range of outcomes for evaluating competing infrastructure investments, AV policies, and other decisions.

Other important research gaps have been identified, with broad topic areas outlined at the 2013 Road-Vehicle Automation Workshop (TRB 2013), as follows:

- Automated commercial vehicle operations
- Cyber security and resiliency
- Data ownership, access, protection, and discovery
- Energy and environment
- Human factors and human-machine interaction
- Infrastructure and operations
- Liability, risk, and insurance
- Shared mobility and transit
- Testing, certification, and licensing
- V2X communication and architecture

Many important, and frequently crosscutting, questions arise from within each of these topic areas. For example, if driverless taxis become legal and commercially and technologically viable, they could serve many trips currently served by privately owned vehicles. This would reduce parking and ownership needs, and have impacts that cut across the automated commercial vehicle operations, energy and environment, infrastructure and operations, and shared mobility and transit focus areas. Furthermore, this list does not make explicit the need for new transportation planning efforts, with most major public investment decisions planned using a 20- to 30-year design horizon. As long as these and other crucial questions go unanswered, the nation will be hampered in its ability to successfully plan for and introduce AVs into the transportation system.

Chapter 1.4: Policy Recommendations

Given the apparent promise of AVs, it seems wise for policymakers and the public to seek a smooth and intelligently planned introduction for, and transition to, this new technology. The state of AV technology seems likely to advance with or without legislative and agency actions at the federal level. However, the manner in which AV technologies progress and will eventually be implemented depends heavily on these efforts. Intelligent planning, meaningful vision, and regulatory action and reform are required to address the various issues discussed above. This report recommends three concrete actions to address these issues:

1. *Expand Federal Funding for Autonomous Vehicle Research*.

Car manufacturers and others have invested many resources in the research and development of AV technologies. Meanwhile, there is a relatively little understanding of how such vehicles will affect the transportation system. This paper has highlighted key missing links in AV research, including the incorporation of market penetration scenarios in planning efforts, as well as topic areas identified at the Road-Vehicle Automation Workshop. A strong federal role in funding this research, similar to the strong federal role in funding numerous technological innovations throughout our nation's history, is essential.

Other gaps in understanding and technology needs will become apparent as AVs enter the marketplace. Due to the potential national benefits from overcoming these gaps, it becomes imperative to involve agencies such as the U.S. Department of Transportation (USDOT), the National Science Foundation, and the Department of Energy. State DOTs, local transportation agencies and planning organizations, and other stakeholders could also help fund such research, to enable regions and nations to anticipate and more effectively plan for AV opportunities and impacts.

2. *Develop Federal Guidelines for Autonomous Vehicle Licensing*.

To facilitate regulatory consistency, the USDOT should assist in developing a framework and set of national guidelines for AV licensing at the state level. Though NHTSA (2013a) has developed broad principles for AV testing, licensing AVs for use by the general public is mostly a state endeavor at this time and should have some federal guidance in order to ensure continuity. With similar sets of standards in place, states will be able to pool efforts in developing safety, operations, and other requirements. One framework for this effort could be the USDOT's (2009a) Manual on Uniform Traffic Control Devices (MUTCD). This approach promotes a single document for adoption by all states, with each state making a limited number of modifications to suit specific, local needs. Under such a framework, AV manufacturers will be better able to meet detailed national requirements and just a handful of possible individual state requirements, rather than trying to match 50 potentially different sets of testing requirements across states.

Existing state licensing should be seen as a complement to national efforts, which could streamline AV licensing and testing, enabling more efficient application of both public and private resources. Policy makers should also consider potential regulatory downsides and the effects of excessive caution, which may be harmful to technological advancement. Moreover, such AV licensing consistencies will likely help limit AV product liability, as argued by Kalra et al. (2009).

3. *Determine Appropriate Standards for Liability, Security, and Data Privacy*.

Liability, security, and privacy concerns represent a substantial barrier to widespread implementation of AV technologies. The sooner federal and state governments address these issues the more certainty manufactures and investors will have in pursuing development. Liability standards will need to strike the balance between assigning responsibility to manufacturers and technologists without putting undue pressure on their products. Robust cyber security to address the vulnerability of these systems will help the industry develop ways to prevent outside attacks.

Consumers of AV technology will likely have some concerns about the use and potential abuse of data collected from their personal travel. Therefore, AV-enabling legislation should consider privacy issues to balance these legitimate concerns against potential data-use benefits. Since vehicles will inevitably cross state boundaries, federal regulation needs to establish parameters regarding what types of AV data should be shared, with whom it should be shared, in what way the data will be made available, and for what ends it may be used – rather than take a default (no action) position, which will likely result in few to no privacy protections.

Chapter 1.5: Part 1 Concluding Remarks

The idea of a driverless car may seem a distant possibility, but automation technology is improving quickly and some features are already offered on current vehicle models. This new technology has the potential to reduce crashes, ease congestion, improve fuel economy, reduce parking needs, bring mobility to those unable to drive, and over time dramatically change the nature of U.S. travel. These impacts will have real and quantifiable benefits. Based on current research, annual economic benefits could be in the range of $27 billion with only 10-percent market penetration. When including broader benefits and high penetration rates, AVs have the potential to save the U.S. economy roughly $450 billion annually. While this does not include some of the associated costs and other externalities, the potential for a dramatic change in the nature and safety of transportation is very possible.

Potential benefits are substantial but significant barriers to full implementation and mass-market penetration remain. Initial AV technology costs will likely be unaffordable to most Americans. States are currently pursuing their own licensing and testing requirements, which may lead to a disparate patchwork of regulations and requirements without federal guidance. A framework for AV liability is largely absent, creating uncertainty in the event of a crash. Security concerns should be examined from a regulatory standpoint to protect the traveling public, and privacy issues must be balanced against data uses. Auto manufacturers have shown their interest in AVs by investing millions of dollars to make self-driving vehicles. Policy makers should begin supporting research into how AVs could affect transportation and land use patterns, and how to best alter our transportation system to maximize their benefits while minimizing any negative consequences of the transition to a largely autonomous fleet of motor vehicles.

PART 2: AN AGENT-BASED MODEL FOR SHARED AUTONOMOUS VEHICLE APPLICATIONS

Chapter 2.1: Overview & Background

As noted in Part 1, Level 3 or 4 AVs may be on our streets and highways by 2017. Nevertheless, it may take more time before the technology is sufficiently mature that regulators allow them to legally operate on mixed-use public roadways in variable speed and weather conditions without any human driver on board to take control in case of emergency. While Part 1 notes some of the broad impacts that AVs may bring, Part 2 examines in greater detail one specific implementation of Level 4 automation: a fleet of shared autonomous vehicles (SAVs) to serve thousands of personal trips each day in a regional center. Indeed, this a vision shared by Google and the EU's CityMobil2 project, both of which are independently seeking to deploy full Level 4 SAVs, though operating at low speeds of approximately 25 mph or less.

Car-sharing programs (such as ZipCar and Car2Go) exist around the globe, and the number of U.S. users has grown from 12,000 in 2002 to over 890,000 in January of 2013 (Shaheen and Cohen 2013). Car-sharing programs operate as short-term rentals, where members are able to rent a vehicle, typically located at an on-street parking location, drive to a nearby destination, and then release the rental when finished with their trip. Some programs like Car2Go allow rentals by the minute, while others like ZipCar require longer rental intervals, and additional annual membership and/or applications fees are often required.

U.S. National Household Travel Survey (NHTS) data (FHWA 2009b) suggest that less than 17% of newer (10 years old or less) household vehicles are in use at any given time over the course of an "average" day, even when applying a 5-minute buffer on both trip ends; this share falls to just 10% usage when older personal vehicles are included and no buffers applied. In short, *Americans have many more cars than they need* to serve current trip patterns in most locations. Yet car-sharing members still face nearby vehicle availability barriers: if a person is worried that he may be stranded, wait a long time, or walk a great distance in order to access a vehicle, he may opt to drive his own car instead.

SAVs, also known as autonomous taxis or aTaxis (Kornhauser et al. 2013), provide a solution, with members able to call up distant SAVs using mobile phone applications, rather than searching for and walking long distances to an available vehicle. Moreover, they provide car-sharing organizations with a way of seamlessly repositioning vehicles in order to better match demand. These SAVs are assumed to be fully self-driving without any need of human operation, other than information regarding a traveler's destination. In this way, SAVs could transform transportation for many: from an owned asset to a subscription or pay-on-demand service, at least in areas where population densities make such systems economically viable.

Such advances may provide significant environmental benefits, particularly in the form of reduced parking and vehicle ownership needs. Moreover, there is the potential for additional vehicle-miles traveled (VMT) reduction: Shaheen and Cohen (2013) estimate that North American car-sharing members reduced their driving distances by 27%, with approximately 25% of members selling a vehicle and another 25% forgoing a vehicle purchase. It is not clear how much of these effects would apply to SAVs, which may be more convenient and potentially more used than human-driven shared vehicles. Each SAV also can/will move itself (unoccupied) to the next traveler or relocate while unoccupied to a more favorable location, for lower-cost parking and faster future passenger service.

Some researchers have sought to model this phenomenon. Ford (2012) developed a shared autonomous taxi model, and relied on travelers to walk to fixed taxi stands, rather than allowing the SAVs to travel driverless to their next passenger, or relocate to more optimal locations. Kornhauser et al. (2013) investigated this idea further, exploring dynamic ride-sharing implications for all person-trips across New Jersey. In this model, one or more passengers boarded at fixed stations, where aTaxis wait a given time before departing, and all passengers having similar destinations share a ride (with an unlimited SAV fleet size assumed). Burns et al. (2013) also investigated this setup, with case study examples of travelers in Ann Arbor (Michigan), Manhattan (New York), and Babcock Ranch, a new small town in Florida. A number of Burns et al.'s modeling assumptions were similar to this paper's investigation, though their focus was on cost comparisons with personal cars. For example, they estimated that per-mile costs fall between $0.18 to $0.34 per mile when switching to SAVs, depending on annual mileage driven, in the Ann Arbor case study. Other benefits may be estimated using Part 1's suggestions[7] for AV savings (on insurance, parking, time value, and fuel), versus technology costs ($10,000), alongside an extra assumed $5,000 per-shared-vehicle-year operating and management cost. In this scenario, when assuming a $5-per-hour travel–time benefit (from less burdensome travel, lowering one's effective VOTT) and $5-per-weekday parking costs, total realized added benefits over a two-year SAV lifespan more than double the extra added technology and operating costs.

This paper focuses on SAVs' travel and environmental implications, and uses different assumptions to model a much smaller share of such trips (around 3.5%, rather than 100%), while also modeling directional distribution effects by time of day. The

[7] Part 1's discussions are largely as published in Fagnant and Kockelman's (2013) report for the Eno Center for Transportation.

investigation tests four different SAV relocation strategies, seeking to relocate unused SAVs to more favorable locations in order to reduce future traveler wait times. This paper examines ownership and VMT questions, investigating how many household-owned vehicles may be replaced by a fleet of SAVs, how much new travel may be induced (due to unoccupied-vehicle travel, rather than more or longer trips, which may emerge from lower perceived travel-time costs or new travel by those currently without driver's licenses), what factors influence such outcomes, and the resulting travel and environmental implications across a variety of reasonable model scenarios. SAVs are assumed to be shared serially in this investigation by different travel parties, and future work could incorporate dynamic ride-sharing as well.

An SAV model was specified, programmed (from the ground up, in C++), and applied, to gauge the environmental impacts of this novel opportunity. Here, the model operates by generating person-trips in each zone, on 5-minute intervals, over 100 days, with each trip having a destination and departure time. These trips are served by SAVs, which ferry travelers between origins and destinations as quickly as they can. Traffic congestion is modeled by time of day, with vehicle speeds slowed at peak hours. When individual SAVs are not in use, a virtual fleet manager uses a variety of strategies to relocate SAVs to more favorable positions, attempting to reduce wait times for future travelers. Travel implications and emissions inventories are assessed by estimating changes in life-cycle inventories, based on changes in the overall vehicle fleet (with any pickup trucks and SUVs substituted for mid-sized SAV sedans), Total VMT is tracked (with added VMT emerging from unoccupied SAVs travel, for relocation or new traveler pick-up), along with cold-starts savings (thanks to busy SAVs) and parking benefits (thanks to a shared fleet).

Twenty-five scenario variations were also run, in order to appreciate the impacts of changing many of the base-case scenario assumptions. These scenario variations examine the impacts of altering trip generation rates, the degree of trip centralization (how many trips are generated in the city center versus the outlying areas), the size of the overall service area, the frequency by which travelers return home via SAV, the extent of peak congestion, the effects of various SAV relocation strategies used and the impacts of limiting the overall size of the SAV fleet. While this model is by no means perfect (for example, an actual city's transportation network and origin-destination tables could be used to refine these evaluations in future work, and just a single vehicle type is used), this investigation provides a preliminary look into the potential implications of a new SAV system operating within the urban environment.

Chapter 2.2: Model Specification

The system operates by first generating trips throughout a *gridded city*. The program runs through the vehicle-assignment model 20 times, to determine approximately how many SAVs will be needed and where they should be placed at the start of the day. This process links trips to SAVs, generating a new SAV for every traveler that has been waiting at least 10 minutes (two time steps). The (integer-rounded) average number of SAVs generated in these 20 model runs is used as the fixed fleet size for all subsequent multi-day analyses. After this warm-start, the program is re-run, but SAVs can no longer be generated.

The city is composed of quarter-mile by quarter-mile grid cells or zones, to generate and attract trips. The base-case scenario's service area is a ten-mile by ten-mile square area (40 x 40 = 1600 zones), about twice the size of Austin, Texas's Car2Go geofence (the area where the vehicle needs to be by the end of the rental). Other Car2Go geofences range from around 40 square miles (in Portland, Oregon) to 60 square miles (Washington, D.C.) and 75 square miles (Seattle, Washington). Zones in the outermost service-area corners are assumed to generate trips at one rate, zones in the city's "core" (the central area with dimensions half the city's length and width) at a higher rate, and zones within 2.5 miles of the city center (the outer urban core) a third, intermediate rate. Trip generation rates in zones lying between these three points are linearly interpolated between the closest two points, depending on their centroids' Euclidean distances to the city center. That is to say, for zones lying within the analysis area but more than 2.5 miles from the city center, rates will be linearly interpolated between the outermost service area and outer core rates; while for zones at 2.5 miles or closer to the city center, rates will be interpolated between the inner and outer core rates. Trips are generated using Poisson distributions per *5-minute time step* and assigned throughout a 24-hour period, based on the temporal distribution of NHTS trip-start rates (FHWA 2009b).

Each generated trip is then assigned a destination, using the following steps:

1. Sample trip distance (D = 1 to 15 miles).
2. Sample E-W dir.: Pr(E) = $\alpha \times$ (#zones E) / (#zones E + #zones W) + $(1 - \alpha) \times 0.5$
3. Sample N-S dir.: Pr(N) = $\alpha \times$ (#zones N) / (#zones N + #zones S) + $(1 - \alpha) \times 0.5$
4. Choose destination: Pr(E-W = 0 & N-S = D) = 1 / (4D + 1);
   Pr(E-W = 0.25 mi. & N-S = D – 0.25 mi.) = 1 / (4D + 1),
   Pr(E-W = 0.50 mi. & N-S = D – 0.50 mi.) = 1 / (4D + 1), ...
   Pr(E-W = D & N-S = 0) = 1 / (4D + 1).
5. If destination is not in the service area, return to step 2.
6. If 20 consecutive destinations selected outside of service area, return to step 1.
7. Valid destination has been located. Proceed to next trip.

Each of these steps (including α's derivation) is explained in greater detail below:

Step 1: Trip distances (D) are randomly drawn (in quarter-mile increments) from 1 to 15 miles away, based on NHTS (trip-distance) data, as shown in Figure 2-1.

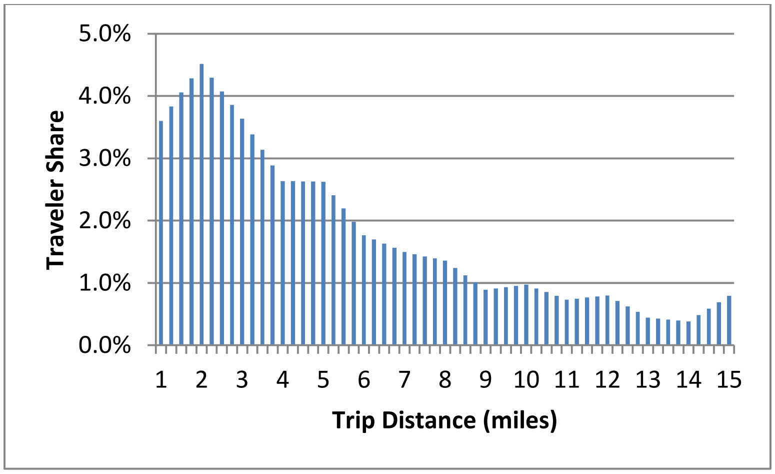


Figure 2-1: Trip Distance Distribution[8]

The 15-mile limit was established because most trips cannot travel for much more than 15 miles without leaving the service area, and forcing higher limits would lead to overly-high trip attractions at far corners (since the corners would be the only reachable destinations at certain, long-trip distances). In real-world business applications, out-of-service area rentals could potentially be made, with added user costs for vehicle relocation or extended-time rentals, though this phenomenon is not modeled here.

Steps 2 & 3: East-west and north-south cardinal directions are then selected. Probabilities are linearly based on two components: the share of zones lying in each direction from the origin (effectively resulting in higher attraction levels towards the city center, particularly at high values of α) and a constant factor of 0.5 (effectively resulting in similar probabilities when choosing between north and south, and east and west

[8] Figure 2-1's source data come from the 2009 National Household Travel Survey (FHWA 2009b).

directions, particularly at low values of α). The "attraction factor" (α) specifies relative degree of strength that each of these factors has when determining destination direction. Before noon, trip attractions pull more strongly towards the city center ($\alpha = 1$); after noontime, the core zones' attraction factor (α) lessens (to about 0.77), such that the total number of trips entering the urban core (defined as the innermost 5-mile by 5-mile area) roughly equals the number leaving over the course of the day. This also helps keep trip-making balanced, such that nearly all travelers return "home" before the next day's simulation. This trip attraction factor is determined for each 24-hour period by generating a series of sample trips and using the method of successive averages (Bell and Iida 1997) to pick a value for α. While this generates different values of α from day-to-day, due to the randomization processes embedded with the trip generation procedure, overall inflows and outflows remain close to even over each 24-hour period.

Step 4: The destination zone is then selected using a uniform distribution from among all possible combinations of the chosen travel distance and cardinal (north-south and east-west) directions. For example, if Steps 1 through 3 produced a 2.25 mile trip distance in a north and west direction, there will be equal 10% chances of traveling 2.25 miles due north, 2 miles north and 0.25 miles west, 1.75 miles north and 0.5 miles west, and so forth. As such, all possible destinations in the north and west directions at 2.25 miles away will have an equal chance of being selected.

Step 5: A new location is drawn if the chosen destination lies outside the service area. In such situations, the trip distance is retained, and a new trip direction is sampled.

Step 6: A new trip distance is drawn if 20 consecutive destinations lie outside the service area. In such settings, a new trip distance and a new trip direction are sampled.

Step 7: When a trip destination is located within the service area, the destination is assigned to the traveler and the program proceeds to the next trip.

Each assigned trip then looks, in turn, for the nearest available SAV, up to a maximum (5-minute) travel time. This process operates by iterating through all travelers using random ordering (in each 5-minute interval) to find available SAVs in the same zone, which are claimed if found. Next, all travelers who did not find an available SAV in their same zone look one zone out and claim that vehicle, if located. This process continues until all travelers have either found an SAV, or cannot locate one within a 5-minute travel distance. Those who cannot be served within the 5-minute period are moved to a “wait list” that is serviced at the beginning of the next period, before any new traveler assignments are made. In the event that two or more locations have free SAVs the same distance away, an SAV is chosen from the zone with the most available SAVs, to help prevent stockpiling too many SAVs in a single zone.

SAVs travel a fixed distance per time period, with effective speeds equal to 3 times the number of zones that SAVs are assumed to travel (in that scenario), in miles per hour, in order to reflect intersection delays and other factors (e.g., an SAV that travels 10 zones in one 5-minute time step has an effective speed of 30 mph[9]). These fixed speeds are pre-set by time of day to determine the maximum number of zones an SAV can travel in 5-minutes, reflecting higher-speed off-peak periods and lower-speed peak periods. SAVs may travel in the horizontal or vertical directions to their destinations (which lie in all directions from their origins), but not diagonally, reflecting a strictly *grid-based street pattern*. Once an SAV is assigned to a traveler, it drives to the traveler (if not already in the same zone), then begins traveling to the final destination. This continues for more than one period, as necessary, and the SAV is released once it arrives at the destination. After dropping a traveler off, SAVs do not continue moving for the rest of the period,

[9] This notion of 10 zones per 5-minute interval comes from the fact that 30 mph × 4 (the number of 1/4 mi. zones per mile) / 12 (the number of 5-minute intervals per hour) equals 10.

reflecting non-moving pick-up and drop-off time (and averaging a little over two minutes in the base-case scenario). SAVs can park in any zone and for any duration of time while waiting for the next traveler. The program also determines whether each traveler wishes to return home via SAV; if so, a dwell time (an activity duration) is chosen from one of eight distributions, depending on arrival time (grouped by 3-hour periods, as shown in Figure 2-2) and based on NHTS dwell-time durations (FHWA 2009b). This process allows travelers journeying at earlier hours to stay at their destination longer, on average, than those traveling later in the day.

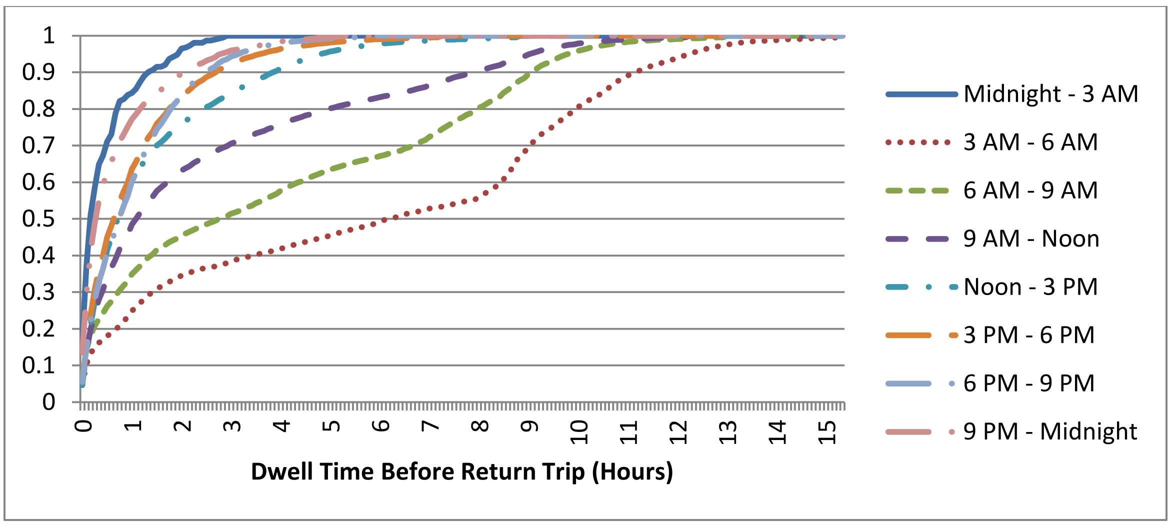


Figure 2-2: Cumulative Distributions for Dwell Times Before Return Trips[10]

Once all travelers that can be reached in a given 5-minute interval been served, the remaining, unoccupied vehicles that have not traveled during the interval consider relocating to a more advantageous position to shorten wait times in the next interval. This is conducted using a virtual fleet manager that determines where all unoccupied vehicles will be during the beginning of the next interval, and issues relocation

[10] Figure 2-1's source data come from the 2009 National Household Travel Survey (FHWA 2009b).

commands to all SAVs. Though additional relocation efficiencies could be incorporated to further minimize traveler wait times, some limits are placed in order to serve the secondary goal of reducing unoccupied VMT. Four strategies (labeled R1 through R4) are pursued to these ends, with increasingly smaller evaluation areas for vehicle relocation. Each of these strategies is used in subsequent ordering during this relocation phase: R1 is followed by R2, and then R3, with R4 acting last. Any SAV that has moved during the 5-minute interval will not move again during the same interval; thus, if a vehicle relocates using strategy R1, it will not relocate again using strategy R3 until the next time interval.

The *first vehicle-relocation strategy (R1)* attempts to match expected demand over large areas with available SAVs. While this strategy assumes an exact knowledge of trip generation rates, real-world providers must rely on historical data, which may lead to more variability, if, for example, area-wide demand is somewhat inconsistent from one Wednesday afternoon to the next. The R1 strategy reflects many similarities to the "max-pressure" feedback policy for a network of signal controllers described by Varaiya (2013). The strategy is decentralized, in that it requires no foreknowledge of new calls (though it is helped by having a good estimate) and actions depend only on adjacent areas.

The R1 strategy divides the city into 25 large blocks, each two miles square. A "block balance" value is calculated for each block, based on the expected demand for and supply of SAVs in the coming 5-minute period (using waiting travelers plus expected new trips to be generated, minus the number of free SAVs that will be in the block at the start of the next period). The sum of all block balances is equal to zero, with each block balance calculated using the formula:

$$Block\ Balance = SAVs_{Total}\left(\frac{SAVs_{Block}}{SAVs_{Total}} - \frac{Demand_{Block}}{Demand_{Total}}\right) \quad (2\text{-}1)$$

If a given block has 10% or more vehicles than ideal[11], excess free SAVs are pushed into adjacent blocks; if a block has 10% or fewer vehicles than ideal, free SAVs (if available) are pulled from adjacent blocks.

Strategy R1 operates by first selecting the block with the highest absolute block balance value (that farthest from 0). If the block balance is positive, this block pushes SAVs that have not moved during the current 5-minute interval into adjacent blocks; if negative, it pulls similarly free SAVs from adjacent blocks. First, the number of available SAVs is determined (in the selected block if pushing, and in adjacent blocks if pulling), as well as the block balances of adjacent blocks. The number of SAVs to be moved in each direction is determined by first selecting an SAV to be pushed onto the nearby block with the lowest block balance, or pulled from the nearby block with the highest block balance and at least one available SAV. Next, block balances are updated, and this process is repeated until no available SAVs remain to be pushed or pulled, the 10% threshold is no longer exceeded, or SAV relocation will improve overall block balances by less than 1 (e.g., pushing an SAV with a +8.4 block balance onto another block with a +6.9 block balance).

After the number of SAVs to be moved in each direction is determined, a corner of the block is chosen using a random draw. Moving in a clockwise direction, the strategy seeks available SAVs one zone out from the (pulling) block. If an available SAV is located and there is demand in that direction, the SAV will be moved. Next, available SAVs two zones from each edge with remaining demand are sought and allocated. This process continues until each vehicle that will be moved in the block has been assigned a direction. Figure 2-3 illustrates one possible assignment process, where

[11] The ideal share is the proportion of expected demand divided by the proportion of available SAVs for a given block, thus the ideal share for any block is 1.0.

the numbers of SAVs to be moved in each direction are shown in adjacent blocks in parentheses, and the SAVs to be moved are shown using letter-number combinations in the central block.

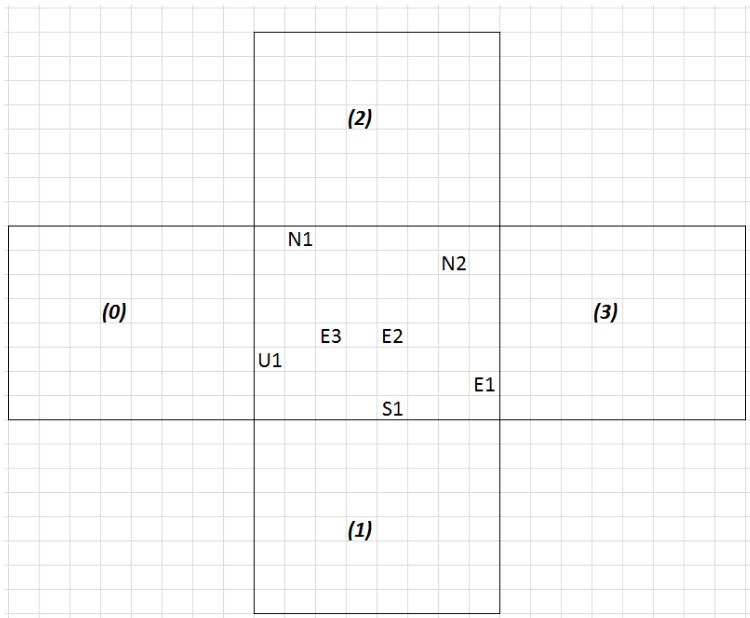


Figure 2-3: Selecting Vehicles for Relocation (Pushing) Using Strategy R1[12]

In Figure 2-3's example scenario, two SAVs are to be pushed northward, three eastward, and one southward; and the northwest corner is randomly drawn to begin this process. As such, N1 will be chosen first, to move north, followed by E1 to travel east, and S1 to travel south. Looking two zones away from the borders, N2 would be chosen to head north, then SAVs will be searched for at increasing distances from the eastern border, until E2 and E3 are identified. Available SAV U1 will remain unmoved.

Once SAVs are identified to relocate and their directions are assigned, they first move just over the boundary into the new block. If the initial zone of entry is unoccupied

[12] Parentheses denote SAV demand in adjacent blocks, and the first letter of each zone indicates the direction the SAVs in the central block is to be pushed

by any other (available) SAV, the pushed SAV stops. If one or more SAVs is already present, it will continue to move in the same direction if an unoccupied zone is reachable within the 5-minute travel distance interval. If an unoccupied zone is not reachable, the SAV looks for the nearest same-direction reachable zone with just one SAV (and then with just two SAVs, if no reachable zone with just one SAV can be located), and so forth, until a destination is identified.

At this point, all identified SAVs in the target block will have been pushed to (or pulled from) nearby blocks. The algorithm next identifies the block with the next-largest absolute block balance value, and this process repeats until all blocks have either been served (by pushing or pulling SAVs) or all remaining blocks have a discrepancy less than 10% (of excess demand or supply of SAVs) from their target value. The *second strategy (R2)* is essentially the same as R1, though 100 one-square-mile blocks are used instead of the 25 larger ones.

The *third strategy (R3)* seeks to "fill in the white (zero-SAV) spaces" using available SAVs occupying zones where two or more SAVs are predicted to be free at the start of the next interval. These SAVs look for unoccupied locations within a half mile (two zones) where there are no other SAVs in any adjacent zone. The *final strategy (R4)* acts as a "stockpile management" strategy, shifting available SAVs into adjacent zones when the free-SAV imbalance (in the next interval) is three or more SAVs. For relocation strategies R3 and R4, a tie-breaker prioritizes moving vehicles to zones with higher generation rates. Figure 2-4 illustrates how all four strategies tend to work, for a given period's supply versus demand conditions, and using actual values from model runs.

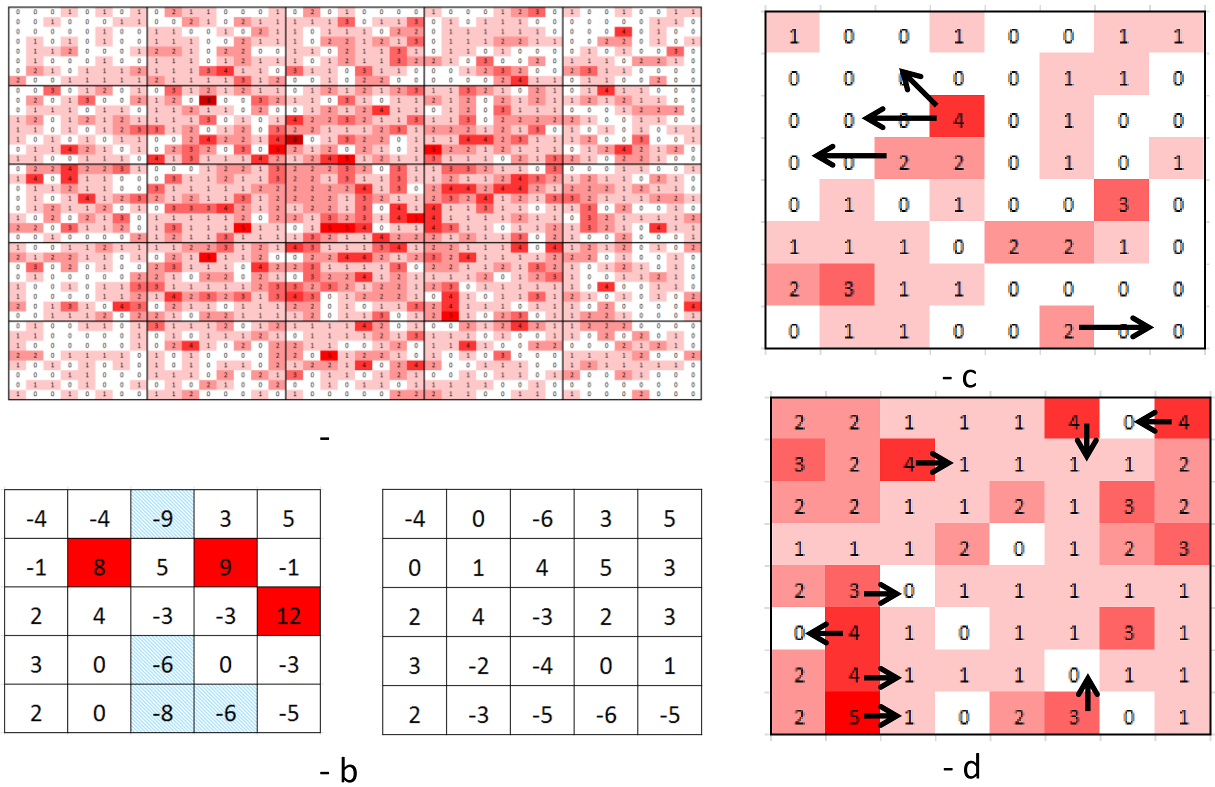


Figure 2-4: Relocation Strategy Examples: (a) Example Starting Location of all SAVs; (b) Block Balances Before Strategy R2 Relocation (Left) and After (Right); (c) R3 Strategy Illustration on a Subsection of Zones; (d) R4 Strategy Illustration on a Subsection of Zones

Figure 2-4a shows locations of all SAVs just before relocation begins, with darker zones representing greater numbers of SAVs in those zones. Figure 2-4b gives predicted block balances, and depicts how strategy R1 operates. Highlighted blocks with negative numbers represent blocks that seek to pull vehicles from adjacent blocks, while highlighted blocks with positive numbers attempt to push excess vehicles into adjacent blocks. Figure 2-4b (right side) shows block balances after rebalancing using strategy R1. Note that some balances remain somewhat uneven, due to SAV availability limitations during the time interval. Figures 2-4c and 2-4d demonstrate how vehicles would relocate using strategies R3 and R4, respectively, provided that there are available SAVs in the originating zones.

For further illustration of overall model operation, Figure 2-5 depicts the movement of one SAV's daily journey, beginning at S and ending at E. Solid arrows represent vehicle movements delivering passengers, dashed arrows represent vehicle relocation movements, the region's core zone is shaded (representing the area used to determine the relative "attraction factor" (α) for trips starting after noon), and block divisions are shown as solid black lines. Note that each arrow represents net movement during a single, 5-minute interval, so short diversions to pick up travelers are not shown and a single trip may span multiple time intervals. Also note that all trips begin and end in a zone's centroid, so there may be a small degree of extra VMT from vehicles traveling internally within the origin and destination zones.

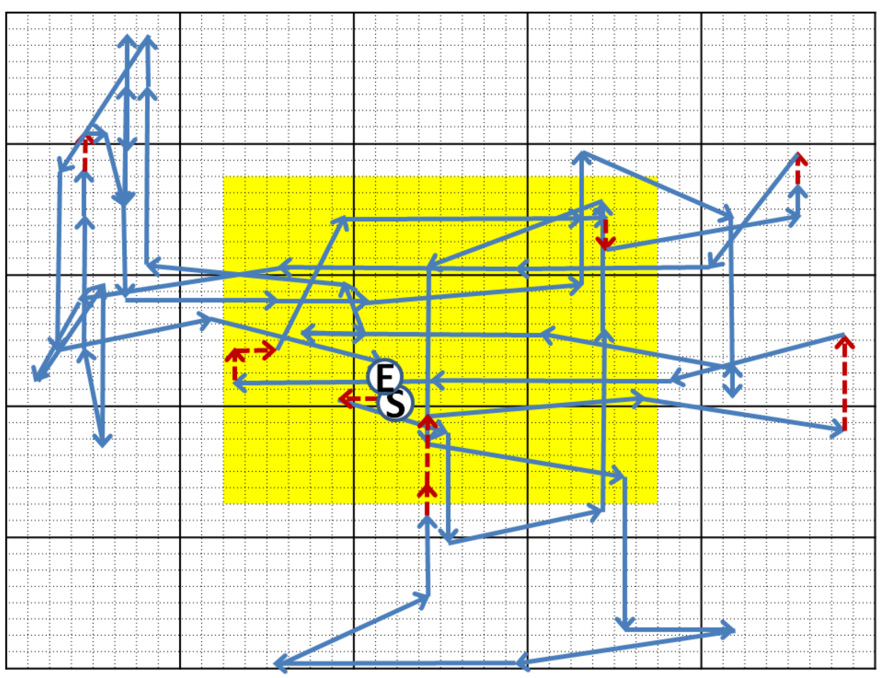


Figure 2-5: 24-Hour Travel Patterns and Operation for an Example SAV

Several observations can be made from this particular vehicle's journey, illuminating key model operations. First, all four relocation strategies are visible here. At the far right, strategy R1 is being used (with the SAV relocating across 2-mile blocks, and thus farther than R2 allows). Just below and to the right of the starting location, an R2 move is visible (here, the SAV is traveling more than two zones but is not crossing a larger 2-mile block boundary). The remainder of relocations are just one-zone (R4) or two-zone (R3) moves, typically not crossing an R1 or R2 block boundary. Also, congestion impacts during peak periods can be observed in the upper-left blocks, where per-period maximum travel distances are shorter than observed elsewhere. Finally, also in the upper-left corner, backtracking may be observed, where the SAV drops off a passenger with a very short wait interval, before taking him back to his original starting location.

In addition to relocation strategies, vehicle refueling, cleaning and maintenance were explicitly modeled. SAVs were assumed to be relatively fuel-efficient vehicles, operating at 40 miles per gallon with 12-gallon tanks. Once any SAV went below a 2-gallon reserve and had dropped its passengers off, a ten-minute wait period was incurred in the same zone, rendering the SAV temporarily unavailable for service, in order to allow for refueling and minor/routine cleaning. More serious SAV maintenance and cleaning was assumed to occur during low-demand times (e.g., overnight) and so not impact the simulated operations.

Chapter 2.3: Case Study Results

A *base-case scenario (S0)* model run was conducted, using 100 simulated days with summary statistics reported upon completion. This scenario is intended to represent a mid-sized city, perhaps the size of Austin, Texas, with about 3.5% of formerly human-driven trips within the service area now being served by SAVs. Table 2-1 notes S0's base assumptions (all of which were later varied in sensitivity analyses, described below). According to 2009 NHTS data, commuter speeds averaged 28.7 mph for metropolitan statistical areas with populations between 1 and 3 million persons (Santos et al. 2011). Additionally, Schrank, et al.'s (2012) Urban Mobility Report estimates that Austin peak travel times are 32% greater than off-peak times. Using these data points, off-peak speeds were assumed to be somewhat higher than baseline commuter speeds (which were probably measured during congested times of day) and set at 33 mph for the base-case scenario. Furthermore, since SAVs are assumed to be traveling more often in the urban core (and therefore in generally more congested areas), differences in peak and off-peak speeds were assumed to be more pronounced, and a 21 mph base-case scenario congested speed was assumed. Relative trip generation rates were based on Austin's population patterns, with average census block population density 2.5 miles from the city center showing 90% of the core population density, and just 30% of core density observed 7 miles out. Table 2-2 summarizes the overall travel impacts.

Parameter	**Value**
Service area	10 mi. x 10 mi.
Outer service area trip generation rate	9 trips per zone per day
Outer core trip generation rate	27 trips per zone per day
Innermost zone trip generation rate	30 trips per zone per day
Off-peak speed	33 mph
Peak speed	21 mph
AM peak period	7 AM - 8 AM
PM peak period	4 PM - 6:30 PM
Trip share returning by SAV	78%

Table 2-1: Base-Case (S0) Model Parameters

Category	Measure	Mean	S.D.
Trips & SAVs	# Person-trips per day	60,551	336
	# SAVs	1,688	0
	# Person-trips per SAV per day	35.87	0.20 (5.15)
Wait Time	# 5-minute wait periods per day	249	109
	Avg. wait time per person-trip (min.)	0.295	0.014 (0.61)
	# Un-served person-trips (across all days)	0	0
	% Person-trips waiting at least 5 min.	0.4%	0.2%
Trip Miles	Total VMT per day	332,900	2,200
	Unoccupied VMT per day	32,060	350
	Avg. person-trip distance (mi.)	5.43	0.01 (3.33)
	Unoccupied miles per person-trip	0.53	0.011
	% Induced travel (added VMT)	10.7%	0.1%
Usage	Min. # SAVs not in use (per day)	19	11
	Min. # SAVs unoccupied (per day)	54	22
	Max. share of SAVs in use / moving (per day)	98.87%	0.63%
	Max. share of SAVs occupied (per day)	96.80%	1.35%
Vehicle Starts	SAV warm starts per person-trip	0.73	0.01
	SAV cold-starts per person-trip	0.054	0.001
	# Warm-starts per day	44,190	370
	# Cold-starts per day	3,287	53

Table 2-2: Base Case (S0) Model Results[13] (Averages of Daily Averages & Standard Deviations of Key Behaviors)

Complete model results show how each base-case SAV serves approximately 31 to 41 travelers per day, with average wait times under 20 seconds[14]. Less than 0.5% of travelers waited more than five minutes, only three persons per day (0.005% of travelers) waited ten minutes or more, and no traveler waited 15 minutes or more on any of the 100

[13] Reported means represent averages of daily averages - across 100 simulated days, and standard deviations reflect an average of the variation of those daily averages - across 100 simulated days. Standard deviations shown in parentheses reflect 100-day averages of within-day standard deviations (so they describe the variability of travel choices within a travel day).

[14] While a 20-second average wait time appears quite optimistic, it reflects the phenomenon that an available SAV will almost always be within one or two zones, for the great majority of travelers under these scenario conditions. There may be additional time required for internal-zone travel, pick-up and drop-off; and this extra time is modeled by not allowing SAVs to continue traveling for the remainder of the 5-minute interval after dropping a passenger off.

days (so none was considered "un-served", with a 30+ minute wait time). This very high level of service should be acceptable to almost anyone traveling by SAV, especially since many travelers are more willing to accept an occasional, longer wait during the PM peak traffic period, where congestion is present and demand is highest. Standard deviations show that, while the average and the "average of average" wait times is 0.30 minutes (or 18 seconds), the average standard deviation of wait times across a day's trips is 0.61 minutes (due largely to relatively high peak-period wait times); and the average of these 100 standard deviations (as shown in Table 2-2) is just 0.01 minutes. About 11% of total VMT stems from vehicles relocating to new zones while unoccupied, and SAV relocation to cheaper parking areas during times of low demand was not modeled.

During the heaviest-use interval (typically just after 5 PM), more than 97% of vehicles were occupied, and just 1% were idle (versus relocating), indicating very high SAV utilization levels (in contrast to the NHTS' maximum-use statistic of 10 percent, as discussed in this paper's introduction). There are just 0.054 cold-SAV starts per person-trip simulated here, versus about 0.64 cold starts per person-trip across the U.S. today.[15]

NHTS records show that each licensed driver in the U.S. averages 3.02 private motor-vehicle-trips per day and the U.S. has 0.99 owned or leased household vehicles per licensed driver (Santos et al. 2011). Thus, Table 2-2's total trip count results suggest that this SAV system has 20,049 member drivers who may normally possess 19,849 personal vehicles. Yet here just 1,688 SAVs are used, suggesting that each SAV has the ability to replace nearly 12 privately owned vehicles, on average. Such findings indicate that almost eleven parking spaces can be eliminated for every SAV. However, this analysis examines only shorter (under 15-mile) trips (to stay within the 10-mile x 10-mile

[15] Kang and Recker (2009) note that the U.S. EPA estimates that it takes approximately one hour of idle time for a catalytic converter to cool and be considered a "cold start", and they estimate that around 68% of U.S.-vehicle trips (with internal combustion engines) are cold starts.

modeled fence); if longer trips are included, SAV use rates may be lower. Moreover, vehicle use rates may be higher in specific contexts: for example, Seattle survey data (PSRC 2006) suggest that household vehicles are used more intensively than the U.S. fleet: 16% of vehicles were reported in use during the highest use 5-minute interval in Seattle compared to just 12% nationally, for vehicles 10 years old or newer. If vehicle utilization rates are similarly higher to the Seattle profile, a single SAV may substitute for 8 or 9 vehicles (rather than nearly 12, as simulated here). Also, these results do not consider average vehicle occupancies (in SAVs or conventional vehicles). As such, reported person-trips shown here should be interpreted as person-trip parties, with one or more travelers, rather than as single-occupant vehicles only. SAV occupancies may be closer to national averages, around 1.67 person miles per vehicle mile (Santos et al. 2011).

Chapter 2.4: Energy & Emissions Implications

Chester and Horvath's (2009) life-cycle inventory estimates were used to evaluate the SAV system's possible emissions and energy use implications, as shown in Table 3. This evaluation assumes that the existing U.S. light-duty-vehicle fleet (BTS 2012), consisting of passenger cars (53% of fleet), pickup trucks (14%), and SUVs and minivans (33%), will be replaced with conventionally fueled SAV sedans. No electric, hybrid-electric, or alternative fuels are assumed here (for the SAVs or the fleet being replaced). While this assumption may work well when replacing a relatively small share of the vehicle fleet, as investigated here, some pickup trucks, SUVs and other larger vehicles may be needed in any SAV fleet, especially as more travelers and trips shift to SAVs. New SAV sedans may also be smaller than the nation's current average sedan size, though this effect too was not modeled. Emissions and energy impacts are estimated based on vehicle operation (in-use, VMT-based emissions and energy), vehicle manufacture (embodied energy), vehicle parking infrastructure (embodied and via parking space maintenance), and trip-start emissions differences. All four impact categories are influenced by fleet change, with vehicle operation also influenced by new/induced VMT (from travel of empty SAVs), parking influenced by reduced needs (due to fewer vehicles), and starting emissions influenced by changes in total number of vehicle starts, as well as the share of cold starts. While the overall number of vehicles will be lower, this analysis assumes that the total manufacture rates for new vehicles will remain about the same. This is because SAVs will travel many more miles per year than conventional vehicles, and so will wear out much sooner (in terms of years) as their mileage rises faster. This also assumes that SAVs will be able to travel more miles before replacement due to unoccupied travel, but is roughly negated by shorter lifespans, since auto parts may wear out through differing combinations of miles driven and years of wear.

Environmental Impact	Passenger Car Life-Cycle Inventories (Values not Shown for Pickup Trucks, & SUVs)				Average US Light-duty Vehicle vs. SAV Sedan Emissions Inventories			
	Operating (Running)	Manufac.	Parking	Vehicle Starts	Average LDV	SAV Total	Difference	% Change
Energy use (GJ)	890	100	15	0	1230	1087	-144	-12%
GHG (metric tons)	69	8.5	1.2	0	90.1	85.0	-5.1	-5.6%
SO_2 (kg)	3.9	20	3.6	0	30.6	24.6	-5.9	-19%
CO (kg)	2100	110	5.2	1400	3833	2546	-1287	-34%
NOx (kg)	160	20	6.4	32	243	200	-43	-18%
VOC (kg)	59	21	5.2	66	180	92	-88	-49%
PM_{10} (kg)[16]	20	5.7	2.7	2.0	28.2	26.4	1.8	-6.5%

Table 2-3: Potential Environmental Impacts of Introducing SAVs (per SAV introduced)

These results indicate beneficial energy use and emissions outcomes for all emissions species when shifting to a system of SAVs, assuming the same trip pattern/demand schedule is maintained (e.g., SAV users do not start making more or longer trips). The criteria pollutants evaluated here are sulfur dioxide (SO_2), carbon monoxide (CO), oxides of nitrogen (NOx), volatile organic compounds (VOC), and particulate matter with effective diameter under 10 μm (PM_{10}). Greenhouse gas (GHG) reductions and total energy use reductions are also anticipated. Under our modeling and vehicle assumptions, using Chester and Horvath's estimates, VOC and CO emissions will experience the most significant reductions, largely due to the substantial quantities generated during vehicle starts (both cold and warm). PM_{10} shows little reduction, along with GHG (even though the SAVs are assumed to be smaller and more fuel efficient than the average U.S. LDV, and so require less energy in their manufacture and operation),

[16] Using EPA's MOBILE6 model, Chester and Horvath (2009) estimated no cold start emissions of PM_{10}. EPA's new MOVES model corrects this deficiency, and suggests that each cold start emits about the same weight of PM_{10} emissions that would be generated in a mile of travel, at 25 mph average speed. Similarly, the average cold start generates about the same level of $PM_{2.5}$ that would come from 2.5 miles of travel, but we do not have embodied energy emissions estimates for $PM_{2.5}$, to define a total reduction here.

thanks to some added driving (for vehicles to access their travelers and, to a lesser extent, to relocate in anticipation of demand imbalances over space [thus shortening average response/passenger-wait time]). These results also assume that overall manufacturing needs will remain very similar, since per day SAV usage levels will be much higher, so there will be a greater (1.5 to 2 year) turnover rate. This being noted, newer vehicles may be more environmentally friendly than older ones, as U.S. Corporate Average Fuel Economy requirements tighten and technologies improve on conventional and alternative-fuel vehicles. Other factors may mitigate new running costs. For example, traditional car-sharing arrangements in North America show members' average VMT falling by 27% (Shaheen and Cohen 2013), and their use of carpooling and non-motorized modes (biking and walking) rising, though transit use often falls (Martin and Shaheen 2011). Moreover, Shoup (2007) estimates that an average of 30% of traffic in central business districts is generated by vehicles seeking to find a parking space close to their occupants' final destination, so reduced parking needs could lead to further emission reductions, along with congestion improvements (thus reducing idling and other driving-based emissions). Finally, SAVs should reduce crash occurrences (and delay vehicle replacement a bit, reducing manufacturing emissions), and may help ease congestion due to AVs being able to drive more smoothly and intelligently, particularly if other non-shared AVs are acting in concert (KPMG and CAR 2012). Such considerations suggest considerable potential for further energy and environmental savings, beyond what is estimated here.

Chapter 2.5: Sensitivity Analysis: Model & Parameter Variations

In order to appreciate how different settings impact SAV benefits and travel outcomes, model specifications and assumptions were adjusted to define 26 distinct alternative scenarios (each run with 100 simulated days of data). Eight types of variation were tested. *Trip generation scenarios* (ST1, ST2 and ST3) changed the base case's (S0's) overall trip generation rates by doubling the inner-core, outer-core, and outer-corner trip generation rates (to 60, 54 and 18 trips per zone per day, respectively), by halving these rates (to 15, 13.5 and 4.5 trips), and quartering them (to 7.5, 6.75 and 2.25 trips), while holding all distribution patterns constant. *Demand-centralization scenarios* (SC1 and SC2) adjusted trip generation rates to reflect constant CBD trip generation rates with wider differences between inner and outer rates (all rates within 2.5 miles of the center at 30 trips per zone, and linearly falling for those outside the urban core to 3 trips per zone at the outer corner) and linear rates, with narrower differences between inner and outer rates (rates linearly falling between the inner core [24 trips per zone] and outer service area [20 trips per zone]). In these scenarios, the total number of trips was held approximately constant. It should be noted that the relative trip distributions occurring over the course of the day remained the same from scenario to scenario, tracking average NHTS behaviors.

Service-area scenarios expanded or contracted the total service area by 2.5 miles in north-south and east-west directions, resulting in 56% more area for the region in SA1 and 44% less area in SA2, while holding the Base Case's individual zone trip-generation rates constant. In the expanded-area scenario (SA1) trip generation rates were assumed to continue to fall in the newly served areas at the same per-mile (from city center) rate as scenario S0. Two additional *return-trip by SAV* scenarios (SH1 & SH2) increased and decreased the rate at which individual travelers use SAVs to return home by 11% (and -11%), though trip generation rates were adjusted to ensure that the total number of one-way trips remained constant across the city. A less-*congested-peak scenario* (SP1) increased peak-period speeds by 3 mph, while shrinking peak periods to just 0.5 hours during the AM and 1.5 hours during the PM. A more-congested peak scenario (SP2) decreased peak speeds by 3 mph, and increased peak periods to 2 hours in the AM peak and 3.5 hours in the PM. A *SAV demand scenario* (SD1) altered the SAV demand profile by time-of-day for SAVs to match Seattle travel patterns (PSRC 2006). This scenario exhibited much greater travel during the AM and PM peaks than NHTS national averages. *Relocation strategies* examined the effects of not using any vehicle-relocation strategies, using just a single strategy (SR1 through SR4), or using all but one strategy (SRM1 through SRM4) in order to compare each strategy's relative effectiveness (from reduced wait times) and costs (from induced VMT). All other scenarios used all four relocation strategies. Finally, limits on the total number of SAVs were established in order to quantify how wait times and quality of service degraded as SAV supplies became limited (SL1600 through SL1200). Table 2-4 shows all strategies and results across several key measures.

Category	Scenario	Description	# SAVs in fleet	Person-trips per SAVs	5-minute wait intervals	Avg. wait time	% Extra travel	Cold starts per person-trip
Base case	S0	Base case scenario	1,688	35.9	249	0.30	10.7%	0.054
Trip generation	ST1	Double trips generated	3,245	37.1	226	0.14	7.3%	0.052
	ST2	Half trips generated	859	33.9	*	0.56	12.2%	0.060
	ST3	Quarter trips generated	433	31.7	301	0.92	13.8%	0.068
Centralization	SC1	Greater trip centralizat.	1,652	36.2	341	0.31	*	*
	SC2	Less trip centralization	1,712	*	213	*	*	*
Service area	SA1	Greater service area	2,272	33.7	337	0.33	*	0.059
	SA2	Smaller service area	1,053	40.3	154	0.26	*	0.048
Return-home trips by SAV	SH1	More return trips	1,674	35.3	206	0.29	*	*
	SH2	Fewer return trips	1,676	*	240	*	*	*
Peak congestion	SP1	Greater peak congestion	1,872	32.3	519	0.35	10.4%	0.060
	SP2	Less peak congestion	1,517	40	214	*	*	0.048
SAV demand	SD1	Greater peak SAV use	2,134	28.3	293	0.24	8.9%	0.096
Relocation strategies	SR0	No relocation	1,691	*	2,425	0.69	4.9%	0.067
	SR1	Only R1	1,674	36.5	433	0.46	7.3%	0.061
	SR2	Only R2	1,707	*	519	0.42	6.4%	0.061
	SR3	Only R3	1,677	*	1,750	0.51	7.0%	0.060
	SR4	Only R4	1,689	*	1,644	0.57	4.9%	0.066
	SRM1	All R minus R1	1,690	*	576	0.34	8.7%	*
	SRM2	All R minus R2	1,704	35.5	239	*	9.5%	0.057
	SRM3	All R minus R3	1,688	*	280	0.36	8.6%	0.056
	SRM4	All R minus R4	1,697	*	258	0.31	*	*
Limitations on # of SAVs	SL1600	SAVs limited to 1600	1,600	37.9	694	0.38	*	0.050
	SL1500	SAVs limited to 1500	1,500	40.5	2,422	0.59	*	0.047
	SL1400	SAVs limited to 1400	1,400	43.5	9,505	1.24	*	0.043
	SL1300	SAVs limited to 1300	1,300	47.0	22,718	2.38	*	0.039
	SL1200	SAVs limited to 1200	1,200	50.9	41,469	3.98	*	0.035

Table 2-4: Idealized Grid-Based Setting Alternative Scenarios' Results[17]

[17] Table 2-4's asterisks (*'s) signify a lack of pratical significance (e.g., values lie within ±2% of the base case) or statistical significance ($p<0.05$), with standard deviations obtained from the 100 days per scenario.

The SAV demand scenario had more substantial impacts on the overall outcomes than any other scenario that did not limit the SAV fleet or available relocation strategies. In Scenario SD1, strong peak-hour demand for SAVs was evident, so the number of trips that a single SAV could serve was nearly 27% lower than in the base case. Moreover, the number of 5-minute wait intervals for travelers placing trip requests (or "5Is") grew by 18%, even with the expanded fleet.

Figure 2-6 depicts the overall SAV fleet shares that are occupied and in-use throughout the day, between the two scenarios.

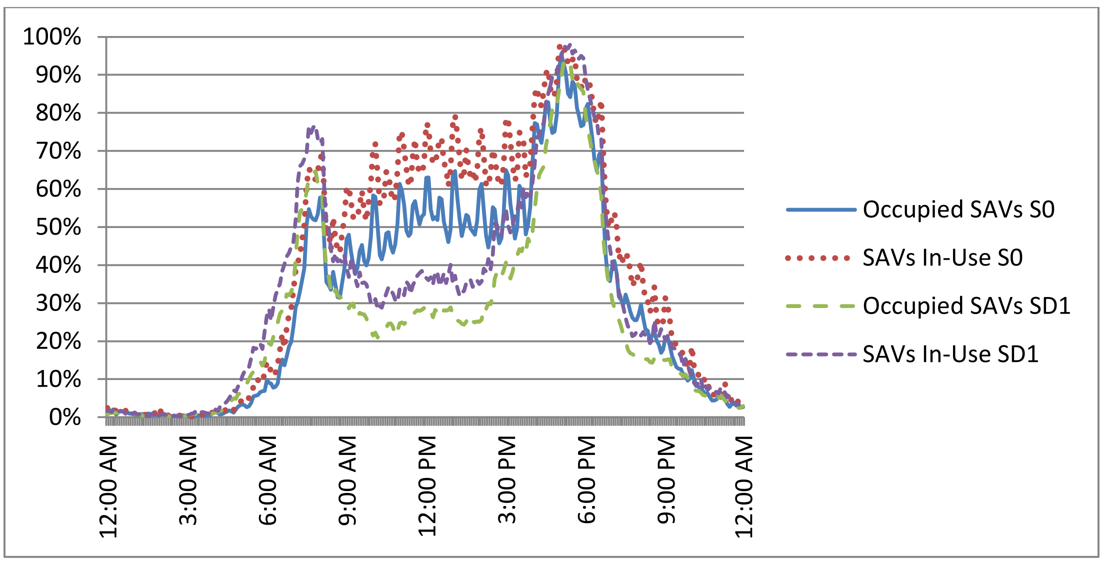


Figure 2-6: Shares of SAVs Occupied and In-Use by Time of Day

Among the other scenarios that alter base-case parameters (i.e., all non-relocation and SAV-limiting scenarios), the extent of peak congestion/lowered speeds (shown in SP1 & SP2) and overall number of trips served (in ST1-3) impacted outcomes to a greater degree than other scenario changes. Changes in trip-pattern centralization (SC1 & SC2) and return-home rates using SAVs (SH1 & SH2) had relatively minimal impacts.

As should be expected, greater peak congestion (SP1) negatively impacted travel outcomes. Even when more vehicles were present (vehicles per person-trip rose 11%, due to the warm-up period run before the first day to keep wait times under 10 minutes), the total number of 5Is rose by 108% under SP1. Conversely, the 5Is fell by 14% in the low-congestion scenario (SP2), even with 10% fewer SAVs per person-trip. Relative to these congestion scenarios, the trip-generation scenarios served impacted average wait times to a much stronger degree, though even average wait times remained under a minute in the quarter-trips scenario (ST3). When trip rates doubled and fleet size rose 92% (ST1), average wait times were 51% lower than the base-case scenario, 5Is fell by 11% on a per-person basis, and the share of induced VMT fell 32%. With SAVs serving only a quarter of the base case (S0's) trips (i.e., under scenario ST3), average wait times rose by 89% and 5Is by 21%. Interestingly, the results suggest that rather than the degree of centralization (SC1 and SC2), the city's overall trip-making density is much more important for achieving beneficial outcomes, with the smaller service area scenario (SA2) showing favorable results, as the lower-demand zones were dropped/no longer served. However, readers should be cautioned that this can also mean fewer trips from the high-demand zones for travelers wishing to go beyond the service fence (SAV-service boundary), though this investigation did not suppress demand to model the effects of more limited destination choices.

The four vehicle-relocation strategies were also tested, alone and in combination, in order to determine each strategy's overall effectiveness[18]. Strategy R1 (large-block relocation) is clearly the most effective, with better outcomes for trips per SAV, 5Is, and empty-SAV travel than all three other strategies combined. Part of R1's success may

[18] While the loss of strategy R2 (SMR2) results in 10 fewer long (5I) wait times than the base case, this may be more due to the extra 16 SAVs in the scenario, rather than an actual improvement from R2's removal.

stem from the trip attraction rates, which pull vehicles to the urban core more strongly during the morning and more strongly to the periphery during the afternoon. When used alone, coarser resolution or "big picture" strategies appear much more effective for reducing wait times than do finer-resolution local strategies, though all contribute to lower wait times.

Operators looking to reduce empty-vehicle travel (i.e., excess VMT) may wish to consider eliminating strategy R3, which should decrease such travel by nearly 20%, though this will likely result in average wait time increases and to a lesser extent more 5Is. Though not modeled here, off-peak strategies may also be employed, to reduce relocation during times of low demand. As scenario SR0 shows, without any relocation strategy in place, travelers clearly suffer: 5Is increase almost ten-fold, and average wait times more than double. However, the base-case scenario (S0) also illustrates the *costs* of having relocation strategies in place, with empty-SAV travel/added VMT rising from 4.9% to 10.7% of total VMT.

Finally, the effects of limiting the number of SAVs were tested, in order to determine how quickly level of service degrades (under scenarios SL1200 through SL1600). Figure 2-7 depicts the share of travelers waiting different time intervals as SAV supply falls (relative to the 1688 base-fleet size). Shares of travelers waiting at each of the specified time intervals increase very gradually, until certain thresholds are hit, at which point they rise quickly at near-linear rates, as SAV count falls.

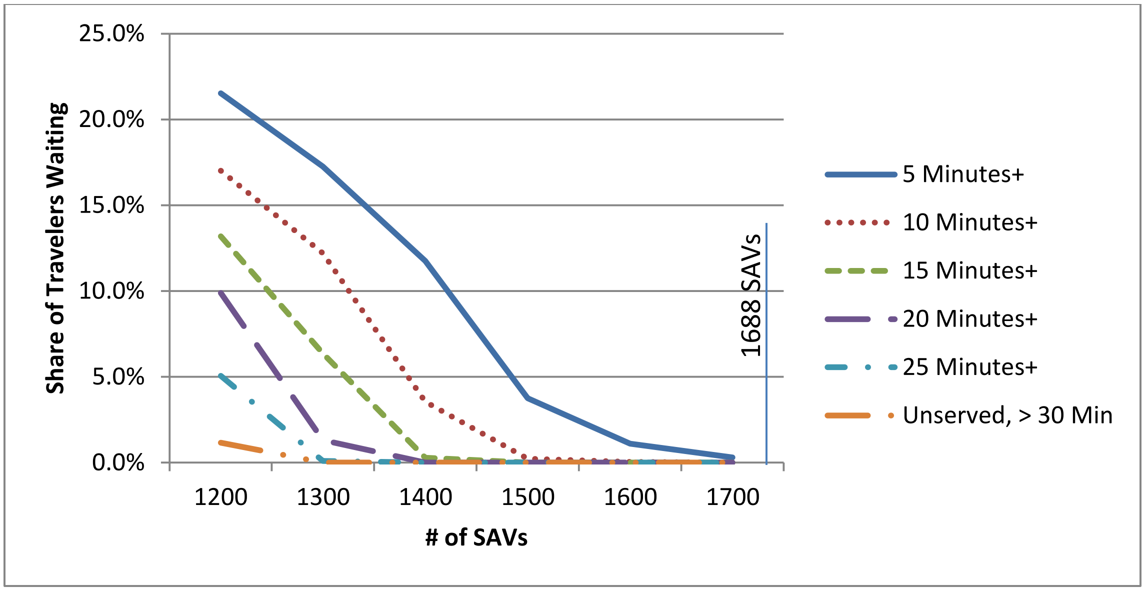


Figure 2-7: Traveler Shares Waiting Longer Intervals as SAVs Become Limited (Base Fleet Size = 1688 Vehicles)

While limiting the system's total number of SAVs has some definite advantages (lower service cost, fewer cold starts, and more trips served per SAV), the traveler delay costs are significant. Nevertheless, a SAV service provider may opt to limit the number of SAVs below the base-case conditions, perhaps charging different rates for quicker versus more delayed vehicle provision to travelers. For example, 1600 SAVs the share of persons waiting more than 5 minutes was just 1.1% and this rose to 3.8% at 1500 SAVs - with 0.2% of travelers waiting 10 minutes or more and around 3 travelers per day waiting 15 minutes plus. Some providers may deem one of these lower service levels acceptable and opt for a smaller fleet size. However, at just 1400 SAVs, service substantially degraded, as the shares of travelers waiting for 5, 10 and 15 minutes or more rose to 11.8%, 3.6%, and 0.3%, respectively. Further vehicle limitations result in even worse wait times. As a counter-argument to reducing SAV fleet sizes, suppliers may wish to set targets for their highest-demand days (e.g., Fridays in August, rather than average days).

Even relatively poor service would likely gain many adherents, especially if suppliers lowered rates for poor service (e.g., offering a discount for travelers waiting more than 10 minutes). Related to this, Barth and Todd (2001) conducted a survey among UC Riverside staff, faculty and graduate students regarding shared (but not autonomous) electric-vehicle use. 39% of respondents indicated that they would likely use the service, and over three quarters of those respondents stated that they would wait up to 10 minutes or more. However, the program in question loaned vehicles free of charge for the first hour of use; paying SAV customers will likely be more demanding.

Chapter 2.6: Part 2 Concluding Remarks

This grid-based SAV model investigation sets the stage for the final dissertation component by developing an overall model framework and using it to conduct a preliminary investigation. This work establishes an approximate SAV replacement rate for conventional vehicles (around 12:1), as well as induced VMT (approximately 11%) and life-cycle emissions impacts (anticipated reductions, across all species). Increased trip demand density is found to improve operations, as is lower levels of congestion. Importantly, of the four relocation strategies tested, the broad 2-mile block-based relocation strategy was by far the most effective, even without the other three relocation strategies.

PART 3: MODELING SAVS IN A NETWORK CONTEXT WITH DYNAMIC RIDE-SHARING

Chapter 3.1: Overview

Part 2 of this dissertation provided a foundation for developing a more comprehensive SAV model framework. This Part 3 implements such a framework in an actual network setting. This investigation mimics the Austin, Texas trip distribution, network and travel patterns and anticipates SAV system implications by serving various shares of travelers who previously traveled using other modes (mostly private automobile).

The improved model discussed here, in Part 3 of this dissertation, introduces a new dimension to the SAV framework: dynamic ride-sharing (DRS). DRS allows for on-demand carpooling, for travelers with similar or overlapping paths across both time and space. The framework developed and applied here allows for persons who are willing to share rides to be linked in the same SAV. In this sense, SAVs may both pick up multiple travelers at the same node if their destinations are in the same direction, or match travelers at new nodes while the SAV is traveling en-route.

Figure 3-1[19] places SAV use (both with and without ride-sharing) within the framework of existing and emerging shared mobility. Each state within Figure 3-1 represents a distinct transportation mode across areas of vehicle automation, shared rides, and shared vehicles. The y-axis represents the degree of technological evolution as time progresses, while the x-axis represents the degree of shared mobility. Links between states indicate prerequisites that must be achieved before a new mode or service can be realized. Currently existing transportation modes include household vehicles, shared

[19] Figure 3-1 was developed based on evaluations of the current state of technology and anticipated future implications, and based on conversations with the other conference organizers of the 2014 Automated Vehicles Symposium breakout group on Shared Mobility and Transit.

vehicles, DRS-enabled vehicles through mobile apps, and even joint DRS-car-sharing platforms (though this combined mode is still evolving). Traditional transit platforms are not shown in Figure 3-1; but buses represent a *higher* degree of shared mobility than any of these modal states, and partransit services may operate similar to SAVs with DRS. This being noted, these more traditional shared modes also typically have a higher degree of traveler inconvenience, and paratransit services can be quite expensive.

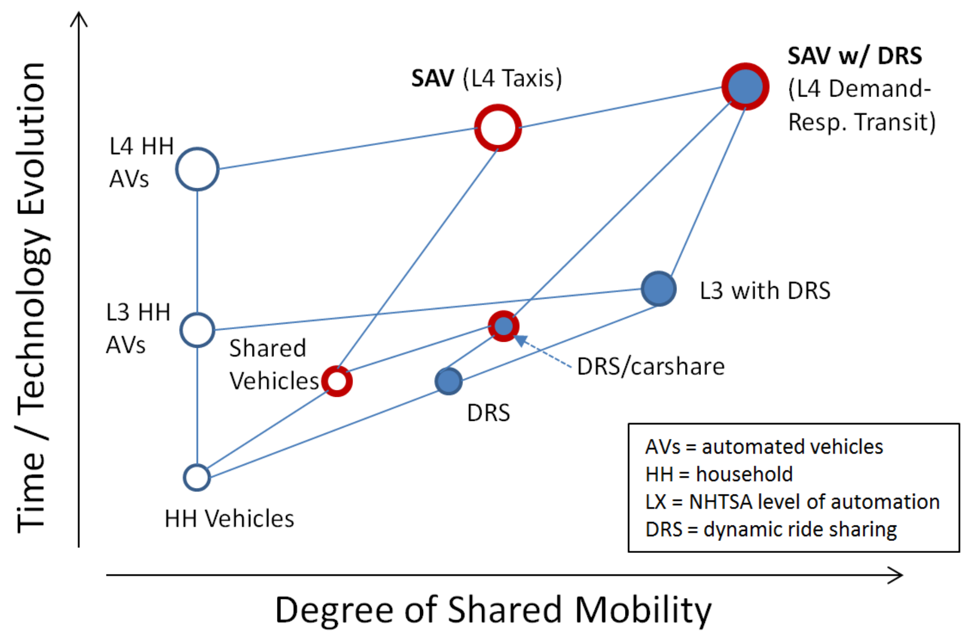


Figure 3-1: Emerging Technology Shared Mobility Framework[20]

As Fig. 3-1 framework illustrates, full vehicle automation (NHTSA Level 4) must be developed to enable SAV use. If these SAVs are developed with an eye towards ride-sharing, an even greater degree of shared mobility may be provided.

[20] Circle size of each transportation modal state represents the degree of automation, filled circles represent transportation modes with shared rides, and thick borders denote shared vehicles.

This investigation is also unique among other SAV investigations to date (e.g., Kornhauser et al. [2013], Burns et al. [2013], Pavone et al. [2011], and Part 2 of this dissertation, as published in Fagnant and Kockelman [2014]) in that the analysis uses an actual transportation network, with Austin-specific origin-destination trip table traffic flows and link-level travel speeds that vary by time of day, in response to variable congestion levels. Incorporation of en-route DRS trip matching is also a special feature of this new investigation.

While DRS has been modeled previously using taxi or automated taxi (aTaxi) paradigms, several salient features distinguish this work from others' past efforts. For example, Maciejewski and Nagel (2012) examined courier and taxi services using multiple pick-up and drop-off stops, but their simulation was limited in scale, since they evaluated nearly all service combinations (with some computational time limitations). As a result, when moving from 100 customers with 1 depot to 1000 customers with 10 depots, their simulation time increased by an order of 100. With thousands of nodes and tens of thousands of customers in this investigation, their approach is simply not feasible for realistic, large-scale applications.

Kornhauser et al. (2013) took a different tack: after gaining its first occupant, a given aTaxi simply waits a specified time before departing, matching to person-trips with the same origin and typically similar or en-route destinations. While this approach enjoys operational simplicity, and may reduce vehicle diversion times to pick-up and/or drop-off other travelers, much may be gained when serving other travelers along the way, particularly at stops that are already scheduled.

Jung et al. (2013) developed a few innovative DRS schemes, including a particularly effective hybrid simulated annealing (SA) methodology, which they referred to as "a generic probabilistic meta-heuristic … capable of finding an approximately accurate solution for the global optimum of a complex system with a large search space" (p. 7). SA operates by assigning an initial state (for example, nearest-vehicle dispatch) and then randomly perturbing assignments to see if the vehicle-assignment solution can be improved. Even if the total objective function is negatively impacted, a small acceptance probability function is used to avoid local minima (i.e., spurious solutions). While this dissertation work may be improved by incorporating the SA method, the approach used here (described below) enjoys certain advantages, predominantly in the area of anticipatory SAV relocation.

Agatz et al. (2011) examined DRS for travelers across Atlanta, Georgia. Their model sought to minimize total (system-wide) VMT and allowed substantial departure-time flexibility: travelers were assumed to accept 20-minute departure windows (10 minutes on either side of an actual, past trip), which substantially improves ride-share matches. In contrast, the DRS methodology described here bins departure times into 5-minute intervals, for relatively fixed desired departure times (according to the departing traveler's preference). As such, lower wait times take greater priority than system-wide VMT reductions.

Chapter 3.2: The Austin Network and Traveler Population

The base Austin regional network, zone system, and trip tables were obtained from the Capital Area Metropolitan Planning Organization (CAMPO), and are used in CAMPO's regional travel demand modeling efforts. The network is structured around 2,258 traffic analysis zones (TAZs) that define geospatial areas within the six-county Austin metropolitan region. A centroid node is located at the geographic center of each TAZ, and all trips departing from or traveling to the TAZ are assumed to originate from or end at this centroid. A set of centroid connectors link these zone centroids to this rest of the Austin regional transportation network. The network consists of 13,594 nodes and 32,272 links, including centroids and centroid connectors.

To determine SAV travel demand, a synthetic population of (one-way) trips was generated from the region's zone-based trip table, using four times of day: 6AM – 9AM for the morning peak, 9AM – 3:30PM for mid-day, 3:30PM – 6:30PM for an afternoon peak, and 6:30PM – 6AM for night conditions. Each of these time-of-day periods are used to identify different levels of trip generation and attraction between TAZs. Within each of these four broad periods, detailed trip departure time curves or distributions were estimated based on Seattle's year-2006 household travel diaries (PSRC 2006), since the Austin household travel survey data set's departure times did not make sense (e.g., the strongest demand during the PM peak was modeled at 3PM, as well as other issues that rose questions about the representative nature of the departure time distribution). Figure 3-2 shows the assumed departure time distribution for all trips.

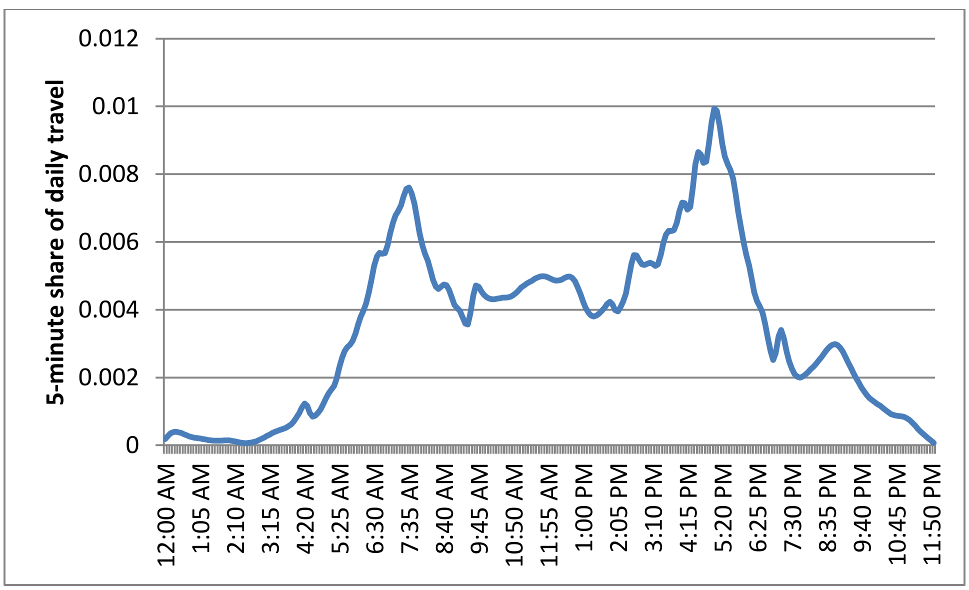


Figure 3-2: Share of Daily Travel, by Time of Day (Based on 5-Minute Bins) (PRSC 2006)

Once the trip population was generated, a full-weekday (24-hour) simulation of Austin's personal- and commercial-travel activities was conducted using the agent-based dynamic-traffic simulation software MATsim (Nagel and Axhausen, 2013). This evaluation assumed a typical weekday under current Austin conditions, using a base trip total of 4.5 million trips (per day), including commercial-vehicle trips, with 0.5 million of the total trips coming from and/or ending their travel outside the 6-county region. Due to MATSim's computational and memory limitations, 5% of the total 4.5 million trips were drawn at random, with corresponding adjustments to the link-level capacities. As such, each vehicle simulated in MATSim was assumed to represent 20 cars, on average. This is standard MATSim practice, suggested in MATSim's online tutorial (Nagel and Axhausen 2013). While this inevitably results in some loss of model fidelity, the overall congestion patterns that emerge should be relatively consistent with a larger or full simulation (if memory constraints are not an issue), since significant congestion typically occurs at at several orders of magnitude beyond the base (20-vehicle) unit used here.

Outputs of the model run were generated, including link-level hourly average travel times for all 24 hours of the day. Next, a 100,000-trip subset of the trip population was selected using random draws, and the 57,161 travelers (1.3% of the total internal regional trips, originating from 734 TAZ centroids) falling within a centrally located 12-mile by 24-mile "geofence" were assumed to call on SAVs for their travel. This geofence area was chosen because it represents the area with the highest trip density, and would therefore be most suitable for SAV operation, in terms of both lower traveler wait times and less unoccupied SAV travel (as SAVs journey between one traveler drop-off to the next traveler pick-up). All trips originating from or traveling to destinations outside the geofence were assumed to rely on alternative travel modes (e.g., a rental car, privately owned car, bus, light-rail train, or taxi). Among trips with origins in the geofence area, 84% had destinations also inside the geofence. This indicates that most people residing within the geofence could typically meet most of their trip needs via an SAV system, though perhaps a couple times a week they may require other modes to access areas outside the geofence. Such a system may be better suited for centrally located residents or households giving up one or more vehicles, but retaining at least one. Figure 3-3a depicts the Austin regional network and modeled geofence location, Figure 3-3b shows the geofence area in greater detail, and Figure 3-3c shows the density of trip origins within the geofence, using half-mile-cell resolution within 2-mile (outlined) blocks, with darker areas representing higher trip-making intensities.

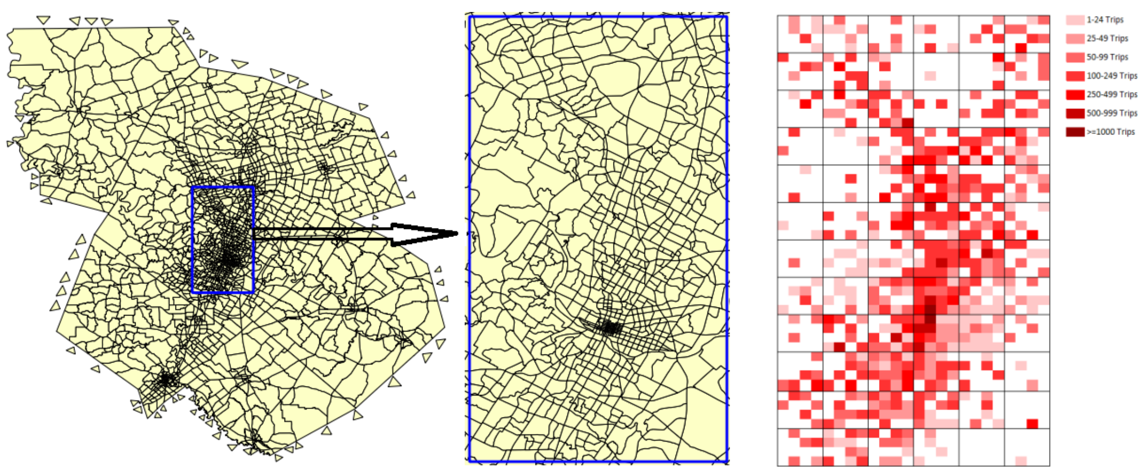


Figure 3-3: (a) Regional Transportation Network, (b) Nework within the 12 mi x 24 mi Geofence, (c) Distribution of Trip Origins (over 24-hour day, at ½-mile resolution)

Chapter 3.3: Model Specification and Operations

The population of trips within the geofenced area, the transportation network, and hourly link-level travel times were then used to simulate how this subset of trips would be served by SAVs, rather than using personally-owned household vehicles. This simulation was conducted by loading network and trip characteristics into a new C++ coded program, and simulating the SAV fleet's travel operations over a 24-hour day. To accomplish this, four primary program sub-modules were developed, including SAV location and trip assignment, SAV fleet generation, SAV movement, and SAV relocation.

3.3.1 SAV Location and Trip Assignment

The SAV location module operates by determining which available SAVs are closest to waiting travelers (prioritizing those who have been waiting longest), and then assigning available SAVs to those trips. For each new traveler waiting for an SAV, the closest SAV is sought using a backward-modified Dijkstra's algorithm (Bell and Iida 1997). This ensures that the SAV that is chosen has a shorter travel time to the waiting traveler than any other SAV that is not currently occupied. A base maximum path time is set equal to 5 minutes, and, if an SAVs is located within the desired time constraint, it will be assigned to the trip. Once an SAV has been assigned to a traveler, a path is generated for the SAV, from its current location to the waiting traveler (if the SAV and traveler are on different nodes) and then to the traveler's destination. This is done using a time-dependent version of Dijkstra's algorithm, by tracking future arrival times at individual nodes and corresponding link speeds emanating from those nodes at the arrival time.

Persons unable to find an available SAV within a 5-minute travel time are placed on a wait list. These waiting persons expand their maximum SAV search radius to 10 minutes. The program prioritizes those who have been waiting the longest, serving these individuals first before looking for SAVs for travelers who have been waiting a shorter time, or who have just placed a pick-up request. As such, an SAV may be assigned to a traveler who has been waiting 10 minutes and is 8 minutes away from a free SAV over another traveler who has been waiting 5 minutes and is just 2 minutes away from the same vehicle (provided that there are no closer SAVs to the first traveler).

Another feature of the SAV search is a process by which the search area expands. First, travelers look for free SAVs at their immediate node, then a distance of one minute away, then two minutes, and so forth, until the maximum search distance is reached or a free SAV is located. This is conducted to help ensure that vehicles will be assigned to the *closest* traveler, rather than simply to the *first* traveler who looks within a given time-step interval.

3.3.2 SAV Fleet Generation

In order to assign an SAV to a trip, an SAV fleet must first exist. The fleet size is determined by running a SAV "seed" simulation run, in which new SAVs are generated when any traveler has waited for 10 minutes and is still unable to locate an available SAV within 10 minutes travel time (i.e., if a vehicle does not free up in the next 5 minutes, the traveler must wait at least 20 minutes). In these instances, a new SAV is generated for the waiting traveler at his/her current location and the SAV remains in the system for the rest of the day. At the end of the SAV seed day, the entire SAV fleet is assumed to be in existence, and no new SAVs are created for the next full day, for which the outcome results are measured and reported. All SAVs begin the following day at the location in which they ended the seed day, reflecting the phenomenon that each individual SAV will not always end up at or near the place where it began its day.

3.3.3 SAV Movement

Once an SAV is assigned to a traveler or given relocation instructions, it begins traveling on the network. During this time the SAV follows the series of previously planned (shortest-path) steps, tracking its position within the network, until 5 minutes of travel have elapsed or the SAV has reached its final destination. Link-level travel speeds vary every hour, thanks to the MATsim simulation results (using 5 percent of the original trip table, on a 5-percent capacity network, to reduce computing burdens in this advanced, dynamic micro-simulation model). SAVs also track the time to the next node on their path, so an SAV's partial progress on a link is saved at the end of the 5-minute time interval, to be continued at the start of the next time interval. If an SAV arrives at a traveler, a pick-up time cost of one minute is incurred before the SAV continues on its path. Similarly, a one-minute cost is incurred for drop-offs, with SAVs able to both serve a new waiting traveler and/or serve current passengers if it had more than one occupant.

3.3.4 SAV RELOCATION

While the SAV location, assignment, generation, and movement framework described above is sufficient for basic operation of an SAV system, any SAV's ability to relocate in response to waiting travelers and the next (5-minute) period's anticipated demand is important for improving the overall system's level of service. It is important to note that this involves a critical tradeoff: as SAVs pre-emptively move in order to better serve current unserved and future anticipated demand (thus reducing traveler wait times), the total amount of "unoccupied" (empty-vehicle) VMT grows. That is, more relocation results in lower wait times but also higher VMT. As such, it is advantageous to strike a balance achieves relatively low wait times without overly increasing VMT. Further investigations into these relocation strategies could explicitly state a tradeoff thorough use of an objective function, minimizing, for example, the sum of monetized traveler wait time (or wait time squared, if excessive wait times are deemed particularly important) plus unoccupied VMT, across travelers and SAVs. Those wait times and

VMT can be converted to dollars using factors of roughly \$23 per hour[21] and \$0.50 per mile (AAA 2012), for example.

Using a similar grid-based model, four different SAV relocation strategies were tested in Part 2 of this work, alone, in combination, and in comparison to a no-relocation strategy. These results showed how the most effective of the four strategies evaluated the relative imbalance in number of waiting travelers and expected demand for trip-making across 2-mile by 2-mile blocks, and then pulled SAVs from adjacent blocks if local-block supply was too low in relation to expected demand, or pushed SAVs into neighboring blocks if local supply greatly exceeded expected (next-period) demand. This resulted in dramatic improvements in wait times, with the share of 5-minute wait intervals (incurred with every 5-minute period a traveler waits for an SAV) falling by 82 percent (from 2422 to 433) when using this strategy (versus no relocation strategy in place), even with slightly fewer SAVs. Since demand throughout the geofenced Austin area is relatively high and centralized, when aggregated into 2-mile by 2-mile blocks, this relocation heuristic strategy should function well. Readers should be cautioned, however, that this strategy's effectiveness may be limited when two or more high-demand areas are separated by a wide, low-demand area (for example, between two or more cities). In such instances, a more efficient relocation approach would be to shift vehicles within each high-demand area rather independently, and relocate vehicles across the areas only as overall imbalances become more significant.

This same block balancing strategy was implemented here, by first calculating a block balance for each 2-mile by 2-mile block, using formula 3-1:

$$Block\ Balance = SAVs_{Total}\left(\frac{SAVs_{Block}}{SAVs_{Total}} - \frac{Demand_{Block}}{Demand_{Total}}\right) \tag{3-1}$$

[21] Litman (2013b) notes that wait times may be valued at 70% of the wage rate, which is just over \$23 per hour for the Austin area, as of May 2013 (BLS 2014). This implies that for every minute each traveler spends waiting, a 38.4 cent cost is incurred.

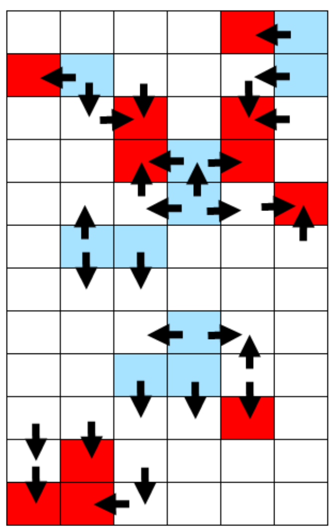
This formula compares the share of SAVs within a given block to share of (expected, next-period) total demand within the same block, normalizing by the total number of SAVs (or fleet size). Therefore, the total block balance represents the excess or deficit number of SAVs within the block in relation to system-wide SAV supply and expected travel demand. Expected travel demand is calculated as waiting trips plus the expected number of new travelers that are likely to request pick-up and departure in the next five-minute interval. The number of new travelers is estimated based by segmenting system-wide trips into one-hour bins, and obtaining average 5-minute trip rates for each block. Any agency or firm operating a fleet of SAVs could probably use historical demand data to inform their fleet's relocation decisions.

Once block balances are assessed, the block with the greatest imbalance is chosen (i.e., the greatest absolute value of Equation 1's result). Those with balance values less than -5 will attempt to pull available SAVs from neighboring blocks, first seeking to pull SAVs (if present) from the surrounding blocks with the highest (positive) balance scores. If a block has a positive balance above +5, it will similarly attempt to push SAVs into neighboring blocks with the lowest balance scores. In both cases, the balance difference between blocks must be greater than 1 in order to justify relocation.

After directions are assigned, the next task is to determine which individual SAVs to push or pull into the neighboring blocks. This is done by conducting path searches to determine which SAVs are closest to the node that is located nearest to the center of the block that the SAV will be moving into. If a pushed SAV is closest to the central nodes in two or more blocks (for example, 5.5 minutes to the block immediately north and 7.4 minutes to the block immediately west), it will be assigned to travel in the direction with the shortest path. These SAV paths are created from their current locations to the central node in the destination block. Each path is then trimmed after 5 minutes of relocation travel, such that the SAV can reassess its position and potentially be assigned to an actual traveler. If it has entered the new block and has traveled at least 2 minutes while in the new block in the direction of the central node, it will be held at that position for a coming assignment; this halt on relocation towards the new block's central node helps ensure that too many pushed SAVs do not all end up at the central node.

At this point, block balancing actions are complete for the given block and the block with the next greatest imbalance is chosen. This process continues until all blocks have either been rebalanced during the current time interval, or their (absolute) block balance scores are no greater than 5. Figure 3-4 depicts an example of the block balancing relocation process, showing balances before relocation assignment, SAV assignment directions by block, and balances after relocation. Integer values are shown here for readability, though actual balance figures are typically fractional.

0	-1	-3	-2	-7	6
-10	8	1	0	-2	8
-4	-1	-19	-2	-7	0
3	0	-10	13	-7	4
3	-2	4	13	2	-7
0	9	9	5	-3	5
0	-3	1	3	-3	3
1	3	3	10	3	-2
0	4	6	6	3	0
0	-3	2	-3	-8	0
-5	-6	-3	4	0	3
-8	-7	-3	0	0	0



0	-1	-3	-2	-5	4
-5	0	-5	0	-1	5
-4	-4	-7	-2	-5	-2
3	0	-4	6	-4	4
3	-1	5	6	4	-5
0	5	6	5	-3	4
0	0	5	5	-3	3
1	3	5	6	5	-2
0	4	5	5	0	0
-1	-4	3	-2	-5	0
-5	-5	-4	4	0	3
-7	-5	-4	0	0	0

Figure 3-4: Example SAV Relocations to Improve Balance in 2-mile Square Blocks (a) Initial Expected Imbalances, (b) Directional SAV Block Shifts, and (c) Resulting Imbalances

The other three relocation strategies noted in Part 2 of this investigation are not used here. These include a similar block-balance strategy, using 1-mile square blocks, relocation of extra SAVs to quarter-mile grid cells with zero SAVs in them and surrounding them (and thus half-mile travel distance away), and a stockpile-shifting strategy that relocates SAVs a quarter mile (1 grid cell away) if too many SAVs are present at a given location relative to the immediately surrounding cells (i.e., local imbalances of 3 of more in available SAVs). While these other strategies were somewhat helpful in reducing delays, their overall impact was less than that of the 2-mile-block rebalancing strategy, even when all three were combined. Moreover, the latter two strategies (involving very local or myopic shifts) may not be as effective in the more realistic network setting modeled here, since not every cell is a potential trip generator here, and differences in nearby trip-generation rates can vary dramatically across adjacent Austin cells. In this Austin setting, while only one of the 72 two-mile by two-mile blocks had no simulated SAV demand, 43.7 percent of the half-mile by half-mile cells had demand (with demand originating from an average of 1.46 centroids per non-zero-demand cell). Among the 503 half-mile cells exhibiting some demand, their cumulative trip generation may exceed demand in adjacent cells by a factor of 10.

3.3.5 DYNAMIC RIDE-SHARING

To improve the model's capabilities, opportunities for DRS were introduced. DRS allows two or more independent travelers to share a single SAV, as long as neither traveler will be overly inconvenienced. To enable this model feature, the SAV search process was modified to allow travelers to access SAVs that are currently either occupied or claimed by others, provided that all travelers are willing to share that SAV. Potential "handoffs" were also evaluated, to see whether any occupied SAVs could drop off current passengers and then pick up the waiting traveler sooner than other (presently empty) SAVs. If the claimed or occupied SAV is the nearest SAV to the new traveler[22], a series of checks is conducted to determine whether the ride should/will be shared. These conditions are as follows:

1. Current passengers' trip duration increases ≤ 20% (total trip duration with ride-sharing vs. without ride-sharing); *and*
2. Current passengers' remaining trip time increases ≤ 40%; *and*
3. New traveler's total trip time increase grows by ≤ Max(20% total trip without ride-sharing, or 3 minutes); *and*
4. New travelers will be picked up at least within the next 5 minutes; *and*
5. Total planned trip time to serve all passengers ≤ remaining time to serve the current trips + time to serve the new trip + 1 minute drop-off time, if not pooled.

While some of these conditions appear to overlap, each is important in its own right. For example, Condition 1 is the base setting, ensuring that travelers currently in SAVs are not overly burdened with added travel time. In other words, this condition ensures that their decision to share a ride is not excessively costly. Condition 2 prevents travelers who are nearly at their destination from suddenly diverting relatively far out of their way to serve another traveler. Condition 3 takes the new traveler's perspective, to ensure that this particular SAV is worth claiming. Condition 4 deals with the dynamic nature of travel: after 5 minutes many SAVs, if not most, will have moved from their current location and another one may be preferred. Finally, Condition 5 ensures that the trip should be matched from a system perspective. It prevents a short trip from being matched to a longer trip in an opposing direction trip that may satisfy the first four

[22] For nearest-SAV tiebreakers, where an occupied SAV is on the same node as an unoccupied SAV, the occupied SAV will be checked for (non-handoff) DRS availability first, followed by a search for a free SAV, with an SAV handoff tested last.

conditions. For example, consider a 40-minute northbound trip paired with a 3-minute southbound trip, both departing from the same node. If the southbound trip is served first, it will add 7 minutes to the northbound trip (including drop-off), would be an unwise ride-sharing decision, but nonetheless be matched without Condition 5.

All combinations of pick-ups and drop-offs for potential trip matches are tested in this way, though not all combinations are considered valid. All pick-ups and drop-offs occurring from/at the same node must be concurrent in time, and each traveler must be picked up before he/she can be dropped off. Multiple travelers may simultaneously exit and/or enter an SAV once it reaches its destination. If multiple pick-up/drop-off combination orderings are valid for a single, shared ride, the combination with the earliest final drop-off time is chosen.

Finally, if the pick-up/drop-off ordering is such that the travelers do not actually share a ride (e.g., the first traveler is dropped off before or while the second traveler is picked up), the ride is considered a "handoff", rather than a shared ride. For handoff trips, the match is not automatically assigned. Rather, the general SAV search process broadens and the match is only confirmed once it is clear that the traveler cannot be picked up sooner by another SAV. It should also be noted that all travelers may engage in SAV handoffs, even if they are unwilling to share a ride.

3.3.6 SAMPLE SAV DAILY TRAVEL

To best understand how this all comes together, an example SAV was tracked throughout an entire 24-hour day, with Figure 3-5 illustrating its operation in three parts. The first diagram (Figure 3-5a), shown in the upper left, illustrates pick-up and drop-off locations and their ordering, as the SAV travels from one location to the next. Lineweights depict the SAV's occupancy, with the thinnest linetype denoting no occupants, the medium depicting one occupant, and the heaviest holding two occupants. This schematic may be paired with Figure 3-5's other two components: Figure 3-5b (upper right image) shows the actual network links used to travel between locations, and Figure 3-5c (lower bar chart) depicts the SAV's 24-hour utilization timeline, showing 5-minute periods for when it was moving, picking up, and/or dropping off. Numbers corresponding to visited nodes (i.e., ordered locations) are also shown on the timeline, to better illustrate this SAV's spatial and temporal path over the course of a day.

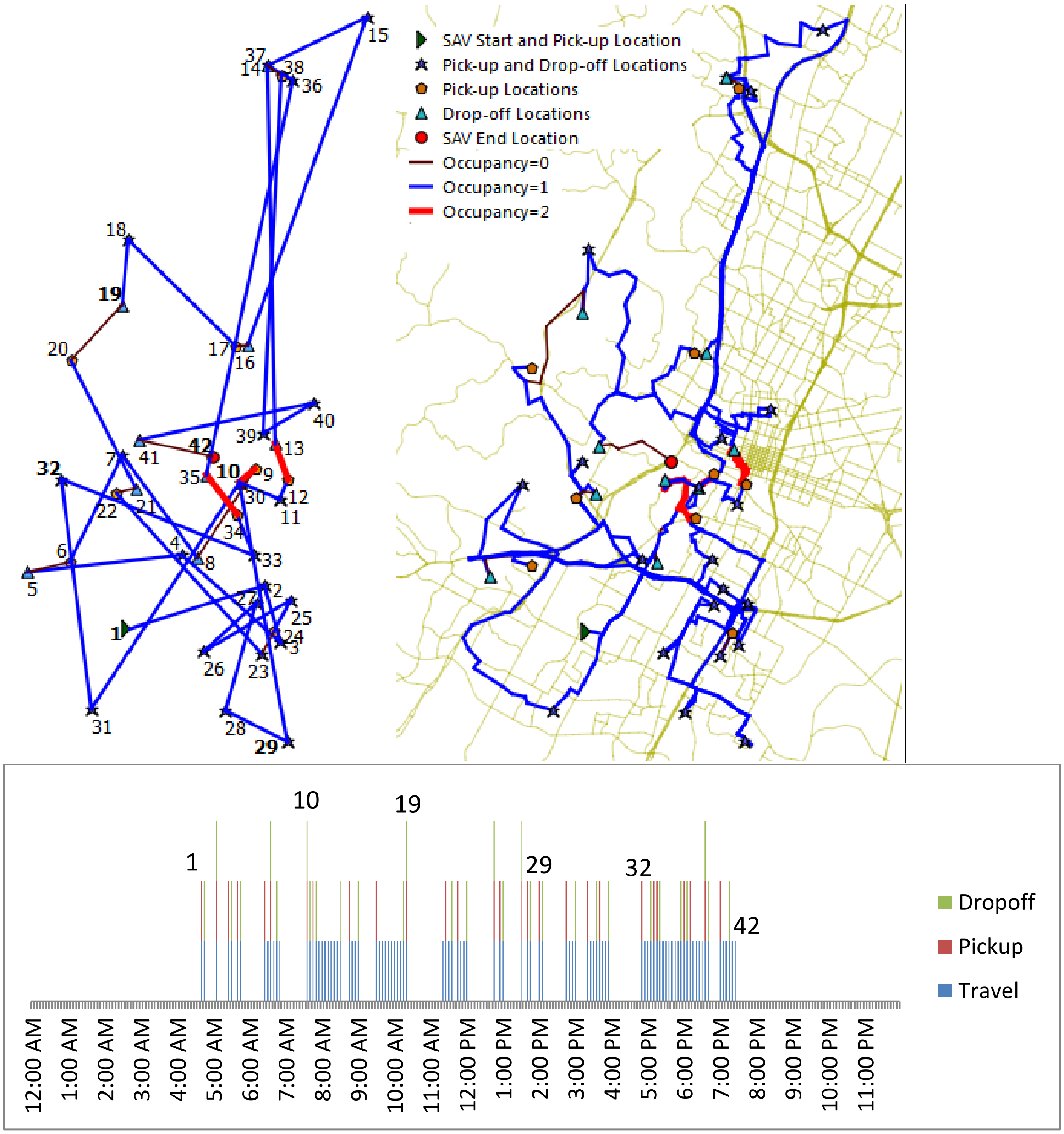


Figure 3-5: Sample SAV 24-Hour Travel Pattern (a) Node Origin and Destination Ordering, (b) Network Link Utilization and Traveler Origin and Destination Locations, and (c) SAV Travel Timeline

This particular SAV began its operation at 4:40 AM and ended by 7:40 PM. It served 31 person-trips and was "in use" for approximately 8.08 hours of the day[23]. During this time the SAV was either carrying passengers (for about 6.71 hours each day[24]), relocating itself (about 0.33 hours each day[23]), or spending one minute picking up and one minute dropping off each traveler it carried (for 1.03 hours per day, total). While there were still a number of trips to be served after this SAV completed its day (around 8% of the daily total), the SAV fleet size was large enough that this SAV was not needed.

Additionally, while its final daily relocation closer to the city center may have better balanced area-wide SAV supply and travel demand, other SAVs evidently were better situated for more immediate access to evening travelers, particularly if the new location was not a TAZ centroid. That is, an SAV that has not relocated has a good chance of picking up its next traveler at the very same location, since its last drop-off location was a TAZ centroid, where trips both originiate and end. However, an SAV that has relocated may not sit on a TAZ centroid, and so may have to travel some distance to get to a next waiting traveler. In instances where travel demand is relatively low, in relation to SAV supply (such as in the evenings and early morning), these SAVs may go unused, as seen here.

Among the 31 total trips served by this example SAV, trip durations varied from 5 minutes to 50 minutes, and averaged 16 minutes (including pick-up and drop-off times of 1 minute each). Three trips were shared: two between 7 and 8 AM, and one between 5 and 6 PM, with shared times lasting less than 10 minutes per trip. There were two

[23] This SAV was used during 97 of the 24-hour day's 288 5-minute intervals, for a total of 8 hours and 5 minutes. This SAV also was stationary for a portion of many of these 97 intervals, when travelers were dropped off early in the interval, but the SAV had not yet been assigned to another (new or already waiting) traveler.

[24] These figures are estimated using the numbers of links traveled while the SAV is occupied and unoccupied, since the exact shares of occupied and unoccupied travel time is unknown.

“rebalancing” relocations, including the final trip movement and one just before 7 AM. Finally, of the 31 person-trips, five involved minor relocations (no occupants inside), to move the vehicle from the SAVs’ previous drop-off location to a new pick-up location.

Chapter 3.4: Model Application and Results

From the 4.5 million trips in the Austin regional (6-county) trip table, an initial subset of 100,000 trips was randomly selected, to represent a small share of Austin’s total regional trips to be served by SAVs. Among these 100,000 person-trips, 56 percent had both their origins and destinations within the 12 x 24 mile geofence modeled here. Their departure times were designed to mimic a natural 24-hour cycle of trips, as described earlier and as shown in Figure 3-2, with the spatial pattern of trip origins shown (earlier) in Figure 3-3c. This single (“seed”) day was then simulated to first generate a fleet of SAVs, to ensure all (seed-day) wait times lie below 10 minutes. Then, a different day was simulated using the same starting trip population (of 4.5 million trips) to examine the travel implications of this pre-determined SAV fleet size, in terms of vehicle occupancies, unoccupied travel, wait times, and other metrics. Scenario variations were also conducted, to represent higher rates of SAV use, and these are discussed in greater detail subsection 3.4.3 of this dissertation.

All SAVs begin the following day at the location in which they ended the seed day, reflecting the phenomenon that each individual SAV will not always end up at or near the place where it began at the start of the day. These results show how approximately 1,715 SAVs are needed to serve the sample of trips if DRS is permitted, or 1,977 vehicles without DRS. This means that each SAV serves an average of 32.8 (or 28.5) person-trips on the single simulated day. Assuming an average of 3.02 person-trips per day per licensed driver (i.e., someone who could elect to drive his/her own vehicle) and 0.99 licensed drivers per conventional vehicle, an SAV in this scenario could reasonably be expected to replace around 10.77 (9.34) conventional vehicles, if travel demands remain very similar to demand patterns before SAVs are introduced.

This SAV fleet size offers an excellent level of service: Average wait times throughout the day are modeled at 1.18 minutes, with DRS enabled (or 1.00 minutes without DRS), with 93.2% (and 94.3%) of travelers waiting less than 5 minutes, 98.6% (or 98.8%) of travelers waiting under 10 minutes, and just 0.21% (or 0.10%) of travelers waiting 15-29 minutes (with non-DRS results shown in parentheses). The longest average wait times occurred during the 5PM – 6PM hour, when demand was highest and speeds slowest/congestion worst, with average wait times of 4.49 (and 3.85) minutes. These numeric results assume that all travelers request their trips exactly on 5-minute intervals, since that is when vehicle assignment decisions are made; in reality, many will call between 5-minute time points, adding (on average) another 2.5 minutes to the expected wait times (following an SAV trip request). Of course, some travelers will elect to call many minutes or hours in advance of needing an SAV, though these results suggest that such reservations may not be too helpful, except perhaps in lower-density and/or harder-to-reach locations. Moreover, advance vehicle assignments can make the system operate worse, especially if the person who placed the call is not ready and the SAV could be serving another traveler, particularly during high-demand periods of the day.

While this paradigm appears socially beneficial in terms of replacing many conventional vehicles with a much smaller fleet of SAVs, it comes with some costs in terms of extra (i.e., empty-) VMT. Non-DRS SAVs are estimated to travel another 8.00 percent distance without occupants, and all this extra VMT is not likely to occur if travelers are driving their own cars. With DRS enabled, total added VMT[25], can be cut to just 4.49%, even though just 6,152 out of 56,324 ride-sharing matches occurred in this low-trip-share simulation (and with just 4.83% of total VMT having 2 or more occupants). The vast majority of shared trips occurred between two persons, with 15,623 VMT covered (over the course of the average day) by the two-person-occupied vehicles, while 3-person occupancies accounted for 393 VMT and 4-person occupancies just 9 VMT (per day, on average).

Of course, many conventional-vehicle travelers do pass their destinations to find a parking place (and many may spend a lot of time and distance searching for a space on the street or within a structured parking lot). So there is “wasted VMT” already occurring in our conventional transportation systems, but with an occupant also arguably wasting his/her time. For example, Shoup (2007) estimated such “cruising for parking” to constitute 30 percent of VMT traveled in some of the world’s busiest downtowns. This extra VMT stems from SAVs traveling unoccupied to pick up the next waiting traveler, and from SAVs relocating between blocks in response to current and anticipated future demand.

Higher per-mile shared-vehicle marginal costs (as compared to per-mile marginal costs for household-owned vehicles) may also reduce total VMT. In a traditional, privately-owned household-vehicle setting, ownership costs are paid up front. In contrast, ownership costs are embedded in an SAV’s rental price. Figure 3-6 illustrates this concept by showing a $2000 per-vehicle capital cost plus $0.20 per additional travel mile for a traditional (household-owned) setting, versus a $0.40 per mile shared-fleet setting.

[25] Added VMT reflects extra (unoccupied) travel by SAVs, and reflects travel reductions due to DRS. Total added VMT is calculated by comparing the amount of travel in a given scenario to the amount of travel for the exact same population, if every person were driving a personal vehicle directly from his/her origin to his/her destination (with no added distance to obtain parking, for example, which is unrealistic in practice).

Figure 3-6 also shows the potential benefits of an SAV program to travelers. Under this household-owned vehicle model example, whenever the household exceeds another 10,000 miles, they purchase a new car. Alternatively, a given household may use a combined owned/shared vehicle framework where they may buy one vehicle that serves 10,000 miles, and use car-sharing for the other 3,000 miles, thus reducing total household expenditures.

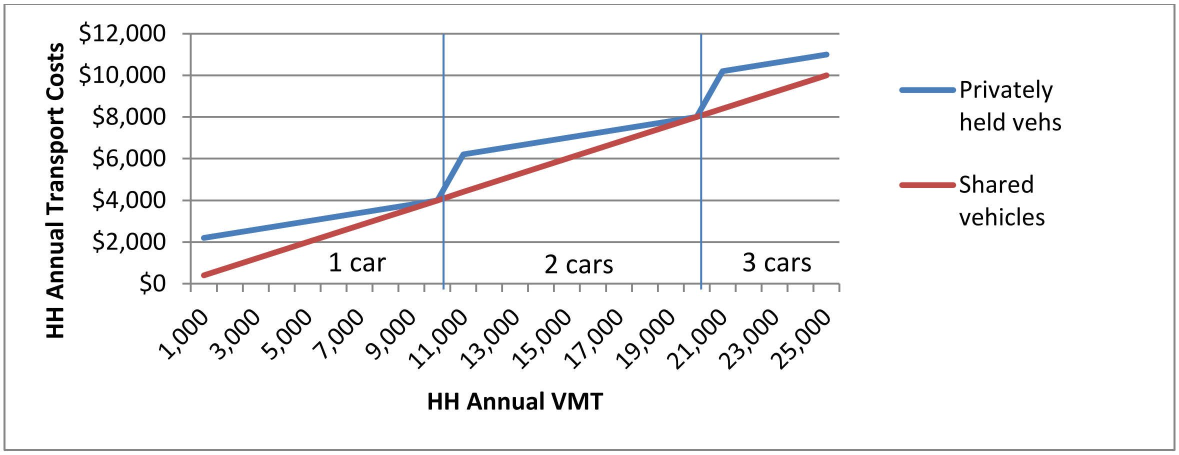


Figure 3-6: Household Transport Costs Under Private Household Ownership of Vehicles and a Car-Sharing Arrangement as a Function of VMT

Other system simulation results were nearly identical between the DRS and non-DRS scenarios speeds. For example, 24-hour travel-*distance*-weighted speeds averaged 43.6 mph. However, when taking a time-weighted system perspective, using total travel distance divided by total travel miles (VMT/VHT), average system speeds are 26.1 mph. This reflects the phenomenon that, if an SAV travels 5 miles at 5 mph and 5 miles at 50 mph, it will take 1.1 hours to travel the 10 miles resulting in an effective system speed of 9.1 mph, rather than a travel-distance weighted speed of 27.5 mph. Moreover, 19.4% of total SAV VMT was at speeds of 20 mph or less, likely on local roads and/or during congested times, while 41.4% of total SAV VMT occurred at speeds over 50 mph, typically during off-peak times and on freeways.

A comparison with New York City's taxi fleet casts this Austin-based SAV system in a very favorable light. The NYC's Taxi and Limousine Commission's (2014) Factbook notes that the city's 13,437 yellow taxis serve an average of 36 trips per day, somewhat more than the 33 trips (with DRS), or 28 trips (without DRS) served by SAVs here. However, our simulations indicate that as total demand goes up, more trips can be served per SAV. 90.3 percent of trips that the NYC taxi fleet serves are on the island of Manhattan, a 22.7 square mile land area (though the entire city is 469 square miles), in contrast to the 288 square miles served here. While the modeled Austin-traveler trips averaged 5.2 miles, yellow taxi trips in NYC average just 2.6 miles, so each yellow taxi travels, on average, 70,000 miles annually, with a stunning 51.5% unoccupied share of VMT (versus the 4.5 and 8.0 percentages simulated here, with and without DRS). While NYC taxi demands and service are distinctive (e.g., an extensive subway system can serve many longer trips), such comparisons draw attention to the dramatic service improvements that SAVs may bring communities.

3.4.1 Electric Vehicle Use Implications

One intriguing question to ask is whether SAV fleets could be served by electric vehicles. Electric SAVs may provide a number of advantages over gasoline-powered SAVs, including, for example, fewer emissions for communities and greater energy security for a nation, and perhaps even cost advantages -- if the price of electric vehicle batteries continues to fall. Some AV technology providers see this as a promising future, with Induct demonstrating a fully driverless and electric low-speed passenger transport shuttle in January 2014 in Las Vegas, Nevada, at the Consumer Electronics Show (Induct 2014).

Simulations are valuable for assessing the potential charging implications of an electric SAV fleet, as recently investigated (for cost comparisons, but not battery-charging implications) by Burns et al. (2013). Here, occupied plus unoccupied vehicle distances per vehicle-trip average 5.89 miles with DRS permitted (and 6.09 miles without DRS), and the SAV fleet was traveling, picking up, dropping off, or otherwise active for 8.62 (and 7.14) hours of the day, with SAVs averaging 2.96 (and 2.91) stationary/non-moving intervals of at least one hour (when no travelers were being served and no relocations were being pursued) each day, and another 1.15 (0.80) intervals between 30 minutes and 59.9 minutes (of stationary/sitting time) each day. Such long wait intervals could be productively used for vehicle battery charging, if desired by fleet operators, and if charging stations are reasonably close by. However, daily travel distances averaged 194 (and 174) miles per SAV, with mileage distributions shown in Figure 3-7. These distances are much longer than the range of most battery-electric (non-hybrid, electric-power-only) vehicles (BEVs).

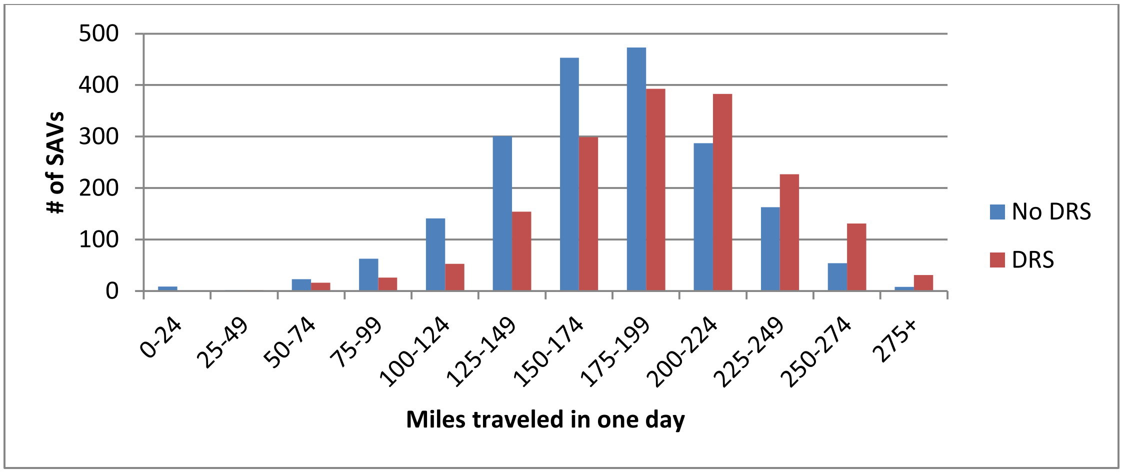


Figure 3-7: Daily Travel Distance per SAV in Austin Network-Based Setting

Most currently available BEVs for sale in the U.S. have all-electric ranges between 60 and 100 miles (e.g., the Chevrolet Spark, Ford Focus, Honda Fit, Mitsubishi i-MiEV, and Nissan Leaf). For these, the U.S. EPA (2014) estimates typical charge times (to fully restore a depleted battery) to vary between 4 and 7 hours on Level 2 (240 volt) charging devices. This could pose a serious issue for all-electric BEVs in an SAV fleet, but not much of an issue for the Tesla Model S (which enjoys a 208- to 265-mile range and a charge time of under 5 hours when using a Level 2 dual charger [EPA 2014]) or plug-in hybrid EVs (PHEVs), like the Chevrolet Volt, Honda Accord Plug-in, Ford C-MAX Energi, Ford Fusion Energi, and Prius Plug-in Hybrid. Furthermore, fast-charging Level 3 (480-volt) systems can charge large batteries in under an hour, so SAVs that need more frequent daytime charging may need to rely on these devices. Of course, some time is required to develop the automation technology and legal frameworks needed to successfully deploy SAVs. In the meantime, battery charging times, BEV ranges and costs will improve, along with deployment of fast-charging facilities and remote inductive charging devices (allowing SAVs to self-charge wirelessly [MacKenzie 2013]).

3.4.2 SAV EMISSIONS IMPLICATIONS

SAV emissions implications were also evaluated, using that the same method described in Part 2 of this dissertation. This method applies life-cycle energy usage and emissions rates associated with vehicle manufacture, per-mile running operations, cold-vehicle starts, and parking infrastructure provision, all using rates estimated by Chester and Horvath (2009). As in Part 2, the current U.S. light-duty vehicle fleet distribution (BTS 2012), as split between passenger cars (sedans), SUVs, pick-up trucks and vans was assumed here, for comparison with an SAV fleet consisting entirely of passenger cars. It is possible that SAVs will include other vehicle types, but many may be built as smaller cars, perhaps even two-seaters like Car2Go is currently using for its shared vehicles and as Google is planning for its SAV fleet (Markoff 2014). Thus, fleet purchase decisions could result in even greater (or lower) emissions and energy savings than estimated here, though smaller vehicles potentially limit ride-sharing (to fewer persons) and cargo-carrying opportunities. Table 3-1 shows anticipated emissions outcomes with and without DRS, as well as estimates generated in Part 2 of this dissertation (using the grid-based SAV model for an idealized city and network).

Environmental Impact	US Vehicle Fleet vs. SAV Comparison (over SAV lifetime)					
	US Vehicle Fleet Avg	**SAVs w/ DRS**	**SAVs w/o DRS**	**% Change w/ DRS**	**% Change w/o DRS**	**Part 2 Estimates**
Energy use (GJ)	1230	1032	1064	-16%	-14%	-12%
GHG (metric tons)	90.1	80.8	83.2	-10.3%	-7.6%	-5.6%
SO_2 (kg)	30.6	24.4	24.6	-20%	-20%	-19%
CO (kg)	3833	2492	2590	-35%	-32%	-34%
NOx (kg)	243	192	198	-21%	-18%	-18%
VOC (kg)	180	91.9	95.2	-49%	-47%	-49%
PM_{10} (kg)	30.2	27.1	27.9	-10.1%	-7.6%	-6.5%

Table 3-1: Anticipated SAV Life-Cycle Emissions Outcomes Using the Austin Network-Based Scenario (Per SAV Introduced)

These anticipated environmental outcomes are quite similar to those estimated in Part 2, thanks to similar vehicle replacement rates, trip service levels, and cold-start trip shares. The greatest change in emissions outcomes between Parts 2 and 3 emerges when total life-cycle inventories are composed of relatively high shares of running emissions (averaging 78.4% for energy use, GHG, NOx, and PM10, vs. 45.6% for other emissions species) and low shares of starting emissions[26] (averaging 5.4% vs. 28.7%, respectively). Changes in starting emissions were relatively constant between Parts 2 and 3 (92% vs. 87% reductions) though VMT increases were significantly different (10.7% vs. 4.5% increases, respectively). As expected, the network-based DRS scenario exhibits better environmental outcomes than the network-based non-DRS scenario, with further energy and emissions savings ranging from 1 to 3%.

3.4.3 Scenario Variations

Following the base model's simulation run, a series of alternative scenarios were simulated, to test the implications of various fleet sizes and various travel demand

[26] See table 2-3 in Part 2 for emissions shares of starting, running and other emissions sources across all pollutant species noted here.

settings. In addition to the base case's non-DRS and DRS runs already described, four scenarios types were tested. These include limiting the non-DRS SAV fleet to just 1715 vehicles (for direct, same-size-fleet comparison with the DRS-enabled fleet), allowing a maximum of 30% or 40% total increased travel time for the first and third DRS conditions noted above (up from the base case assumption of 20%), varying shares of the SAV-using population willing to ride-share (from 10% to 90%), and varying the size of the population served. Part 2's idealized 10 mi. x 10 mi. quarter-mile grid-based-system results are also included here (with 60,551 travelers served), for comparison purposes. Table 3-2 shows the results of the fleet size limitations, the higher allowable DRS travel time scenario, and Part 2's idealized grid-based scenarios.

Measure	No DRS	DRS	1715 SAVs w/ no DRS	Grid-Based[27]	+ 30% DRS trav. time	+ 40% DRS trav. time
# SAVs	1977	1715	1715	1688	1643	1601
Vehicle replacement rate	9.34	10.77	10.77	11.76	11.24	11.53
Extra VMT	8.00%	4.49%	8.68%	10.7%	2.67%	1.52%
Avg. wait time (min.)	1.00	1.18	1.87	0.29	1.27	1.37
Avg. PM peak wait (min.)	3.85	4.49	8.96	-	4.82	4.99
Avg. total service (min.)	14.07	14.71	14.97	-	15.20	15.69
% Waiting ≥ 10 min	1.19%	1.45%	5.65%	0.01%	1.71%	1.90%
% Waiting ≥ 15 min	0.10%	0.22%	2.08%	0.00%	0.27%	0.43%
# Shared trips	0	6151	0	0	9233	11,723
% Shared miles	0.00%	4.83%	0.00%	0.00%	8.32%	11.20%

Table 3-2: Austin Network-Based Model Results under Various Scenarios

3.4.3.1 Same-Sized Fleets for DRS and Non-DRS Scenarios

One valuable finding from these scenario results emerges when examining the DRS vs. non-DRS scenarios, particularly when using a same-sized fleet of just 1715

[27] The 10-mile by 10-mile idealized-context grid-based simulation can be found in Part 2 of this dissertation.

SAVs. By sharing nearly 11% of trips (but less than 5% of VMT), fleet-wide added travel (as compared to the same number of trips served by privately-held, household vehicles) can be cut by 43%. Wait times also fall (including the share of longer wait periods), though total service time (from initial placed pick-up request to final trip drop-off time) increase only slightly, from 14.71 to 14.97 minutes per person-trip. This implies that in-vehicle travel time is likely being substituted for out-of-vehicle wait time at a ratio of approximately 0.6:1 when using DRS.

3.4.3.2 Grid-Based Comparisons

It is also interesting to compare the results shown here for the non-DRS scenario (in a realistic 12-mile by 24-mile travel-demand setting) with Part 2's grid-based evaluation results (in an idealized 10-mile by 10-mile setting). The latter, pure-grid scenario, with quarter-mile cells and smooth (idealized) demand profiles, out-performs the much more realistic, actual-network-based Austin scenario, across all categories of conventional vehicle replacement, wait times, and unoccupied travel. As shown in Table 3-2, this grid-based evaluation suggested that each SAV could replace two to three more conventional vehicles than this more realistic setting (i.e., it yieled a replacement rate of 11.76 to 1 rather than 9.34 to 1), while cutting average wait times nearly 70% (from 1.00 to 0.30 minutes), with 32% more unoccupied (empty-SAV) VMT (10.7% added VMT in the gridded case vs. 8.0% in the Austin-network setting), though these new VMT travel values are quite close, with just 7.3% added VMT in the grid setting if only relocation strategy R1 is used. The differences in these two settings' results come from a host of very different supporting assumptions.

First, the travel demand profile differed significantly between the two evaluations. The grid-based evaluation assumed a smaller service area and higher trip density, with

60,551 trips per day across a 100 square-mile area, versus 56,324 trips per day across a 288 square-mile area. Average trip-end intensities also varied quite smoothly across quarter-mile cells in the grid-based application (with near-linear changes in travel demand rates between the city center and outer zones), whereas the Austin setting exhibits much greater spatial variation in trip-making intensities (as evident in Figure 3-3c). The simulated setting also added more fleet vehicles based on initial simulations, to keep wait times lower than would probably be optimal for real fleet managers; this Austin fleet sizing is less generous, and presumably more realistic, but traveler wait times remain very reasonable.

Another key distinction between the simulated, grid-based and Austin network evaluations emerges in average speeds and average trip distances. Here, travel-weighted 24-hour running speeds average 26.1 mph, whereas constant speeds of 21 mph and 33 mph were assumed in the simulated context, and the 21 mph speed only applied during a 1-hour AM peak and 2.5-hour PM peak period (with 33 mph SAV travel speeds at all other times). Trip distances were constrained to 15 miles in length in the prior application, while this application permits a much wider range of travel behaviors. Finally, this setting allows for a real network – sometimes dense, but often sparse, adding circuity to travel routes; in contrast, the simulated setting assumed a tightly space (quarter-mile) grid of north-south and east-west streets throughout the region. Circuity in accessing travelers and then their destinations is harder to serve, especially at lower average speeds, across a wider range of trip-making intensities.

It is interesting how well the Austin fleet still serves its travelers, given the series of disadvantages that exist in this more realistic simulation. Lower trip densities mean that SAVs must travel farther on average to pick up travelers, and slower speeds mean that SAVs will be occupied for a longer duration during the journey, tying them up and preventing them from serving other travelers, and potentially hampering relocation efficiency. Also, while shorter trips lessen travel times, it also means that relocation and unoccupied travel will comprise a greater share of the total. All of these factors suggest that a larger fleet will be needed to achieve an equivalent level of service. But the vehicle-replacement rates remain very strong, at 9.3 or more conventional vehicles per SAV, even without DRS.

3.4.3.3 HIGHER DRS TRAVEL TIME TOLERANCES

Another set of scenarios then examined the impacts of adjusting one of the fundamental parameters required to match a ride. The added maximum amount of time that any ride-sharing traveler would have to spend (from his/her placed call to request an SAV, to his/her final drop-off at destination) in the base-case DRS scenario was set to 20%. This parameter was increased to 30% and then 40% to determine effects on overall operations. Results showed that changing the extra travel time maximum from 20% to 30% yielded significant benefits at relatively low cost, in terms of total service times (wait time plus travel time), while the change from 30% to 40% (extra travel time) produced only minor benefits, at much higher cost. For example, the first increase (from 20% to 30%) reduced the amount of extra or empty-SAV VMT by 4.4 miles (per new/added shared-trip) at a cost of 8.9 minutes of added total service time per new shared-trip[28], while also shrinking the SAV fleet size by 72 vehicles or 4.2 percent (a size designed to ensure wait times do not exceed 15 minutes). A fleet operator may find this trade-off (in fleet size for total travel times) reasonable and opt to use a 30% assumption. When increasing the maximum extra travel time ride-sharers are willing to wait by another 10%, to 40% total, VMT was reduced by only 2.4 miles at a cost of 11.1 minutes

[28] These new shared-trips are not wholly new person-trips. They are simply the rise in the number of trips shared over the course of the average simulated day, when the 20% threshold parameter is loosened.

of added service time per shared trip, and fleet size fell by just 42 SAVs, indicating that this setting is likely too high to be worthwhile for travelers.

3.4.3.4 Varying Shares of DRS-Willing Travelers

Since SAV operators may offer riders a choice to simply consider, or decline, the possibility of ride-sharing, a series of scenarios also vary the share of travelers willing to ride-share, from 10% to 90%. Travelers who are willing to ride-share are assumed to share a match if they find another DRS-willing traveler in an SAV or who has claimed one, provided that the match meets the five criteria noted above. Travelers not willing to ride-share will simply never be matched. As expected, scenario outcome values for the SAV fleet size and total system VMT fall with more travelers opting to ride-share, while average total service time, number of shared trips, and percentage of shared miles rise. "Proximity values" were then computed to quantify how close the new scenario results come to the fullly-DRS scenario's outcomes, versus the non-DRS scenario's outcomes. These proximity values are defined for each evaluation metric *i* and share of DRS-using travelers *k*, using Formula 3-2:

$$DRSProximity_{i,k\%} = \frac{DRS_{i,0\%} - DRS_{i,k\%}}{DRS_{i,0\%} - DRS_{i,100\%}} \tag{3-2}$$

Outcomes for each of the evaluated metrics are shown in Figure 3-8.

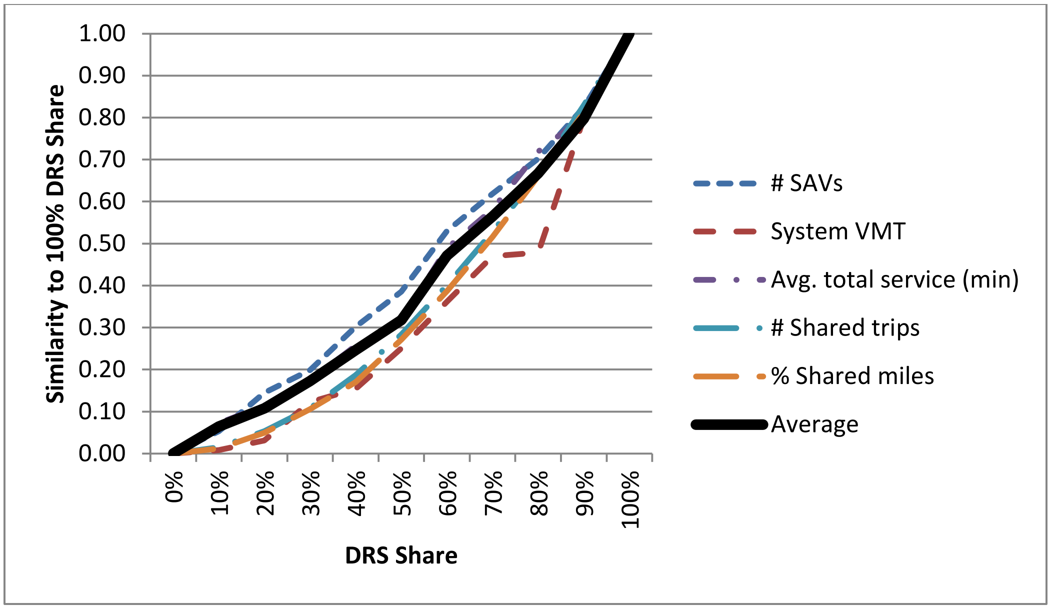


Figure 3-8: Proximity Values of Key Metrics, Relative to the 100% DRS Scenario

These results show how the relationship between the mixed-DRS/non-DRS traveler shares with the 0% and 100% and populations is non-linear; instead, it exhibits a near-quadratic form, varying somewhat based on the metric evaluated, and containing a degree of noise from one scenario run to the next. This result is reasonably intuitive since, in order to secure a match, both the new traveler and the current passenger must be willing to share a ride. Therefore, as the total number of willing-to-ride-share travelers grows, the effects of ride-sharing grow exponentially.

3.4.3.5 Increasing Travel Demand

The final scenario variations tested the impact of scaling the fleet to serve a higher or growing demand. Assuming that SAV services prove successful in one or more cities and regions, it is likely that demand for SAV services will grow in those settings, along with fleet sizes. This is particularly important to understand, because with just 1.3% of trips served, less than 5% of all served travel (in terms of VMT) has more than one person in the traveling party. As suggested by the DRS and non-DRS traveler model scenarios described earlier, increasing the total number and density of persons willing to share a ride may have a non-linear relationship. Thus, with increasing trip density, it should be possible to share more trips, reduce overall VMT, and reduce the share of empty VMT.

To these ends, the total base travel demand was grown by factors of 2 and 5[29], to represent approximately 2.47% and 6.01% of total regional trips, or 4.6% and 11.1% of all trips internal to the 12 mile x 24 mile geofence. The conventional vehicle replacement rate per SAVs was held constant at 10:1, in order to determine travel implications outside of disparate relative fleet sizing, with scenario outcomes shown in Table 3-3.

% Trips Served within Geofence	**2.3%**	**4.6%**	**11.1%**
# SAVs in fleet	1,846	3,640	9,037
# shared rides per day	5,755	12,933	35,053
% of shared VMT	4.5%	5.3%	5.9%
% added travel	4.9%	1.8%	-0.2%
Average service time per person-trip (min.)	14.47	14.09	13.93
% travelers waiting ≥ 10 min.	0.77%	0.09%	0.02%

Table 3-3: SAV Operational Metrics When Serving Larger Trip Shares

These results are consistent with those shown in Part 2 of this dissertation and with the mixed DRS/non-DRS share scenarios noted earlier. With increased market share, conventional vehicle replacement should improve, as well as wait times and total service times. Moreover, a higher share of the served population will find ride-sharing matches, resulting in greater VMT reductions (as compared to a non-SAV fleet), even

[29] The base number of trips drawn from the regional population was increased by factors of 2 and 5, but the total number of trips with origins and destinations within the geofence did not change by exactly these same factors, due to random variations in the trip samples drawn for each scenario.

after accounting for unoccupied- (empty-) vehicle relocations. With an even greater served market share or more flexible ride-sharing travelers, it should be possible to reduce total fleet VMT even further below that evident in today's conventionally-owned vehicle systems. Readers should also be aware that the reason for not testing greater shares of travelers was due to lack of computer memory in handling large quantities of travelers and vehicles. Future work may attempt to address this by storing and retrieving some data elements to disk space via output files, rather than in active memory.

3.4.4 Optimal SAV Fleet Sizing

While the framework noted above is useful in anticipating SAV impacts, a key component for refinement is fleet sizing. As shown in Part 2 of this dissertation, SAV fleet size has direct implications for SAV replacement of conventional vehicles, as well as induced travel, cold-start emissions, and life-cycle environmental impacts. Moreover, operators will wish to size their fleets appropriately, in order to stay cost competitive while offering users a relatively high level of service.

With this motivation in mind, a new framework was developed to determine an optimal fleet size. Here, it is assumed that operating costs are \$70,000 per SAV (representing \$50,000 costs for AV technology and another \$20,000 for vehicle costs[30]. An additional \$0.50 per mile for operating costs are also assumed here (AAA 2012). Per-SAV capital costs were annualized using the formula:

$$A = \frac{P \cdot i}{1-(1+i)^{-N}} \tag{3-3}$$

where A is the annualized SAV capital cost, P is the SAV purchase price, N is the expected number of service years, and i is the discount rate (Newnan and Lavelle 1998).

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[30] Boesler (2012) notes the U.S.'s top 27 selling vehicles sold for between \$16,000 and \$27,000. Since SAVs are assumed here to be relatively compact cars or mid-size cars, so a \$20,000 base price assumption for the conventional vehicle was made here.

SAVs are assumed to have a service life of 250,000 miles, which is consistent with the expected 7-year service life of Toronto, Canada taxis (which travel over 248,000 miles [400,000 km] in the average lifetime, according Stevens and Marams [2009]), though it is possible that SAVs may be serviceable longer, thanks to smoother automated driving.

Wait times were assessed a penalty, at 70% of the average wage rate (Litman 2013b), which is just over $23 per hour for the Austin area, as of May 2013 (BLS 2014). This implies that for every minute each traveler spends waiting, a 38.4 cent cost is incurred (by the traveler directly, and by the SAV provider indirectly, as assumed here). While these wait penalties do not directly reflect discounted fares that fleet operators may offer to travelers (unless, perhaps, the wait is truly excessive), wait time is implicitly linked to demand. That is, with lower wait times, more travelers may opt to use SAVs, thus strengthening overall demand; conversely, if wait times are often long, demand and willingness to pay for SAV use may diminish. Therefore, for this analysis, fleet sizing was conducted as if wait costs are real to/felt by the fleet provider, though they are removed when reporting the final return on investment (once the fleet size is determined).

TaxiFareFinder.com estimates Austin taxi travel to cost approximately $2.65 per trip, as a flat or fixed fee, plus another $2.70 per mile, and then a 15% tip on top of those base costs. Assuming an average person- trip distance of 5.64 miles (from the SAV-served trips desired of the population here, internal to the geofence), this works out to an average of $17.57 for a one-way trip. Since SAVs may replace the taxi market with a more efficient and cost-effective system, an average cost (to the trip-maker) of just $1 per SAV trip mile, or $5.64 per-trip revenue to the operator, is assumed here.

To fully understand this framework, it is important to understand not just the average day, but the likely variation in travel demands, from day to day, across at least a year. To approximate the variability of a year, day-to-day variations in personal VMT from the 2009 U.S. National Household Travel Survey (NHTS) was obtained, for non-commercial trips less than or equal to 50 miles (FHWA 2009b), over the course of an entire year: from May 1, 2008 to April 30, 2009. Several key points should be noted regarding this data, for the cumulative national travel patterns, as well as travel data for the state of Texas and for the Dallas-Ft. Worth (DFW) metroplex, the region in Texas with the greatest number of NHTS trip observations. First, all three data sets (with samples sizes of 19 thousand, 107 thousand and 713 thousand persons – each logging all trips taken over a randomly assigned, single survey day, with no preference for weekdays, for example) exhibit an approximate lognormal distribution (of VMT per day), with standard deviations of 8.3%, 13.6% and 30.8% (across days of the year-long NHTS) for the U.S., Texas and (DFW) travel surveys, respectively.

Much of this variation may be attributed to the number of trips recorded per day: there were an average of 1953 person-trips per day in the U.S. data set, 294 per day in Texas, and 52 per day in DFW. Everything else constant, smaller sample sizes always come with greater random variation, within days, and across days. Moreover, the number of trip records per day was not evenly distributed (for example, there were no DFW trips recorded on April 30, 2009). Therefore, much of the extra DFW variation may come from sampling rate variations (and the fact that each day is a whole new set of respondents, rather than the same sample of people), rather than day-to-day (total) demand variations over the course of a year. While this phenomenon still exists for the Texas data set, the larger sample mitigates its impact. It should also be noted that while there will be household-to-household travel variation for the SAV-served fleet, the served travelers modeled here (at over 37,000 persons even on the lowest-demand day) will be much larger than the number of daily respondents, even from the national dataset. And

SAV members do not change from day to day, as the NHTS samples do, providing valuable stability in demand.

Even after accounting for the impacts of household-to-household variation, there should still be more variation in the local dataset than the statewide data set, which in turn should have more variation than the national data set. This is due to the fact that local events (like rainstorms, music and art festivals, and professional basketball or university football games) impact local travel, but tend to offset one another's timing statewide. They thus have a smaller impact statewide, and a potentially negligible impact nationally. For example, a thunderstorm or carnival may impact travel in and around the DFW region, which would be reflected somewhat in the statewide data. However, the impacts nationally would be quite minimal, since the DFW population is only around 2% of the U.S. total.

Another factor at play is variation in trip origins, travel distances, vehicle occupancies, and other behaviors, from day to day. While this dissertation's simulated trip-making strives to reflect day-to-day variations in total travel distances (by using the NHTS variations in this key variable), it does not account for day-to-day trends in other facets of choice, which may affect fleet operations (e.g., if all Sunday person-trips are made with travel partners [as high-occupancy vehicles, for example], rather than solo, SAV demands may fall more than modeled here). This is largely due to the difficulty of estimating the corresponding changes that would be required from the underlying trip tables. (Similarly, most regions around the world simulate/model simply an average weekday, to anticipate future link flows and congestion levels.)

The statewide (Texas NHTS) data set was ultimately chosen as the set of trip demands that probably best represents the variation one can expect in sizing an SAV fleet for central Austin. The reason for this is that the DFW-only NHTS sample was too small (and thus too variable, especially day to day) to represent the day-to-day variability in *total* demand by tens of thousands of SAV users, even if some travel variations across Texas offset one another from region to region. (For example, relatively low demand during a Saturday storm in Houston can partly offset relatively high demand accompanying a football game in Dallas-Ft. Worth on that same day.)

Of course, 294 (different) survey respondents per NHTS survey day, on average, across the state of Texas, also sounds low, versus the over-56,000 (relatively stable) travelers served per (average) day in these simulations; so actual day-to-day demand variations in Austin may be much more moderate than seen in the (rotating) Texas sample. In order to check the reasonableness of this approach of anticipating SAV fleet demand variability, day-to-day traffic-count data, collected using Automatic Traffic Recorders (ATRs) by the State of Utah, were examined here, as an estimate of regional VMT variations. 15 ATR locations were evaluated for a set of urban principal and minor artierals in Salt Lake City, Utah (UDOT 2014), and each site's AADT values were sorted by month and day of week (resulting in a set of 84 [7 days/week x 12 months/year] distinct days). Among these 84 example days, the maximum increase in a year's worth of Salt Lake City AADT counts or VMT estimates was 18% above the average (AADT) values (for Fridays in March), and the lowest was 32% below (on Sundays in November). While these AADT variations are more moderate than the extreme variations found in the NHTS Texas responses[31], they provide a valuable check on reasonableness. The average increases in household travel from the NHTS data for the top 5% of days in the survey

[31] Extreme variations noted here from the NHTS dataset were identified as individual days, then averaged across the top or bottom 5% (18 days), while variations from the Utah ATR data were aggregated by day and month, comprising just four or five days, but not necessarily all of which are in the top or bottom 5% for the most extreme month-day-of-week combinations. The highest single travel days show a 40% increase for the Texas household dataset and a 23% increase for the Utah ATR dataset, while both datasets show a 42% decrease for the lowest travel day. Additionally, ATR data also includes commercial truck travel, which would not be served by SAVs

year are 76% in the DFW region alone, 28% looking across the State of Texas, and 14% across the entire U.S., while the average decreases for the bottom 5% of days are -72%, -33% and -23% in those same regions, respectively. In comparing ATR travel variations to those in the NHTS, it seems that the within-Texas variation is reasonable, while DFW's day-to-day variations are too extreme to represent a single region's actual demand variations. Nevertheless, as one moves to smaller and smaller regions (e.g., the demand of a single neighborhood), demand variation (from survey day to survey day) is expected to rise and could at some point reach that evident in the n=294-per-day DFW households.

NHTS travel data from the state of Texas were used to estimate seven distinctive demand days, with the total number of trips scaled up or down to reflect overall variations in expected VMT. From this data, seven types of days were created. Two of these 7 days are designed to reflect the 18 highest- and 18 lowest-demand days, to represent the top and bottom 5 percentiles among demand days for SAVs in the region. The five other days are designed to reflect the five inner quintiles for the rest of the year; thus, each of those exhibits the mean/average demand (in terms of VMT) for each ordered band of 66 days each (with 65 days in the middle quintile). Figure 3-9 shows how these 7 representative days compare to the cumulative distribution of the 365 days data available in the 2009 NHTS data for Texas. As evident in the figure, the low days range from 67% of the average VMT demanded in the region, to 128%, while the lowest to highest VMT day in the data set actually ranged from 58% to 140%. In other words, from a typical low-demand day to the typical high-demand day simulated here, VMT via SAVs almost doubles, while the true extremes in VMT differ by 140% . These values reflect substantial demand variation over the course of a typical year, but probably less than that for many other services and products (e.g., hotel rooms and ice cream cones).

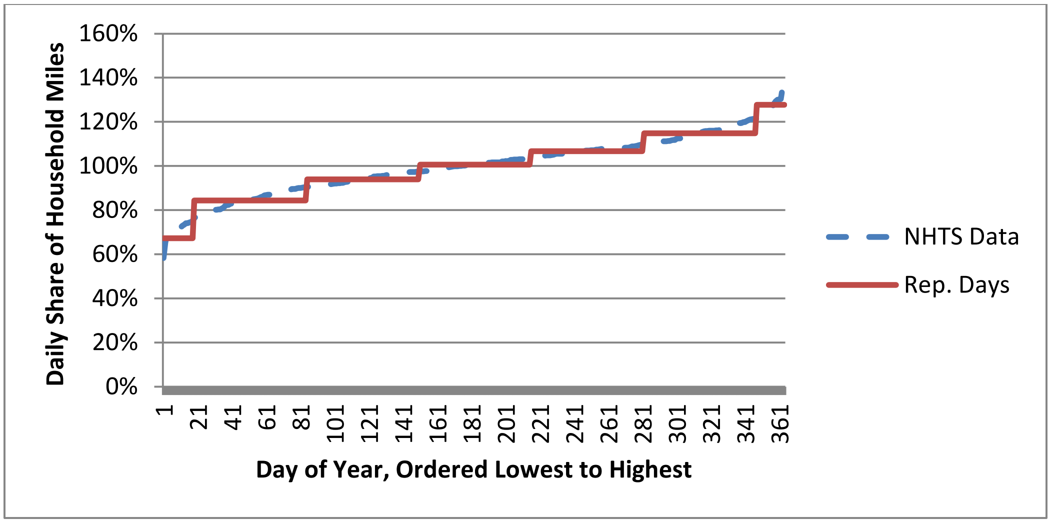

Figure 3-9: Daily Household Travel in Texas, as a Share of Daily Average

While these 7 representative days do not directly model the true worst-case and best-case demand levels presumably evident several days a year, the impacts of reduced service (due to under-supply of SAVs) or over-supply of SAVs on these days may be mitigated in multiple ways. For example, if a special event is expected locally, the fleet operator may shift SAVs from one region to another (for example from over-supplied Houston to under-supplied Austin, Texas during Austin's South-by-Southwest [SXSW] music festival). Such events may be correlated with other travel complications for any vehicle, like limited parking, increasing the relative attractiveness of SAVs, even though traveler wait times will be higher. For extreme events there is presumably a higher degree of customer/traveler acceptance of longer wait times. For example, just like people generally expect and accept that traffic will be bad around a stadium in the hour following a football game, people should have greater tolerances for longer waits if the reason is apparent. Payment rebates for excessive delays can also offset traveler disappointment, along with higher prices when high demand is expected, to ensure adequate supply (by promoting other modes [like bus and bike] along with SAV ride-sharing). Lower prices during times of over-supply (low demand) can also be used, to help make the most of the operator's fleet investment.

With this framework, a series of simulations were run with varying fleet sizes, using a Golden Section Search optimization procedure (Shao and Chang 2008). The Golden Section Search methodology assumes functional concavity (i.e., monotonically increasing until the maximum is reached, and then monotonically decreasing for the remainder of the interval) and works as follows:

1. Boundary conditions for SAV fleet size (x_1, x_2) are first established (here x_1 = 1500 and x_2= 2200 SAVs) and evaluated to determine the expected profits ($f(x_1)$, $f(x_2)$) of each.
2. Two points are chosen (x_3, x_4) between these two extreme/boundary values and evaluated ($f(x_3)$, $f(x_4)$). To proceed, at least one of these new $f(x_i)$ values must be greater than both $f(x_1)$ and $f(x_2)$.
3. If f(x3) > f(x4), the fleet size corresponding to the maximum profit must lie on the interval between (x1, x4), so (x1, x4) is established as the new boundary, with known value f(x3) falling within this interval. Otherwise, if f(x4) > f(x3), the new interval will be (x3, x2), with value f(x4) lying inside.
4. A new fleet size value (x5) between the new boundary conditions is chosen, and evaluated f(x5); and the process continues until an optimal fleet size is identified within ±5 SAVs.

This process may be best understood by examining Figure 3-10.

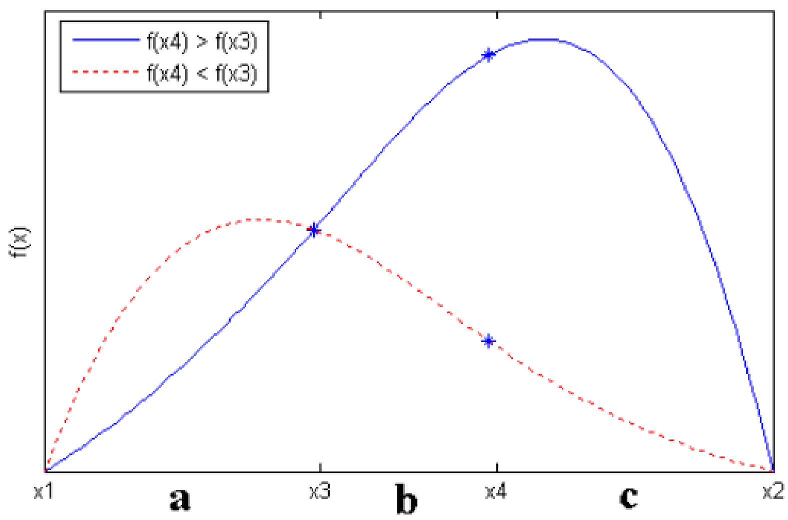

Figure 3-10: Golden Section Search Method Example (Shao and Chang 2008)

Figure 3-10 shows two potential profit profiles, one where f(x3)>f(x4) and the other where f(x4)>f(x3). Assuming that the underlying profit function with respect to fleet size is convex, so that at least one of the two intermediate *x* values for profit, f(x3) and f(x4), lies above both f(x1) and f(x2), the interval must lie between x1 and x2. Moreover, if f(x3)>f(x4), the new interval must lie between x1 and x4; while, if f(x4) > f(x3), the new interval must lie between x3 and x2.

The method used to select intermediate points x3 and x4, as well as subsequent points x5, x6, etc., is conducted by using the Golden Ratio such that:

$$\frac{a}{b} = \frac{c}{b} = \frac{b+c}{a} = \varphi = \frac{1+\sqrt{5}}{2} = 1.6180398 \quad (3\text{-}4)$$

This ensures that with each subsequent search algorithm iteration, only one additional fleet size will be needed for profit evaluation before adjusting the search interval boundaries, all while maintaining a constant ratio for the internal evaluation points (i.e., the Golden Ratio).

Based on application of this method, an optimal fleet size of 2118 SAVs was estimated, equivalent to a 8.7 conventional vehicles per 1 SAV replacement rate, and serving, on average, 26.6 internal person-trips per day in this 12 mi x 24 mi section of Austin. A secondary application was also tested with operating costs cut in half, to $0.25 per mile (to reflect possible reductions in fuel usage and reduced vehicle wear due to smoother operation). This dramatically boosted profits, and resulted in a much smaller fleet size, of just 1704 SAVs, equivalent to a 10.8 household vehicle replacement. Figure 3-11 shows how total (expected) annual return on investment for an SAV fleet operator varies with fleet size in these two scenarios, before removing traveler wait costs (since the operator likely will not pay these directly).

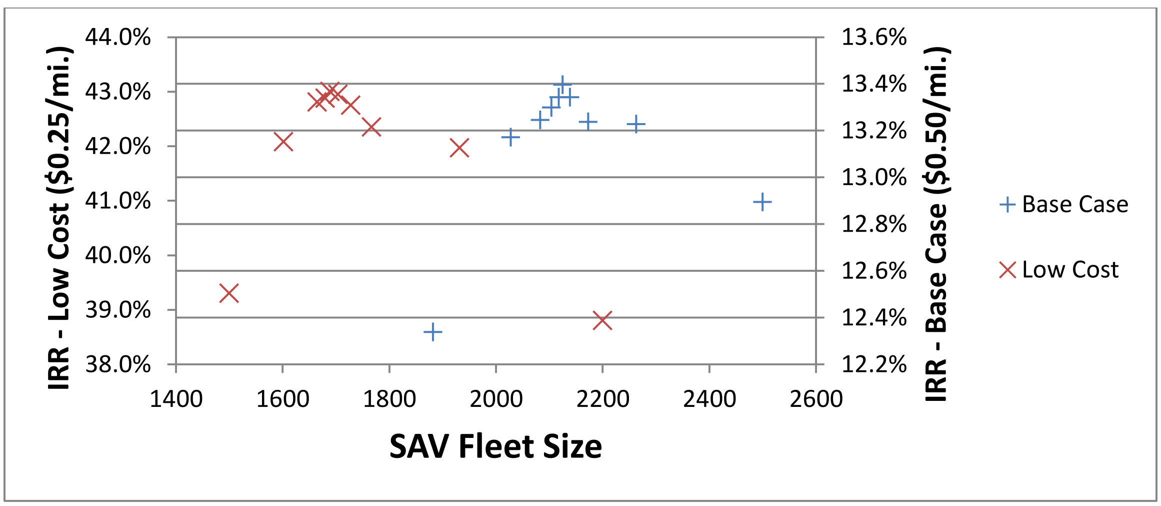

Figure 3-11: Estimated Annual Internal Rates of Return (Including Wait Costs) across Variable SAV Fleet Sizes

It is also informative to note that total return on investment remained relatively stable over this process, lying between 12.3% and 13.4% in the base case ($0.50/mi.)

scenario across almost all fleet sizes[32], and between 38.8% and 43.0% in the low-cost ($0.25/mi.) scenario, even with substantial 33% and 47% variations in fleet size, respectively. Table 3-4 shows component costs for the two evaluated boundary fleet values for the base case scenario and the optimal 2118 SAV fleet size, to further illuminate fleet sizing implications.

Fleet Size	Mileage costs	Capital Costs (at 7%)	Wait Costs	Revenue	Profit per Trip (w/ wait costs)	Profit per Trip (no wait costs)
1882	$3.001	$1.979	$0.421	$5.640	$0.240	$0.661
2118	$2.995	$2.007	$0.320	$5.640	$0.319	$0.639
2500	$2.988	$2.054	$0.252	$5.640	$0.346	$0.598

Table 3-4: Per-Trip SAV Costs, Revenues and Profits

From these results, it appears that all fleet size scenarios result in similar outcomes due to very similar per-trip mileage, high annual mileage (resulting in a high retirement/turnover rate of vehicles), and relatively low wait times. Since differences in mileage costs across fleet size values are approximately zero, the tradeoff becomes capital costs versus wait costs. As the IRR grows larger, the disparity between capital costs in the various scenarios grows; so a smaller fleet is preferred for the low-cost scenario, while a larger fleet is best for the base-case scenario. If wait time costs are removed from the equation to reflect actual costs to be paid by the operator, return on investment for an optimal fleet size reaches 13.4%, and rises to 19.4% once wait costs are removed. As noted earlier, while smaller fleet sizes would theoretically increase profits further, they may also result in lower demand levels, so an optimal fleet size of 2118 SAVs is recommended here, for the base-case conditions.

[32] Wait costs were excessive with just 1500 SAVs, eliminating almost all profit in the base-case scenario.

Of course, many factors may change these results, as shown in the alternative scenario with lower operating costs. Since mileage costs do not change substantially with fleet size, smaller optimal fleet sizes may likely be achieved by increasing fares, assuming constant demand. As such, neither the 8.7 nor the 10.7 replacement rate should be taken as a fixed optimal value. Rather, operators should understand that an optimal SAV-conventional household vehicle replacement rate in this type of context should be around 10-to-1, and a methodology like the one used here may be employed to determine specific fleet sizes, given a proper understanding of the underlying context. In addition to changing demand and fares, these contexts may vary by potentially limiting SAV speeds, expanding the geofence into low trip intensity areas, or widening the service area in general, which would result in longer averge trips. In summary, these results suggest that sizing the SAV fleet for an average day works relatively well for the rest of the year, and profits are quite possible, even when accounting for variations between high-demand and low-demand days and higher per-SAV purchase costs.

Chapter 3.5: Part 3 Concluding Remarks

These Austin-based simulation results suggest that a fleet of SAVs could serve many if not all intra-urban trips with replacement rates of around 1 SAV per 9.3 conventional vehicles. However, in the process SAVs may generate around 8.1% new unoccupied/empty-vehicle travel that would not exist if travelers were driving their own vehicles. With dynamic ride-sharing active (and allowing for up to 30% extra total service time) a replacement rate of 1 SAV per 10.8 conventional vehicles and just 4.6% empty-vehicle VMT may be achieved, with 4.8% of all served VMT shared (by distinct or independent traveling parties). Prior, Part 2 results indicated that, as demand intensity (over space) for SAV travel increases, the number of conventional vehicles that each

SAV can replace grows, wait times fall, and unoccupied/empty-vehicle travel distances fall, which is confirmed here in the higher shared-trip scenarios. All this points to a higher cost per SAV in the early stages of deployment (in terms of new VMT), though such costs should fall in the long term, as larger SAV fleet sizes lead to greater efficiency.

Moreover, these results have substantial implications for parking and emissions. For example, if an SAV fleet is sized to replace 10.0 conventional vehicles for every SAV, total parking demand will fall by around 9 vehicle spaces per SAV (or possibly more, since the vehicles are largely in use during the daytime). These spaces would free up parking supply for privately held vehicles or other land uses. In this way, the land and costs of parking provision could shift to better uses, like parks and retail establishments, offices, wider sidewalks, bus parking, and bike lanes.

With regards to vehicle emissions and air quality, many benefits may exist, even in the face of 4.6 percent higher VMTs, as was demonstrated both here and in Part 2 of this dissertation. For example, SAVs may be purpose-built as a fleet of passenger cars, replacing many current, heavier vehicles with higher emissions rates (like pickup trucks, SUVs and passenger vans). SAVs will also be traveling much more frequently throughout the day than conventional vehicles (averaging 30 trips per day rather than 3, and in use 8 hours each day, rather than 1 hour), so they will have many fewer cold starts than the vehicles they are replacing. Cold-start emissions are much higher than after a vehicle's catalytic converter has warmed up, and these results suggest 85% fewer cold starts (defined as rest periods greater than 1 hour), when replacing conventional, privately held vehicles with SAVs.

This SAV framework also presents opportunities that may be quite profitable for future operators. The work conducted here demonstrates current taxi fare rates may fall to less than half their current levels while delivering sizable returns on investment of 19% or more, assuming $70,000 purchase costs per SAV. These favorable rates and returns fall even further as technology progresses and vehicle manufacturning costs fall, in turn sparking even greater demand. Of course, if service is truly fast and cheap but not enough rides are shared, it is possible that this system could attract many former non-motorized and transit trips, resulting in excess VMT and worsened congestion, an outcome to be avoided from a public policy perspective.

Finally, SAVs hold great promise for harnessing vehicle automation technology, offering higher utilization rates and faster fleet turnover. By using SAVs intensely (estimated here to be 194 miles per SAV per day, or 70,640 miles per year [or 174 miles and 63,335 miles, respectively, without DRS]), they will presumably wear out and need replacement every three to five years. Since vehicle automation technology is evolving rapidly, this cycling will allow fleet operators to consistently provide SAVs with the latest sensors, actuation controls, and other automation hardware, which tend to be much more difficult to provide than simple SAV system firmware and software updates.

CONCLUSIONS AND FUTURE WORK

Increasing degrees of vehicle automation will ultimately introduce profound impacts across transportation systems. New benefits will hopefully emerge in terms of safety, congestion, parking, and pollutant emissions, though the transport system may experience congestion costs from added vehicle-miles traveled (VMT). While we do not know when fully automated vehicles (AVs) will be able to operate without any driver or occupant on board, once this threshold is breached it will enable the introduction of new transportation modes, such as shared automated vehicle (SAV) systems, which is the focus of this dissertation work.

This dissertation spans many topic areas: from public policy and technology evaluation, to demand modeling and fleet-level simulations. Arguably the most substantial methodological contributions stemming from this effort are the algorithms for unoccupied SAV relocations (as discussed in Parts 2 and 3) and DRS choices (discussed in Part 3 of this dissertation). The work develops, designs, implements and tests novel frameworks for provision of efficient and cost-effective fleet utilization to serve tens and hundreds of thousands of travelers each day, in a complex, actual network setting. The SAV relocation efforts (while vehicles are unoccupied, and awaiting new calls for their services) tested a range of strategies, first in an abstracted grid-based setting, and later using Austin's detailed transportation network for the most effective strategy. These relocation strategies varied in their perspective (e.g., anticipated supply-demand balances in quarter-mile vs. one-mile and two-mile zone systems), and sought to simultaneously moderate unoccupied SAV travel and traveler wait times. The DRS formulation was also implemented and tested in Austin's network setting, with a related objective of minimizing vehicle-miles traveled (by pooling two or more persons in the same vehicle) and total travel service times (wait time plus in-vehicle travel times). These detailed vehicle relocation and DRS strategies represent substantial contributions to the field, and may influence coming research as well as actual service roll-outs.

The results of this work suggest that fully automated vehicles may deliver $35-$40 billion in annual economic benefits, via safety, mobility and parking improvements, with just 10% market penetration, and nearly $450 billion once the 90% market penetration level is reached. Additionally, the number of American lives saved each year could climb from over 1,000 lives at the 10% adoption-rate level, rising to almost 22,000 as 90% market penetration is reached. AVs may also be quite attractive to consumers, once costs come down. Though current added costs, estimated to be around $100,000 per vehicle, make them unaffordable for most people, if such automation costs come down to $37,500 per vehicle, in near-term commercial introduction, a person who will save $5 per day in parking and $10 per hour in perceived travel time benefits will realize a 12% return on investment, after accounting for likely fuel and insurance savings. If technology costs fall further, to $10,000 per vehicle via mass production, someone with just a $1 per hour value of time benefits and no parking cost savings could realize an 8% return. While much uncertainty exists regarding the precision of these estimates, such values provide meaningful order-of-magnitude estimates for future analysis. Of course, realizing these potential benefits requires more than just technological advances and costs: other significant barriers to a successful rollout include crash liability, program security, and user privacy.

This dissertation also provides a detailed examination of SAVs' potential demand implications, signaling a potential revolution in personal transport. Each SAV may be able to replace around 10 privately owned (household) vehicles, and free up land that was previously used as parking space. SAVs have advantages over conventionally shared vehicles in that they are able to relocate, unoccupied, in order to better match the available supply of free SAVs with existing and anticipated trip demands. These simulation results suggest that focusing on a global system-wide perspective for unoccupied vehicle relocation is much more effective than merely looking at localized SAV placement within a small area. Similarly, SAVs are probably preferred over conventional (human-driven) taxis, since their costs can be much lower, even with a relatively high cost of $70,000 per SAV ($1 per mile SAV versus $3.75 per mile taxi).

SAVs may also be used to service transit stations and corridors for high-speed or commuter rail travel, as well as air travel, providing an effective and efficient solution to the first-mile/last-mile problem. They may bring safe, efficient and affordable transport to the elderly, the disabled, the young, and those too impaired to drive. As this investigation has shown, life-cycle emissions impacts may also be beneficial in terms of energy use (and energy security); greenhouse gases (and climate change); and emissions of SO_2, CO, NOx, VOC and particulate matter, particularly if smaller, “right-sized” SAVs (and electric SAVs) are used.

While this investigation shows that SAVs may generate new VMT (when traveling to pick up and drop off passengers), other factors may stem or even eliminate this phenomenon. First, SAVs may greatly facilitate dynamic (real-time) ride-sharing, as noted in Part 3 of this investigation. Information systems may pool smartphone-using travelers with nearby or en-route origins and destinations, and overlapping trip times. While this may have limited effect at lower levels of market penetration (since matches are scarce in such settings), impacts could be quite sizable as trip densities rise, even resulting in less total VMT than with persons using conventionally-owned household vehicles (which have an average occupancy well under 2.0 persons per vehicle-mile and per vehicle-trip).

Second, SAVs will likely be rented by the mile or the minute, and the cost of the vehicle will be embedded in the rental price, rather than paid for up-front. As a result, the marginal cost per each additional mile traveled will be higher for a shared vehicle, than a household-owned vehicle, which may result in lower household VMTs.

Ultimately, VMT impacts, conventional vehicle replacement ratios, emissions, and many other outcomes depend heavily on implementation details. Market penetration, relocation strategies, dynamic ride-sharing methods, trip pricing, geofence service areas, and SAV occupancy sizing will likely be key drivers in determining these outcomes. This work provides a series of case study applications, simulation techniques, and evaluation methodss to anticipate and appreciate the potential impacts of AV adoption, SAV applications, and DRS opportunities – and relative influence of key variables in such systems. The methods used and scenario outcomes discussed provide guideposts for both innovators (who seek to implement a large-scale SAV fleet), as well as transportation planners and policy makers (who must plan for their arrival).

While this dissertation work assesses possible SAV implications in great detail, much future work remains in the SAV arena. First, this work assumes that travel patterns mirror those found in the Austin region as a whole, an assumption that likely will not hold. In reality, certain classes of persons are likely to be over-represented and others under-represented. For example, those too young to drive, young drivers with limited car access, the elderly, the disabled, alcohol-impaired persons, singles, car-less households, persons flying in from out of town, and those located near the city center may all be more likely to use SAVs while families with young children, those near the outer edge of the geofence, and households with many vehicles and able-bodied drivers may be less likely to use SAVs. All this could result in trip intensities with even greater activity nearer to the city center, the airport, retirement homes, and during the evening hours when persons are returning from bars. Nevertheless, while such improvements will be beneficial, the work conducted here provides a strong perspective on potential outcomes.

Alternative DRS frameworks could also be implemented, by placing a greater premium on ridesharing, perhaps by allowing greater flexibility in departure times, rather than focusing on reduced wait times, as done here. These types of systems have been evaluated by others, and may greatly reduce system-wide VMT, though some inconvenience cost would be experienced by some travelers. One potential solution is to implement a three-tier system, where travelers can opt for a flexible (DRS) departure-time window, a fixed (DRS) departure time (as assumed here), or forego using DRS altogether.

Other work could seek to develop a better SAV assignment methodology (e.g., MacAlpine et al.'s [2014] bi-partite matching scheme that utilizes a more system-optimal perspective, vs. making SAV assignments to the closest travelers, as modeled now); refine application of Part 3's empty-SAV relocation methods (and incorporate some of those described in Part 2 to Part 3's network setting); model an entire regional network and even inter-city (long-distance) travel demands (versus a somewhat limited geofenced area); more closely evaluate benefits and costs to private individuals and the public at large (in terms of more closely applying Part 1's findings towards the SAV framework in Parts 2 and 3); model electric (plug-in) SAVs in terms of charging station locations and charing-time requirements; evaluate low-speed SAV implications for nearer-term applications; and explore the potential synergies for SAVs as they become increasingly connected to travelers, infrastructure and other vehicles.

While the future remains uncertain, these results indicate that fully automated vehicles are likely to bring substantial benefits to the traveling public, along with many potential environmental benefits, especially via SAV and DRS-enabled systems. Each

SAV has the potential to replace many conventional vehicles, freeing up parking and leading to more efficient household personal vehicle ownership choices. Though extra VMT stemming from unoccupied travel is a potential downside, vehicle fleet changes, a reduction in cold-start emissions, and dynamic ride-sharing may be able to counteract these negative impacts and lead to net beneficial environmental outcomes, all at an affordable price. With appropriate policymaking and thoughtful enterprise, people around the world should be able to shed under-utilized cars and light trucks, avoid parking and maintenance hassles, and engage in more active travel, while meeting travel needs at lower overall cost. That is the hope. It is up to all of us to make it a reality.

Appendix: Sample Network-Based Code

The C++ program code required to run Parts 2 and 3 of this dissertation are quite lengthy, each with over 6000 lines of code. To give readers a sense of the coding implementation, all function headers from Part 3's network-based model are included here, in the Appendix, as along with several key functions. Please note that some debugging comments have been removed from the function bodies.

Function Headers:

```
// init & re-init functions
void generateNewSAVs(int& nSAVs, sav savList[savListSize], node nodeList[nodeSize]);
void initVars (int& numNodes, int& numLinks, int nTrips[numTOD], int& nSAVs,
       double& xMax, double& yMax, double& xMin, double& yMin, time_t& startTime,
       double mphBins[nMphBins], int& ridesShared, double occMiles[maxOccupancy + 1],
       double& cumMiles, double& totProfit, double& travServed,
       double waitBins[nWaitBins], double trpWtBins[nWaitBins],
       double dayShares[nEvalDays], int& evalDay);
void reInitVars (trip tripMx[numTOD][tMxSize], int nTrips[numTOD], sav
       savList[savListSize], int& nSAVs, node nodeList[nodeSize],
       double mphBins[nMphBins], int& ridesShared, double occMiles[maxOccupancy + 1]);

// read network & trips functions
void addressNodeLinks(link linkList[linkSize], link revLinkList[linkSize], int numLinks,
       node nodeList[nodeSize], int numNodes);
void copyLinkList (link linkList[linkSize], link revLinkList[linkSize], int numLinks);
double findNearestNode (double x, double y, node nodeList[nodeSize], int numNodes, double
       xMax, double yMax, double xMin, double yMin, double& nDist);
int findNodeID (int nid, node nodeList[nodeSize], int numNodes);
void partitionLinks (link* linkList, int first, int last, int& pivotIndex);
void partitionLinksTo (link* revLinkList, int first, int last, int& pivotIndex);
void partitionNodes (node* nodeList, int fist, int last, int& pivotIndex);
void readNetwork (node nodeList[nodeSize], link linkList[linkSize], link
revLinkList[linkSize], int& numNodes, int& numLinks, double& xMax, double& yMax,
       double& xMin, double& yMin);
void readNodes (FILE* netFile, node nodeList[nodeSize], int& numNodes, double& xMax,
       double& yMax, double& xMin, double& yMin);
void readLinks (FILE* netFile, link linkList[linkSize], link revLinkList[linkSize],
       int& numLinks, node nodeList[nodeSize], int numNodes);
void readLinkTTs (link linkList[linkSize], int numLinks);
void readTrips (trip tripMx[numTOD][tMxSize], int nTrips[numTOD],
       node nodeList[nodeSize], int numNodes, double xMax, double yMax, double xMin,
       double yMin);
void readTrips2 (trip tripMx[numTOD][tMxSize], int nTrips[numTOD], node
       nodeList[nodeSize], int numNodes, double xMax, double yMax, double xMin,
       double yMin, int tripDay, int tripMo);
void sortLinksFrom (link linkList[linkSize], int first, int last);
void sortLinksTo (link revLinkList[linkSize], int first, int last);
void sortNodes (node* nodeList, int numNodes);
void sortNodesID (node* nodeList, int first, int last);
void swapLink (link& firstLink, link& secondLink);
void swapNode (node& firstNode, node& secondNode);

// run SAV basic functions
void addSAVtoNode (node nodeList[nodeSize], int oNode, int savID);
void assignSAV (trip& thisTrip, sav savList[savListSize], int savNum, double travTime,
node nodeList[nodeSize], int numNodes, link linkList[linkSize], int numLinks, int tNum,
```

```
        int departT, int currT);
void buildPath (int origin, int dest, sav& thisSAV, int backLink[nodeSize],
        link linkList[linkSize]);
void decArrTimes (sav savList[savListSize], int s, double decTime);
void dropOff (sav savList[savListSize], int SAVnum, trip tripMx[numTOD][tMxSize],
        int currT, double currLT, ofstream& fout, node nodeList[nodeSize]);
bool findCar (node nodeList[nodeSize], link linkList[linkSize], link
revLinkList[linkSize], int numNodes, int numLinks, trip& thisTrip,
        sav savList[savListSize], trip tripMx[numTOD][tMxSize], double maxTime, int tNum,
        int departT, int currT, int& savFree, int& ridesShared, double maxDRSTime);
void genNewCar (trip& thisTrip, node nodeList[nodeSize], int numNodes,
        link linkList[linkSize], int numLinks, sav savList[savListSize], int& nSAVs,
        int tNum, int departT, int currT);
void getFirstNode (sav& thisSAV, link linkList[linkSize], double mphBins[nMphBins],
        double occMiles[maxOccupancy + 1]);
void getMPH (double length, double ttime, double mphBins[nMphBins]);
void getNextNode (sav& thisSAV, link linkList[linkSize], node nodeList[nodeSize],
        int numNodes, int numLinks, double mphBins[nMphBins],
        double occMiles[maxOccupancy + 1]);
void loadNewTTs (int t, link linkList[linkSize], int numLinks);
int lookForSAVOnNode (int thisNode, node nodeList[nodeSize], sav savList[savListSize],
        double& distToNode);
void moveSAVs (sav savList[savListSize], int nSAVs, trip tripMx[numTOD][tMxSize],
        int nTrips[numTOD], node nodeList[nodeSize], int nNodes, link linkList[linkSize],
        int nLinks, int t, double mphBins[nMphBins], double occMiles[maxOccupancy + 1],
        ofstream& fout, int evalDay);
void moveSAVAmongNodes (int currNodeLoc, int newNodeLoc, node nodeList[nodeSize],
        int savNum);
void pickUp (sav savList[savListSize], int SAVnum, trip tripMx[numTOD][tMxSize],
        int currT, double currLT, ofstream& fout, node nodeList[nodeSize]);
void pickupAndDropoff (bool& pickingUp, bool& droppingOff, sav savList[savListSize],
        int s, int t, double& tDist, int numPsgs, bool& keepMoving,
        trip tripMx[numTOD][tMxSize], ofstream& fout, node nodeList[nodeSize]);
void placeNewSAV (sav savList[savListSize], sav newSAV, int& nSAVs);
bool recPathSearch (int dest, node nodeList[nodeSize], int numNodes,
        link linkList[linkSize], double backDist[nodeSize], int backLink[nodeSize],
        int currNodes[nodeSize], int& nCurrNodes, int reachNodes[nodeSize],
        int& nReachNodes, double maxDist, bool& foundSoln, int departT);
void recSAVSearch (node nodeList[nodeSize], link revLinkList[linkSize], int numNodes,
        trip& thisTrip, sav savList[savListSize], double maxTime, int currNodes[nodeSize],
         int& nCurrNodes, int reachNodes[nodeSize], int& nReachNodes,
        double backDist[nodeSize], double& travTime, int backLink[nodeSize],
        int& closeSAV, int currT, bool& foundDRS, bool& foundNonDRS,
        link linkList[linkSize], int numLinks, trip tripMx[numTOD][tMxSize], int tNum,
        int departT, int& ridesShared, double maxDRSTime, double& maxServeTime,
        bool& handOff, bool& handOffAssn, sav& tempSAV, int& drsCloseSAV);
void removeSAVfromNode (node nodeList[nodeSize], int targetNode, int savID);
void replanPath (sav& thisSAV, node nodeList[nodeSize], int numNodes,
        link linkList[linkSize], int numLinks, int savNum);
void runSAV (node nodeList[nodeSize], link linkList[linkSize],
        link revLinkList[linkSize], int numNodes, int numLinks,
        trip tripMx[numTOD][tMxSize], int nTrips[numTOD], sav savList[savListSize],
        int& nSAVs, bool coldStart, double zoneShares [lgNxZones][lgNyZones][nZoneTODs],
        int centNodes [lgNxZones][lgNyZones], double mphBins[nMphBins],
       int& ridesShared, double occMiles[maxOccupancy + 1], int evalDay);
void serveCurrTrips (node nodeList[nodeSize], link linkList[linkSize],
        link revLinkList[linkSize], int numNodes, int numLinks,
        trip tripMx[numTOD][tMxSize], int nTrips[numTOD], sav savList[savListSize],
        tripIndex waitList[waitListSize], int& numWaiting, int t, int& savFree,
        int& ridesShared);
void serveWaitTrips (node nodeList[nodeSize], link linkList[linkSize],
        link revLinkList[linkSize], int numNodes, int numLinks,
        trip tripMx[numTOD][tMxSize], sav savList[savListSize], int& nSAVs,
        tripIndex waitList[waitListSize], int& numWaiting, int currT, bool coldStart,
        int& savFree, int& ridesShared);
```

```
void setPath (int orig, int dest, sav& thisSAV, node nodeList[nodeSize], int numNodes,
link linkList[linkSize], int numLinks, double& pathDist, double maxDist, int departT,
        int savNum);
void updateBackDist (double backDist[nodeSize], double baseDist, int toNode,
        link linkList[linkSize], int reachNodes[nodeSize], int& nReachNodes, int linkN,
        int backLink[nodeSize], int departT);
void updateWaitStats (int waitMx[numTOD][12], int tm, int trps, int serveWait,
        int serveCurr, int beginWait, int midWait, int endWait, int nSAVs);
void updateWaitTimes (trip tripMx[numTOD][tMxSize], tripIndex waitList[waitListSize],
        int numWaiting);

// relocation functions
void assignPullDirs(double blockBalances[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones], int blockX, int blockY,
        int& north, int& south, int& east, int& west, double thresh,
        int centNodes[lgNxZones][lgNyZones]);
void assignPushDirs(double blockBalances[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones], int blockX, int blockY,
        int& north, int& south, int& east, int& west, double thresh,
        int centNodes[lgNxZones][lgNyZones]);
void createZoneShares(double zoneShares [lgNxZones][lgNyZones][nZoneTODs],
        int centNodes [lgNxZones][lgNyZones], trip tripMx[numTOD][tMxSize],
        int nTrips[numTOD], node nodeList[nodeSize], int numNodes, double xMax,
        double yMax, double xMin, double yMin);
bool findBestBlock(double blockBalances[lgNxZones][lgNyZones],
        bool examinedBlock[lgNxZones][lgNyZones], int& blockX, int& blockY,
        double minRelocThresh);
double findPull (int ox, int oy, int dx, int dy, sav savList[savListSize],
        node nodeList[nodeSize], int numNodes, link revLinkList[linkSize], int numLinks,
        int& savNum, int centNodes[lgNxZones][lgNyZones]);
void getBlockBalances(double targetZoneShares[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones],
        double blockBalances[lgNxZones][lgNyZones], int nFreeSAVs, double totExpTrips);
void getCurrSAVLocs(sav savList[savListSize], int nSAVs, node nodeList[nodeSize],
        double currSAVZoneShares[lgNxZones][lgNyZones], int& nFreeSAVs);
void getTargetZoneShares (double zoneShares[lgNxZones][lgNyZones][nZoneTODs],
        tripIndex waitList[waitListSize], int numWaiting, sav savList[savListSize],
        int nSAVs, trip tripMx[numTOD][tMxSize], node nodeList[nodeSize], int tm, double&
        totExpTrips, double targetZoneShares[lgNxZones][lgNyZones]);
void lookForSAVOnNodeBlocks (int thisNode, node nodeList[nodeSize],
        sav savList[savListSize], int ox, int oy, int& closeSAV);
void pullSAVs(double blockBalances[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones], int blockX, int blockY, int north,
        int south, int east, int west, sav savList[savListSize], node nodeList[nodeSize],
        int numNodes, link linkList[linkSize], link revLinkList[linkSize], int numLinks,
       int centNodes[lgNxZones][lgNyZones], int departT);
void printBlockStatus (double targetZoneShares[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones],
        double blockBalances[lgNxZones][lgNyZones]);
void pushSAVs(double blockBalances[lgNxZones][lgNyZones],
        double currSAVZoneShares[lgNxZones][lgNyZones], int blockX, int blockY, int north,
        int south, int east, int west, sav savList[savListSize], node nodeList[nodeSize],
        int numNodes, link linkList[linkSize], link revLinkList[linkSize], int numLinks,
        int centNodes[lgNxZones][lgNyZones], int departT);
void recSAVSearchBlocks (node nodeList[nodeSize], link revLinkList[linkSize],
        int numNodes, sav savList[savListSize], int currNodes[nodeSize], int& nCurrNodes,
        int reachNodes[nodeSize], int& nReachNodes, double backDist[nodeSize],
        int& closeSAV, double& closeSAVDist, int ox, int oy);
void relocSAVsZones (double zoneShares[lgNxZones][lgNyZones][nZoneTODs],
        int centNodes[lgNxZones][lgNyZones], tripIndex waitList[waitListSize],
        int numWaiting, sav savList[savListSize], int nSAVs, trip tripMx[numTOD][tMxSize],
        node nodeList[nodeSize], int numNodes, link linkList[linkSize],
        link revLinkList[linkSize], int numLinks, int tm);
void resetPushSAVs (int& targetNum, int& currN, int& currS, int& currE, int& currW,
        double& currDistN, double& currDistS, double& currDistE, double& currDistW);
void trimPath (sav& thisSAV, int blockX, int blockY, link linkList[linkSize],
```

```
        node nodeList[nodeSize]);
void updateBackDistBlocks (double backDist[nodeSize], double baseDist, int fromNode,
        double linkDist, int reachNodes[nodeSize], int& nReachNodes,
        node nodeList[nodeSize], int ox, int oy);

// dynamic rideshare functions
void assignDrsDropoffOnly (sav savList[savListSize], int savNum, trip& thisTrip,
        link linkList[linkSize], int numLinks, node nodeList[nodeSize], int numNodes,
        int numStops, int currT, int tNum, int departT);
void checkDRS (int currOrd[maxOccupancy * 2], sav savList[savListSize], int targetSAV,
        trip& thisTrip, link linkList[linkSize], int numLinks, node nodeList[nodeSize],
        int numNodes, double& bestTime, double& newTime, int numStops, int numDropoffs,
        int currTm, double currMaxTime, double maxSearchTime, double maxTotTime,
        double dblChk[10], double& currPUTime);
bool checkNodeDRS (trip& thisTrip, node nodeList[nodeSize], int numNodes,
        sav savList[savListSize], link linkList[linkSize], int numLinks,
        trip tripMx[numTOD][tMxSize], int thisNode, int currTm, int tNum, int departT,
        int& closeSAV, double maxSearchTime, double& maxServeTime, bool& handOff,
        sav& tempSAV, double maxTime, bool foundNonDRS);
bool checkDropoffOnly (sav savList[savListSize], int targetSAV, trip thisTrip,
        int bestOrd[maxOccupancy * 2], int doOrd[maxOccupancy], int& numStops);
bool checkValidOrd(int currOrd[maxOccupancy * 2], int numStops, sav savList[savListSize],
        int targetSAV, trip thisTrip, int numDropoffs, bool& handOff, bool foundNonDRS);
double getMaxCurrDoTime(sav savList[savListSize], int targetSAV, trip thisTrip,
        link linkList[linkSize], int numLinks, node nodeList[nodeSize], int numNodes,
        int currT, double& maxTotTime);
double getMaxPsgDoTime(int psgNum, sav savList[savListSize], int targetSAV, int currTm);
double getMaxTotTime(sav savList[savListSize], int targetSAV, double baseCurrTime);
int getNode(int currOrd[maxOccupancy * 2], int o, int targetSAV,
        sav savList[savListSize], trip& thisTrip, int numDropoffs);
void resortOrd(int currOrd[maxOccupancy * 2], int loI, int hiI);
void savePath(sav newSAV, int newPath[pathSize], int& pathCt);
void setDrs(int bestOrd[maxOccupancy * 2], int doOrd[maxOccupancy],
        sav savList[savListSize], int savNum, trip& thisTrip, link linkList[linkSize],
        int numLinks, node nodeList[nodeSize], int numNodes, int numStops, int currT,
        int tNum, int departT, double currMaxTime, double& maxServeTime, bool& handOff,
        sav& tempSAV, double dblChk[10], double currPUTime);
void setFirstOrder (int currOrd[maxOccupancy * 2], sav savList[savListSize],
        int targetSAV, trip& thisTrip, int& numStops, int& numTravs, double& currMaxTime,
        link linkList[linkSize], int numLinks, node nodeList[nodeSize], int numNodes,
        int currT, bool& finished, double& maxTotTime, double dblChk[10], bool& handOff,
        bool foundNonDRS);
void setNextOrder (int currOrd[maxOccupancy * 2], sav savList[savListSize],
        int targetSAV, trip& thisTrip, int numStops, int numDropoffs, bool& finished,
        bool& handOff, bool foundNonDRS);
void setDoNode (int bestOrd[maxOccupancy * 2], int doOrd[maxOccupancy * 2], int ordI,
        int& doI);
void setOrd(int bestOrd[maxOccupancy * 2], int doOrd[maxOccupancy * 2],
        sav savList[savListSize], int targetSAV, trip thisTrip, int& numStops,
        int numDropoffs);
void transferPath(sav& newSAV, int newPath[pathSize], int pathCt);

// end of program functions (summarize & report results)
void saveResults(trip tripMx[numTOD][tMxSize], int nTrips[numTOD],
        sav savList[savListSize], int nSAVs, double waitBins[nWaitBins],
        double trpWtBins[nWaitBins], double& cumMiles, double& totProfit,
        double& travServed, double dayShare);
void sumResults (trip tripMx[numTOD][tMxSize], int nTrips[numTOD],
        sav savList[savListSize], int nSAVs, time_t startTime, double mphBins[nMphBins],
        int ridesShared, double occMiles[maxOccupancy + 1]);
```

int main()

```
{
    // variable declarations
```

```
        int numNodes, numLinks, nSAVs, ridesShared, evalDay, dum;
        double xMax, yMax, xMin, yMin, cumMiles, totProfit, travServed;
        bool coldStart = true;
        time_t startTime;

        node nodeList [nodeSize];
        link linkList [linkSize];
        link revLinkList [linkSize]; // mirror of linkList, sorted by toNode
        trip tripMx [numTOD][tMxSize];
        sav savList[savListSize];
        int nTrips [numTOD];
        double zoneShares [lgNxZones][lgNyZones][nZoneTODs];
        int centNodes [lgNxZones][lgNyZones];
        double mphBins[nMphBins];
        double occMiles[maxOccupancy + 1];
        double waitBins[nWaitBins];
        double dayShares[nEvalDays];
        double trpWtBins[nWaitBins];

        // begin program
        initVars  (numNodes,  numLinks,  nTrips,  nSAVs,  xMax,  yMax,  xMin,  yMin,
startTime,  mphBins,  ridesShared,  occMiles,  cumMiles,  totProfit,  travServed,  waitBins,
trpWtBins, dayShares, evalDay);

        readNetwork(nodeList,  linkList,  revLinkList,  numNodes,  numLinks,  xMax,  yMax,
xMin, yMin);
        readTrips2(tripMx,  nTrips,  nodeList,  numNodes,  xMax,  yMax,  xMin,  yMin,
tripInitDay, tripInitMo);
    //    readTrips (tripMx, nTrips, nodeList, numNodes, xMax, yMax, xMin, yMin);
        createZoneShares(zoneShares,  centNodes,  tripMx,  nTrips,  nodeList,  numNodes,
xMax, yMax, xMin, yMin);

        int totTr = 0;

        for (int tm = 0; tm < numTOD; tm++)
        {
            totTr = totTr + nTrips[tm];
        }

        cout << "Nodes = " << numNodes << " Links = " << numLinks << " Trips = " <<
totTr << endl;

        // run cold start
        runSAV (nodeList,  linkList,  revLinkList,  numNodes,  numLinks,  tripMx,  nTrips,
savList,  nSAVs,  coldStart,  zoneShares,  centNodes,  mphBins,  ridesShared,  occMiles,
evalDay);
        coldStart = false;

        cout << "Finished coldstart." << endl;
    //    cin >> dum;

        if (tripFirstMo != tripLastMo || tripFirstDay != tripLastDay)
        {
            // run multiple days
            for (int m = tripFirstMo; m <= tripLastMo; m++)
            {
                for (int d = tripFirstDay; d <= tripLastDay; d++)
                {
                    reInitVars  (tripMx,  nTrips,  savList,  nSAVs,  nodeList,  mphBins,
ridesShared, occMiles);

                    readTrips2(tripMx,  nTrips,  nodeList,  numNodes,  xMax,  yMax,  xMin,
yMin, d, m);
                    createZoneShares(zoneShares,  centNodes,  tripMx,  nTrips,  nodeList,
numNodes, xMax, yMax, xMin, yMin);
```

```
                        runSAV (nodeList, linkList, revLinkList, numNodes, numLinks,
tripMx, nTrips, savList, nSAVs, coldStart, zoneShares, centNodes, mphBins, ridesShared,
occMiles,
                                evalDay);

                        saveResults(tripMx, nTrips, savList, nSAVs, waitBins, trpWtBins,
cumMiles, totProfit, travServed, dayShares[evalDay]);
                        sumResults (tripMx, nTrips, savList, nSAVs, startTime, mphBins,
ridesShared, occMiles);
                        evalDay++;
                    }
                }

            } else {
                // just a single day
                reInitVars (tripMx, nTrips, savList, nSAVs, nodeList, mphBins,
ridesShared, occMiles);

                if (tripInitDay != tripFirstDay || tripInitMo != tripFirstMo)
                {
                    readTrips2(tripMx, nTrips, nodeList, numNodes, xMax, yMax, xMin, yMin,
tripFirstDay, tripFirstMo);
                    createZoneShares(zoneShares, centNodes, tripMx, nTrips, nodeList,
numNodes, xMax, yMax, xMin, yMin);
                }

                runSAV (nodeList, linkList, revLinkList, numNodes, numLinks, tripMx,
nTrips, savList, nSAVs, coldStart, zoneShares, centNodes, mphBins, ridesShared, occMiles,
evalDay);

                sumResults (tripMx, nTrips, savList, nSAVs, startTime, mphBins,
ridesShared, occMiles);
            }

            cin >> dum;

            return 0;
}
```

void runSAV(…)

```
// main program for SAV operation

void runSAV (node nodeList[nodeSize], link linkList[linkSize], link
revLinkList[linkSize], int numNodes, int numLinks, trip tripMx[numTOD][tMxSize], int
nTrips[numTOD], sav savList[savListSize], int& nSAVs, bool coldStart, double zoneShares
[lgNxZones][lgNyZones][nZoneTODs], int centNodes [lgNxZones][lgNyZones], double
mphBins[nMphBins], int& ridesShared, double occMiles[maxOccupancy + 1], int evalDay)
{
    int trpCt = 0;
    tripIndex waitList[waitListSize]; // index of waiting trips
    int numWaiting = 0;
    int dum = 0;
    int savOcc, savFree, savClaimOcc, savTot, totNumTrips;
    double freeTime = 0;

    ofstream fout;
    fout.open("SAV_track.txt");

    // begin at first time period and complete a full day
    for (int t = 0; t < numTOD; t++)
    {
        if (1) //(nTrips[t] > 0)
        {
```

```
            cout << endl << "Time = " << t << ", Day = " << evalDay << ". Period trips =
" << nTrips[t] << " with " << numWaiting << " waiting. nSAVs = " << nSAVs << endl <<
endl;

            for (int n = 0; n < nTrips[t]; n++)
            {
                trpCt++;
            }
        }


        if (evalDay == 3 && t == 189)
        {
            dum = 0;
        }


        if (t % ttPeriod == 0)
        {
            cout << "Loading new link-level travel times..." << endl << endl;

            loadNewTTs(t, linkList, numLinks);
            loadNewTTs(t, revLinkList, numLinks);
        }

        savOcc = 0;
        savFree = 0;
        savClaimOcc = 0;
        savTot = 0;
        totNumTrips = 0;

        if (1)
        {
            for (int s = 0; s < nSAVs; s++)
            {
                if (savList[s].occupancy > 0)
                {
                    savOcc++;
                } else if (savList[s].claimOcc > 0) {
                    savClaimOcc++;
                }

                savFree = savFree + 1 - savList[s].occupancy - savList[s].claimOcc;
                savTot++;
            }
            savFree = savTot - (savOcc + savClaimOcc);

            cout << "Total SAVs = " << savTot << ". " << savOcc << " occupied, " <<
savClaimOcc << " claimed, & " << savFree << " free." << endl;

            for (int t1 = 0; t1 < t; t1++)
            {
                totNumTrips = totNumTrips + nTrips[t1];
            }

            cout << "Total trips = " << totNumTrips << " with " << ridesShared << " rides
shared." << endl;
        }

        // assign SAVs to waiting trips
        cout << "Serving wait trips " << numWaiting << " waiting" << endl;
        serveWaitTrips (nodeList, linkList, revLinkList, numNodes, numLinks, tripMx,
savList, nSAVs, waitList, numWaiting, t, coldStart, savFree, ridesShared);

        cout << "Served wait trips. SAVs free now = " << savFree << ", " << numWaiting <<
" waiting" << endl;
```

```
        // assign SAVs to current trips
        serveCurrTrips (nodeList, linkList, revLinkList, numNodes, numLinks, tripMx,
nTrips, savList, waitList, numWaiting, t, savFree, ridesShared);

        cout << "Served current trips. SAVs free now = " << savFree << ", " << numWaiting
<< " waiting" << endl;

        // update wait times for trips on the waitList
        updateWaitTimes (tripMx, waitList, numWaiting);

        // relocate SAVs
        relocSAVsZones (zoneShares, centNodes, waitList, numWaiting, savList, nSAVs,
tripMx, nodeList, numNodes, linkList, revLinkList, numLinks, t);

        // determine if each SAV is active or still free
        for (int s = 0; s < nSAVs; s++)
        {
            if (savList[s].claimOcc == 0 && savList[s].occupancy == 0 && savList[s].reloc
== false)
            {
                freeTime++;
            }
        }

        moveSAVs (savList, nSAVs, tripMx, nTrips, nodeList, numNodes, linkList, numLinks,
t, mphBins, occMiles, fout, evalDay);

    } // proceed to next time period

    freeTime = freeTime / (nSAVs * numTOD);

    cout << trpCt << " total trips served. SAVs free for " << freeTime << " share of the
day." << endl;
    fout.close();

    return;
}
```

void recSAVSearch(…)

```
// recursive search to find the best SAV available, if one can be found

void recSAVSearch (node nodeList[nodeSize], link revLinkList[linkSize], int numNodes,
trip& thisTrip, sav savList[savListSize], double maxTime, int currNodes[nodeSize], int&
nCurrNodes, int reachNodes[nodeSize], int& nReachNodes, double backDist[nodeSize],
double& travTime, int backLink[nodeSize], int& closeSAV, int currT, bool& foundDRS, bool&
foundNonDRS, link linkList[linkSize], int numLinks, trip tripMx[numTOD][tMxSize], int
tNum, int departT, int& ridesShared, double maxDRSTime, double& maxServeTime, bool&
handOff, bool& handOffAssn, sav& tempSAV, int& drsCloseSAV)
{
    double nextMinCost = 1000000;
    int currNode, bestNode, savNum, linkN, fromNode, toNode, rnIndex;
    double distToNode;
    bool reachedMax = false;
    bool foundNewDRS = false;

    // find reachable node with lowest travel cost
    for (int n = 0; n < nReachNodes; n++)
    {
        currNode = reachNodes[n];
        if (nextMinCost > backDist[currNode])
        {
            bestNode = currNode;
            rnIndex = n;
```

```
            nextMinCost = backDist[currNode];
        }
    }

    // remove bestNode from the list of new reachable nodes
    reachNodes[rnIndex] = reachNodes[nReachNodes-1];
    nReachNodes--;

    // add the node to the list of visited nodes and update the node's new backnode connections
    currNodes[nCurrNodes] = bestNode;
    nCurrNodes++;

    for (int l = 0; l < nodeList[bestNode].numRLs; l++)
    {
        // get link #, fromNode & toNode
        linkN = nodeList[bestNode].firstRL + l;
        toNode = revLinkList[linkN].toN;
        fromNode = revLinkList[linkN].fromN;

        updateBackDist (backDist, backDist[toNode], fromNode, revLinkList, reachNodes, nReachNodes, linkN, backLink, currT);
    }

    // if maxTime is reached or if the number of new reachable nodes is 0, then exit
    if (nextMinCost > maxTime)
    {
        reachedMax = true;
    }

    // search the node to see if it has a free SAV
    if (!reachedMax)
    {
        // check for free SAVs
        savNum = lookForSAVOnNode (bestNode, nodeList, savList, distToNode);
        if (savNum != -1 && backDist[bestNode] + distToNode < travTime)
        {
            foundNonDRS = true;
        }
        if (nextMinCost < maxDRSTime)
        {
            // checkDRS
            foundNewDRS = checkNodeDRS (thisTrip, nodeList, numNodes, savList, linkList, numLinks, tripMx, bestNode, currT, tNum, departT, closeSAV, maxDRSTime, maxServeTime, handOff, tempSAV, maxTime, foundNonDRS);
        }
        if (foundNewDRS && !handOff)
        {
            // first check DRS
            ridesShared++;
            foundDRS = true;
        } else if (foundNonDRS) {
            // next check free SAV
            closeSAV = savNum;
            travTime = backDist[bestNode] + distToNode;
            maxTime = travTime;
            handOff = false;
        } else if (foundNewDRS && handOff && maxTime > maxServeTime * 60) {
            // finally check handoff
            maxTime = maxServeTime * 60;
            drsCloseSAV = closeSAV;
            handOffAssn = true;
            foundDRS = true;
        }

        if (nReachNodes > 0 && (!foundDRS || handOff))
```

```
        {
            // run a recursive search for SAVs
            recSAVSearch (nodeList, revLinkList, numNodes, thisTrip, savList, maxTime,
currNodes, nCurrNodes, reachNodes, nReachNodes, backDist, travTime, backLink, closeSAV,
currT, foundDRS, foundNonDRS, linkList, numLinks, tripMx, tNum, departT, ridesShared,
maxDRSTime, maxServeTime, handOff, handOffAssn, tempSAV, drsCloseSAV);
        }
    }

    if (reachedMax && handOff)
    {
        if (handOffAssn)
        {
            // we will be conducting a handoff. Set tempSAV as the target SAV.
            savList[drsCloseSAV] = tempSAV;
            tripMx[departT][tNum].carLink = true;
            savList[drsCloseSAV].replanPath = true;
            handOffAssn = false;

        }
    }

    return;
}
```

void checkNodeDRS(…)

```
// determination to see if we can share a trip with an available SAV on a given node

bool checkNodeDRS (trip& thisTrip, node nodeList[nodeSize], int numNodes, sav
savList[savListSize], link linkList[linkSize], int numLinks, trip
tripMx[numTOD][tMxSize], int thisNode, int currTm, int tNum, int departT, int& closeSAV,
double maxSearchTime, double& maxServeTime, bool& handOff, sav& tempSAV, double maxTime,
bool foundNonDRS)
{
    int targetSAV, numStops, numDropoffs, numTrav;

    double newTime, currMaxTime, maxTotTime, currPUTime;
    double bestTime = 1000000;
    int bestOrd[maxOccupancy * 2];
    int currOrd[maxOccupancy * 2];
    int doOrd[maxOccupancy * 2];
    bool finished = false;
    bool drs = false;
    bool waitHandOff = false;
    bool eval, newHandOff;
    double dblChk[10];

    closeSAV = -1;

    dblChk[3] = maxSearchTime / 60;

    // for each SAV on the node
    for (int s = 0; s < nodeList[thisNode].nSAVs && !drs; s++)
    {

        targetSAV = nodeList[thisNode].savNList[s];
        numTrav = savList[targetSAV].occupancy + savList[targetSAV].claimOcc;
        if (numTrav < maxOccupancy && numTrav > 0)
        {

            eval = true;
            for (int t = 0; t < thisTrip.numSAVsNoDRS && eval; t++)
            {
                if (thisTrip.savsNoDrs[t] == targetSAV)
```

```
                {
                    eval = false;
                }
            }

            if (eval)
            {
                // check drs and best ordering of stops
                setFirstOrder (currOrd, savList, targetSAV, thisTrip, numStops,
numDropoffs, currMaxTime, linkList, numLinks, nodeList, numNodes, currTm, finished,
maxTotTime,
                               dblChk, newHandOff, foundNonDRS);
                dblChk[0] = savList[targetSAV].remainArrTime[0] / 60; // minutes from now
                dblChk[1] = savList[targetSAV].maxArrTime[0] - currTm * timeStep; //
minutes from now

                while (!finished)
                {
                    checkDRS (currOrd, savList, targetSAV, thisTrip, linkList, numLinks,
nodeList, numNodes, bestTime, newTime, numStops, numDropoffs, currTm, currMaxTime,
maxSearchTime, maxTotTime, dblChk, currPUTime);

                    if (newTime < bestTime && (!newHandOff || (newHandOff && currPUTime *
60 < maxTime)))
                    {
                        closeSAV = targetSAV;
                        bestTime = newTime;
                        handOff = newHandOff;
                        // set bestOrder
                        for (int i = 0; i < maxOccupancy * 2; i++)
                        {
                            bestOrd[i] = currOrd[i];
                        }
                    } else if (newTime < bestTime && newHandOff && currPUTime * 60 <
maxServeTime) {
                        // we have a handoff that exceeds the current max time
                        waitHandOff = true;
                    }

                    setNextOrder (currOrd, savList, targetSAV, thisTrip, numStops,
numDropoffs, finished, newHandOff, foundNonDRS);
                }
                if (closeSAV == -1 && !waitHandOff)
                {
                    thisTrip.savsNoDrs[thisTrip.numSAVsNoDRS] = targetSAV;
                    thisTrip.numSAVsNoDRS++;
                } else if (closeSAV != -1) {
                    drs = true;
                    setOrd(bestOrd, doOrd, savList, targetSAV, thisTrip, numStops,
numDropoffs);
                    setDrs(bestOrd, doOrd, savList, targetSAV, thisTrip, linkList,
numLinks, nodeList, numNodes, numStops, currTm, tNum, departT, currMaxTime, maxServeTime,
handOff, tempSAV, dblChk, currPUTime);
                }
            }
        }
    }

    return drs;
}
```

void relocSAVsZones(…)

```
// relocates SAVs to match SAV supply with existing and anticipated travel demand
```

```
void relocSAVsZones (double zoneShares[lgNxZones][lgNyZones][nZoneTODs], int
centNodes[lgNxZones][lgNyZones], tripIndex waitList[waitListSize], int numWaiting,
sav savList[savListSize], int nSAVs, trip tripMx[numTOD][tMxSize], node
nodeList[nodeSize], int numNodes, link linkList[linkSize], link revLinkList[linkSize],
int numLinks, int tm)
{
    double targetZoneShares[lgNxZones][lgNyZones];
    double currSAVZoneShares[lgNxZones][lgNyZones];
    double blockBalances[lgNxZones][lgNyZones];
    bool examinedBlock[lgNxZones][lgNyZones];
    double totExpTrips = 0;
    double minRelocThresh;
    int nFreeSAVs, blockX, blockY, north, south, east, west;
    bool doneReloc = false;

    // initialize examinedBlock
    for (int x = 0; x < lgNxZones; x++)
    {
        for (int y = 0; y < lgNyZones; y++)
        {
            examinedBlock[x][y] = false;
        }
    }

    getTargetZoneShares(zoneShares, waitList, numWaiting, savList, nSAVs, tripMx,
nodeList, tm, totExpTrips, targetZoneShares);

    // only relocate if we have a minimum demand threshold in the period
    if (totExpTrips > minRelocTrips)
    {
        getCurrSAVLocs(savList, nSAVs, nodeList, currSAVZoneShares, nFreeSAVs);
        getBlockBalances(targetZoneShares, currSAVZoneShares, blockBalances, nFreeSAVs,
totExpTrips);

        // get minimum threshold for block balance discrepancy to trigger relocation
        minRelocThresh = (nFreeSAVs * minRelocShare) / (lgNxZones * lgNyZones);
        if (minRelocThresh < baseMinReloc)
        {
            minRelocThresh = baseMinReloc;
        }

        // relocate SAVs for blocks with substantial imbalances, until all assignments
have been made
        while (doneReloc == false)
        {
            // find the block with the greatest imbalance
            doneReloc = findBestBlock(blockBalances, examinedBlock, blockX, blockY,
minRelocThresh);

            if (doneReloc == false)
            {
                if (blockBalances[blockX][blockY] > 0)
                {
                    assignPushDirs(blockBalances, currSAVZoneShares, blockX, blockY,
north, south, east, west, minRelocThresh, centNodes);
                    pushSAVs(blockBalances, currSAVZoneShares, blockX, blockY, north,
south, east, west, savList, nodeList, numNodes, linkList, revLinkList, numLinks,
centNodes, tm);
                } else {
                    assignPullDirs(blockBalances, currSAVZoneShares, blockX, blockY,
north, south, east, west, minRelocThresh, centNodes);
                    pullSAVs(blockBalances, currSAVZoneShares, blockX, blockY, north,
south, east, west, savList, nodeList, numNodes, linkList, revLinkList, numLinks,
centNodes, tm);
                }
            }
```

```
        }
    }

    return;
}
```

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