SHARING VEHICLES & SHARING RIDES IN REAL TIME: OPPORTUNITIES FOR SELF-DRIVING FLEETS

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ABSTRACT

Access to shared and fully-automated or "autonomous" vehicles (SAVs) is coming, and expected to be popular and cost-effective, especially for city dwellers. This chapter synthesizes and summarizes research on SAVs, including dynamic ride-sharing (en route), range-constrained electric SAV (SAEV) operations, SAV fleet costs, and variable road pricing in a world of AVs, where vehicle-miles traveled (VMT) rise and congestion worsen. Researchers consistently find that a single SAV with long range and fast refueling can replace 6 or more household vehicles in countries with high vehicle ownership, even when serving long-distance trips. That number falls a bit when SAVs are range constrained and/or have long recharging times. Zero-occupancy VMT, called empty VMT, will be a problem for urban network congestion levels if travelers do not share rides with strangers (increasing average vehicle occupancy) and road tolls are not included. Expected costs are consistently under USD $0.75 per revenue-mile, assuming the self-driving technology add USD $25,000 or less to conventional vehicles.

Keywords*: Shared mobility, autonomous, shared autonomous vehicles, dynamic ride-sharing, electric vehicles, future transport.*

BACKGROUND

Fully-automated or autonomous vehicles (AVs), referred to as Level 4 AVs according to SAE International[1], are in an advanced testing phase in the U.S. states of Arizona, California, Pennsylvania, and Texas, among others. It will be no surprise if AVs are widely available for public use in the next five years. Technology companies, like Waymo (AV subsidiary of Alphabet Inc.) and Uber (Transportation Network Company, or TNC), are spearheading innovation in AV technology alongside original equipment manufacturers (OEMs), and significant progress has been made in as little as the last decade. Boasting benefits in several realms, such as travel time, energy and safety, AVs are geared to disrupt the market in the next decade (Kockelman et al., 2016 & 2018). The benefits they have to offer, however, do come with a high price-tag. As in any industry, the cost of innovation is eventually burdened on the consumer, and, consequently, AVs are expected to be expensive to own, at least in the early stages of deployment. This chapter focuses on a particular near-term, and potential long-term, alternative to AV ownership – shared AVs (SAVs).

A fleet of SAVs operated by one entity and shared by a community can be used to make trips and operate with minimal human intervention. One central control-unit will likely be sufficient to perform all operations for the entire fleet, thereby, significantly cutting down the required human capital. SAVs are also expected to be more profitable than current forms of car sharing and ride-hailing services, largely owing to the absence of driver-related costs and human error (Fagnant and Kockelman, 2015). The improved safety of AVs will also mean that operators may pay lower insurance premiums, and this will allow them the flexibility to charge lower fares whilst having a similar or better profit margin as compared to today's ride-hailing services (Clements and Kockelman, 2017). Aside from the profitability of the fleet from an operator's perspective, they will also be a convenient yet affordable, door-to-door service for everyone. Nowadays, people tend to use their personal vehicles inefficiently, i.e., with several empty seats and for only about one hour a day, on average (Fagnant and Kockelman, 2018). Personal vehicles may be the most convenient alternative now, but they may start to seem expensive in contrast to SAVs. When they begin to make better use of these unused seats via dynamic ride-sharing (or DRS, where strangers share rides for a part of their trip), SAVs can keep fares to a minimum. Shared usage, especially in conjunction with cleaner technology like electric propulsion, can produce impressive environmental benefits (Farhan and Chen, 2018).

Shared mobility is an obvious next step to utilizing AVs efficiently and research on this topic is in its infancy. This chapter aims to review the different dimensions of studies previously completed on this topic and provides an anticipated trajectory for future research. Some of the key elements covered here are the operational aspects of SAV use, travel demand for shared mobility, costs of these services, impact of electrification, and policies to better accommodate this evolving option.

Research on SAVs has been a hot topic for less than a decade, but numerous researchers from around the globe have generated many valuable articles on different facets of SAV use. In terms

[1] SAE demarcates 5 levels of autonomy, with level 4 and 5 being fully-autonomous and the other lower levels needing human input. Level 5 differs from 4 in the AVs ability to drive off-road and without connectivity or feedback from the infrastructure (https://saemobilus.sae.org/content/j3016_201609).

of nomenclature used in this chapter most researchers use the term ‘SAV’ for 4-seater vehicles, and aBuses for with larger-capacity shared autonomous vehicles. Terms like ‘Autonomous Mobility-on-Demand’ (AMoD), ‘Shared use Automated Mobility Services’ (SAMS), and ‘Autonomous Taxis’ (ATs or aTaxis) are also used. The following sections detail different dimensions of SAV and aBus research, ending with descriptions of literature gaps worthy of further exploration.

FROM SHARING VEHICLES TO SHARING RIDES

ZipCar began its operation in early 2000 and was key in popularizing carsharing. The growing popularity of AVs due to the DARPA challenge (Buehler et al., 2009) encouraged several researchers to delve into a mixture of AVs and carsharing. Burns et al. (2013) used aggregated trip data for three U.S. cities (Ann Arbor, Michigan; Babcock Ranch, Florida; Manhattan, New York) to solve, both analytically (using pre-defined relationship to system metrics) and using simulation, for an approximate fleet requirement. Their results suggested that a fleet range of 2,000 to 18,000 SAVs were required depending on the region’s trip density and total number of trips in peak period. Similarly, fleet utilization varied between 70-90% in peak periods and had reasonable response times. Although their research made significant assumptions (like uniform origin-destination [O-D] distribution) to simplify the process of estimation, it was one of the first studies on SAVs, quantifying metrics like empty driving and customer wait times. Some of these shortcomings were addressed by Spieser et al. (2014) in their study for Singapore using a more robust methodology. Using real trip data from a travel survey fused with network statistics from a taxi dataset, they showed that Singapore’s travel demand could be satisfied with just one-third of the then existing vehicle fleet. Both these studies strongly recommended the transition to SAVs, but also advised caution on the increase in vehicle-miles traveled (VMT) that can result from unoccupied travel. Fagnant and Kockelman (2014) were able to quantify this rise in VMT at 11% from studying travel patterns on a grid representing downtown Austin, Texas. A higher replacement rate of 11 to 1 (i.e., the number of conventional vehicles that can be replaced by 1 SAV) was observed in this study, which is nearly four times as much as Spieser et al.

Brownell and Kornhauser (2014) explored the used of SAVs at a much larger level. Travel behavior for the entire state of New Jersey was aggregated in grids, arising from satellite feed pixels, due to the lack of a detailed road network. Their analysis tested SAVs as a paratransit service, and primarily showed that allowing O-D aggregation for pickup and dropoff (rather than fixed stops) increased average vehicle occupancy (AVO), i.e., number of travelers accommodated in one vehicle, due to increased convenience and comfort from closer pickup and dropoff points. Similar to Spieser et al. (2014), the entire state’s travel demand could be served by one-third of the personally-owned fleet, but it is important to note that Brownell and Kornhauser (2014) simulated a preliminary version of DRS. Burghout et al. (2015) was able to use a detailed network for Stockholm, Sweden but with a limitation of only zone level O-D available for personal-vehicle trips. They were able to test three subsets of DRS matched at the zone level, i.e., trips with common O-D pairs, trips with common O’s but different D’s, and trips with different O’s but common D’s. Owing to zone level information, intra-zonal travel time was assumed, and travel times were fixed at a fraction of the free-flow speed. An overall reduction in VMT was observed, thanks to DRS, with a fleet just 5% the size of the private fleet serving all trips. Although a version of DRS was tested by Brownell and Kornhauser (2014) and Burghout et al. (2015), severe aggregation and use of static travel times may have led to optimistic results of AVO and replacement rate (in hindsight) for the scenarios tested. It was common consensus by now that realistic behavior using dynamic traffic assignment (DTA), i.e., a simulation-based analysis, was required to understand the impact of an SAV fleet, and especially that of DRS.

Large-Scale Agent-Based Simulations

Simulation-based studies tried to incorporate realistic behavior but realism was added step by step over time, beginning with understanding an SAV fleet's operation without DRS. The increased need for realism in travel demand modeling, in terms of both spatial and temporal scales, resulted in the development of an agent-based model called the multi-agent transport simulation, or MATSim (Horni et al., 2016), and it quickly became popular for its ability to run DTA on a large scale. Fagnant et al. (2015) simulated SAVs on an idealized grid-network, of longitudinal and lateral links of equal length, representing downtown Austin, Texas, and using hour-by-hour travel times from MATSim. A sample of trips from the region's travel demand model was simulated to use SAVs to account for uncertainty of the initial market toward AVs, while also spatially constraining the SAV operation to the downtown area. Their 24-hr weekday simulation found that each SAV could make all the trips originally made by nine conventional vehicles, and this was much higher than the replacement rate of 3 to 1 found in Spieser et al. but much lower than the 20 to 1 estimated by Burghout et al. This was extraordinary considering that Austin's population was only one-fifth that of Singapore in 2015, i.e., Austin likely had a much lower trip density, but it may also have stemmed from their downtown comparison, as opposed to Spieser et al.'s study of the entire region. However, Fagnant et al. also found an estimated 8% increase in VMT from SAVs operating unoccupied. On the bright side, their results did show better utilization of the fleet, and, therefore, possibility of reduced emissions from fewer cold starts and faster turnover of the fleet. Bösch et al. (2016) also conducted a similar analysis, using demand generated for Zurich, Switzerland in MATSim, running SAV simulations outside the MATSim environment. Their results of a 10 to 1 vehicle replacement ratio validated Fagnant et al.'s high rate, even when as little as 10% of the demand was served from an assumed low market penetration. From their 1000 scenarios simulated, they were able to show that fleet size was a function of coverage area rather than the demand served. In both these MATSim-related simulations, the main drawback was that SAVs were not simulated internally with congestion feedback.

Taking the next step in SAV simulations, Bischoff and Maciejewski (2016) integrated a dynamically-responsive SAV fleet within MATSim to observe congestion effects. Their work simulated 100,000 SAVs for Berlin, serving 2.5 million trips, and observed a 10 to 1 replacement rate for conventional vehicles, thus supporting the simplifications made by Fagnant et al. and Bösch et al. (2016). Results from their simulation showed increase in drive time (up to 17%) as compared to before the SAV service, which can be a proxy for VMT increase as observed by Fagnant et al., but no significant delays were seen. Although absence of significant congestion was attributed to better flow by SAVs potentially coordinating on the roadway, this is unlikely in the near-term because of safety concerns and human drivers fearing tight headways to SAVs, at least initially.

Simulating Dynamic Ride-Sharing

An increase in VMT was a common conclusion in the literature at this point which would eventually lead to increased congestion, despite several personally-owned vehicles being replaced. With prior research supporting the benefits of DRS, albeit with limitations, a natural next step was to observe network-wide impacts when an SAV service is operated with DRS. Fagnant et al.'s (2015) model on the gridded-network for Austin, Texas was extended by Fagnant and Kockelman (2018) to include DRS capabilities. Several conditions for added travel time to riders were included to filter away unrealistic ride-matching (with travelers experiencing high wait times or added delays) and an overall increase in the SAV fleet’s serviceability was observed. This study, which was published online in 2016, showed that the 8% increase in VMT that was previously observed, was at least partially mitigated, even with only a sample of the population using DRS. Adding more flexibility to the ride-matching procedure (like allowing greater than a 40% increase in travel time from DRS as opposed to direct O-D travel time, but with wait time constrained to approximately 10 min) capped rising VMT at 1%. When more travelers (11% of the region’s demand) where simulated to use the service, the overall VMT decreased. DRS was, therefore, seen as a potential solution to the rising congestion.

Maciejewski et al. (2017) documented ride-matching and traffic flow related algorithms used by Bischoff and Maciejewski, and introduced modifications to MATSim (specifically, by programmatically solving the dynamic vehicle routing problem) that allowed them to simulate DRS. This was further enhanced by Hörl (2017) further, where hetested how an SAV fleet behaved when rides were shared versus solo travel. By simulating a fleet where half the vehicles explicitly offered DRS while the other half offered a personal ride, Hörl was able to show that DRS may be preferred at off-peaks due to the low cost of a shared ride, together with DRS having low demand that reduced chances of matching, and, consequently, added delay. Personal rides were preferred during the peak to benefit from low travel times. Using the popular Sioux Falls test network, Hörl also simulated the fleet twice, once offering DRS and once offering only personal rides, to discuss efficient seat usage and attained a 1.64 maximum AVO with DRS, but was unable to comment on VMT because of the artificial network used. Better utilization of empty seats may be seen as a proxy for curbing rising VMT, but route deviations arising from DRS may have outweighed the saved VMT.

Around the same time, Levin et al. (2017) developed a similar DRS application in a simulator that incorporated more realistic traffic flow for their case study of Austin, Texas. Their study provided a more measured assessment of AVs benefits, as opposed to more optimistic results from past studies that did not take into account congestion effects using realistic flow models. Shorter travel times and reduction in VMT was observed only when a small fleet of around 2,000 SAVs served nearly 63,000 trips in Austin’s CBD with DRS for 2 hours in the AM peak. Increasing fleet size decreased the necessity to share rides and decreased fleet utilization (i.e., many SAVs were idle). Each SAV was serving, on average, 31 trips in one day (each trip averaging 2.3 mi), which is comparable to that observed by Fagnant and Kockelman (2018) in their simulation with 11% of the region's demand.

Up until now, studies focused primarily on SAV use, be it with or without DRS. Martinez and Viegas (2017) studied a fleet of SAVs operating in Lisbon, Portugal, and included mode choice in their simulation. Two types of shared vehicles were available to choose from: 4-seater AVs and either 8- or 16-seater aBus, in addition to walk, or subway as available modes with the choice made based on an estimated model (substituting taxi and buses for their AV alternative). As a first in the literature, overall VMT was reduced by an astonishing 30% in their study when SAVs and aBuses were available, with results indicating significant emission benefits as well. A large AVO of 2.0 in SAVs and 4.2 in aBuses is likely the most significant contributor to this large decrease in VMT. This combined fleet of SAVs and aBuses could replace nearly 10 conventional vehicles.

Another study to include mode choice was Liu et al. (2017) who also studied SAV fare impacts, but without DRS. They modeled choice between conventional vehicles, transit and SAVs, and served requests using an SAV, with a wait time threshold of 10 minutes. Although they observed significant energy and emission savings by considering better drive cycles for AVs (Kockelman and Boyles, 2018), the increase in VMT from the absence of DRS, and resulting congestion, was found at all fare levels. However, this will depend on how AVs are priced in the future. Further, the authors highlighted the importance of modeling destination choices for future studies to capture changes in trip distribution whilst using low-cost SAVs. Heilig et al. (2017) solved this problem with a case study for Stuttgart, Germany. Their model allowed choices for walking, biking, transit and sharing rides in SAVs, along with destination choice. They found overall VMT in Stuttgart reduced by about 20% using a relatively small fleet, just 15% the size of the existing private vehicle fleet, but similar to Bösch et al.'s (2016) findings who did not simulate DRS. Interestingly, the walk, bike and transit modal shares in Liu et al.'s future scenario increased, similar to Heilig et al. (2017) , although one might assume that low-cost alternatives of 50¢/mi for SAVs would prevent this. Zhao and Kockelman (2018), used a more familiar approach of a four-step demand model, and tested fare sensitivities when destination choice was modeled. Spanning 9 scenarios, they showed that VMT increased under different operating costs, parking costs, tolls.

Operational Nuances

The SAV literature's focus eventually shifted from direct applications of SAV and DRS operations to understanding more nuanced information relating to concepts like proactive vehicle relocations and ride-matching processes, as noted next.

An SAV fleet's operational efficiency and ride-matching rate were tested by Hörl et al. (2018) and Ruch et al. (2018) using a common framework. The studies focused on testing two ride-matching algorithms (a simple heuristics and a bipartite optimization routine) and two rebalancing techniques for case studies of Zurich and San Francisco using MATSim's traffic assignment module. Their results suggested that smart matching and rebalancing algorithms are able to quickly match travelers to their SAVs, and can give a competitive advantage in the market when several companies are competing for demand. However, from a single operator perspective, reduction in wait times proved to be beneficial. Hyland and Mahmassani (2018) tested six distinct dispatch strategies for an SAV fleet without DRS simulated using the Manhattan, New York grid. Their study revealed that any future SAV fleet is better off with an optimization framework in order to either reduce fleet size or empty VMT, and that this also depends on the spatial structure (e.g., dense or sprawling) of the region. Their research helps inform initial SAV operators dispatch strategies based on the region and their objective.

Large availability of travel data from cellphone records, prompted Gurumurthy and Kockelman (2018) to conduct a benchmark test for DRS. Their study, based on travel in Orlando, Florida, generated the region's demand and simulated them as served by an SAV fleet with DRS. The initial aggregate dataset was discretized temporally and spatially and DRS-based data analytics showed that around 60% of single-occupant trips in the region could be served by 60,000 SAVs, or 25 travelers per vehicle. This is lower than the 31 person-trips served per SAV in Fagnant and Kockelman (2018) but the discrepancy arose mainly from the sprawling region and special nature of recreational trips in Orlando. This study validated Hyland and Mahmassani's (2018) hypothesis on spatial structure with around 3% added VMT when ride-matches were maximized. However, it is important to note that even under sprawling conditions, DRS was found to be viable.

ENERGY AND EMISSIONS

Utilizing the SAV fleet better than existing personal vehicle fleet will lead to some emission improvements. Fagnant and Kockelman (2014) showed that reduction in cold and warm starts (to 0.05 and 0.7, respectively, per person trip) from shifting to an SAV fleet can reduce CO_2 emissions and particulate matter in the air. These results stayed true even with a better simulation framework by Fagnant et al. (2015) showing an 85% reduction in cold starts. SAVs and aBuses offering DRS as in Martinez and Viegas (2017) were able to reduce CO_2 emissions by almost 40% across all road modes.

Electrification can mitigate some of the issues caused by SAVs with internal combustion engines. These include eliminating engine idling, lower emissions to counteract added VMT and a quieter experience for the customer. EVs are also well suited for the ultra-rigorous use of an SAV fleet with likely less maintenance needs without the complexity of an ICE powertrain. The idea of electrified SAVs (or SAEVs) has gained the interest of researchers lately with many conducting agent-based models to understand how these systems operate. Researchers' goal is generally to determine the feasibility of electrifying an SAV fleet, so the first step is looking at system performance. EVs are limited with relatively short range and slow charge times compared to gasoline-powered vehicles and their refuel times, so it is not obvious if they can deliver timely, on-demand transportation service without computer simulation. Chen et al. (2016), Kang et al. (2016), Yang et al. (2017) and Loeb et al. (2018), all simulate SAEV fleets, focusing on response times and necessary fleet sizes. These papers published between 2016 and 2018 have modeled SAEV fleets with increasing complexity.

Chen et al. (2016) modeled SAEVs in a generic grid imitating a large, metropolitan area with a dense, urban core. Trips were generated based on their proximity to the center of the area. The fleet and charging stations were generated based on demand through a "warm start" period to encourage reasonable vehicle start locations and charging station placement. Their goals were to understand how charge time and vehicle range affected the fleet size and the number of charging stations needed to serve demand quickly. They found a fleet of 200-mile range vehicles could be 20% smaller than one composed of vehicles with 80-mile range and 30-minute fast-charging reduced fleet size by 30% compared to 4-hour charge times. Combining fast-charging and long range gave a 44% decrease in fleet compared to lower ranges and slower charging. The number of charging stations needed to meet demand did not vary much based on these modeling settings, but the number of chargers at each station could be cut by 45% when upgrading from slow charging to fast charging for the short range case and cut by 86% for the long-range case. Vehicle response times for trip requests was 7 - 10 min on average, unoccupied travel accounted for 10 - 14% of SAEV VMT (a very small portion of which was for charging) and each vehicle could replace up to 6.8 privately owned vehicles based on daily trip-making rates.

Yang et al. (2017) used a more specific and detailed simulation environment modeled after Shanghai China. They collected a month's worth of taxi travel behavior data from 13,761 vehicles, over 23% of Shanghai's taxi fleet. This was used to map Shanghai into a grid, and trips were generated in each tile according to collected data (similar to methods used by Brownell and Kornhauser, 2014). Vehicles in the simulation environment were dispatched in an unusual first-come, last-served system, where vehicles that ended a trip most recently were dispatched first. This was in order to reduce vehicle idle time. Several vehicle ranges were tested, varying from 93 to 217 miles. 73% of vehicles were able to conduct a full day's taxi operations without charging when equipped with 217-mile range. Full-load ratio (the ratio of occupied VMT to total VMT) was 89% in the simulation compared to 67% in (non-autonomous) observed data. They calculated that the SAEVs could reduce the total taxi fleet size by 41%, but each SAEV idled for an average of 15 hours a day, which means the replacement rate could likely be higher.

Kang et al. (2016) took a slightly different approach by modeling an autonomous car-sharing service, where vehicles perform charging trips and meet passengers autonomously, but are human-driven when occupied by a user so as to more seamlessly emulate the experience of a traditional car-sharing service. Rather than simply borrow trip data from literature, Kang et al. estimate demand through an iterative process with a profit-maximizing objective. Their model is an in an 11 × 11 mile square simulating Ann Arbor, Michigan. Similar to Chen et al.'s findings, they determined that metrics like wait time are not effected by vehicle range and charge times so long as the vehicle fleet is sufficiently large. Charging stations were placed throughout the region at locations which minimize the average distance needed to travel to them. They assumed 30 minutes were needed to charge a 24 kWh (80-mile) battery to 80%. They found reasonable wait times of 11.9 min, a bit slower than 9.7 minutes for a non-electrified fleet.

Farhan and Chen (2018) incorporated DRS into Chen et al.'s (2016) model with an optimization framework to obtain best matches. Their results showed that fleet sizes could be further decreased with DRS, and DRS was effective even when vehicles fit only two travelers. The number of charging stations required also decreased with a net increase in benefits, but a drop in VMT was not confirmed.

Loeb et al. (2018), inspired by Chen et al. (2016), used a detailed SAEV simulation environment, modeling the Austin, Texas region using a true network and zonal data as supplied by the local metropolitan planning organization. Trips on the network were modeled with state-of-the-art activity based modeling and dynamic traffic assignment in MATSim. Many concepts were borrowed from Chen et al., such as generating charging stations based on trip demand and testing a series of charging speeds and vehicle ranges. Unlike Chen et al. (2016), however, fleet sizes were fixed for each scenario and many more scenarios were tested. They found that response time was heavily dependent on charging speeds, going from under 4 min at 30-min charge times to over 9 minutes with 4-hour charge. Vehicle range did not have nearly the same impact on response times, except with 4-hour charging time which forced response time from 9 minutes at 93-mile range to 35 minutes at 62-mile range (electric range that was fairly typical at the time but would not be acceptable in today's new EV market). Fleet size was by far the most impactful for response time. A fleet size equivalent to 9 travelers per vehicle gave response times of nearly 25 minutes with 30-min charge times and 62-mile range. Increasing the fleet size to just 7 travelers per vehicle dropped response times to under 8 minutes for the same range and charge time. For all scenarios, unoccupied VMT hovered around 20% of all VMT.

Lu Miaojia et al. (2018) used Ann Arbor's travel demand model to quantify the energy use with SAVs and SAEVs, showing that both these fleets did not significantly help with curbing energy use or emissions compared to present-day vehicle fleets. There was an overall increase in energy use from empty VMT, and switching to electric propulsion increased SO_2 emissions (a toxic pollutant) due to the emission intensity observed in Michigan's electric-grid. However, the overall energy use decreased for SAEVs as compared to gasoline-powered SAVs. Another study by Lee and Kockelman (2019) used results from some of prior simulation studies mentioned here (Loeb et al., 2018; Loeb and Kockelman, 2019) and supported the positive effect that SAEVs will have in terms of energy and emissions reduction. Even though these vehicles will need to add charging trips to their itinerary, their research show that, overall, even with pessimistic estimates, the energy use was lower and emission reduction was higher when a fleet of SAEVs are used compared to non-electrified vehicles.

COSTS OF SAV SERVICE

Operational viability of a fleet of SAVs or SAEVs forms an important point of discussion in this field of research. However, it is equally important to understand the financial aspect of these services. Ride-hailing services by TNCs these days are not making a profit. A large percentage of the fare revenue goes to the driver. Those that cannot turn a profit will have no market to operate, especially without federal funding like in the case of public transit. Burns et al. (2013) included a cost analysis of the simplistic SAV service that they simulated. Low response times, in the order of seconds, combined with high conventional-vehicle replacement ratios in their study showed that SAVs were feasible at as little as \$0.30 – \$0.40 per mile. This is nearly one-tenth the fares that taxis charge (about \$3/mi). These results offer for more robust calculations. Spieser et al. (2014) compared SAVs to personal vehicles (both conventional and autonomous), taking into account the explicit yearly costs (operation, retrofitting, and maintenance included) and value of travel time. SAVs were viable at \$0.45 per mile, which was lower than both personal AVs and conventional vehicles. Fagnant and Kockelman (2018) showed that an assumed operating cost of \$0.50 per mile would require that the fleet's fare be assessed at about \$1.00 per mile for a profitable operation when capital costs and traveler waiting costs were included. Bösch et al. (2018a) developed a detailed cost calculator to piece together the different contributions to the cost of an SAV service. Their study concluded an operational cost range of $0.50 per mile, for SAVs with DRS, to $0.70 per mile for private ride in SAVs, which means that a profitable fare may be close to $1.00 per mile that Fagnant and Kockelman (2018) predicted. Bösch et al. (2018b) further used MATSim to run costs assessed in Bösch et al. (2018a) but across different modes, such as personal rides, shared rides, and transit. They established the tradeoff between VMT and total delay arising from these services, and suggested that the high costs associated with increased VMT can still be offset by gains from reduced travel times observed with SAV services. This is assuming that AV technology is able to maintain smaller headways resulting in higher effective road capacity.

Similar calculations were carried out for the electric alternative. Many researchers delve into this topic from the angle of marketability as Kang et al. (2016) touched on. Iacobucci et al. (2018) proposed a unique concept that would allow SAEVs to save users money on their electricity bill. The plan revolved around Virtual Power Plants (VPPs), a service popular in Japan that combines many energy sources (with a focus on renewable sources) to supply power to consumers at predetermined levels of demand. This predictable power load reduces stress on the grid and thereby reduces the cost of electrical delivery. The study takes place in Tokyo and generates trips using survey data. It is assumed that enough wind and solar generators can be built to cover all non-EV electrical demand. Diesel generators would be available to keep up with excess electrical demand from the SAEVs. The proposed VPP service would also include bundled SAEV service. The study models scenarios with and without vehicle-to-grid (V2G) connectivity. V2G allows vehicles to discharge power back to the grid to smooth power loads in times of high power demand. They found major cost savings with their VPP, but those were dominated by the savings that come from users not needing to own a car. Their system reduced electricity costs by 32% without V2G and by 75% with V2G. SAEVs significantly increased carbon emissions in the study area. This is partly because Japan's current fleet of mostly hybrids is already relatively efficient, and secondly because SAEVs introduce extra VMT due to empty travel.

Chen et al. (2016) also looked at the prices associated with EVs, vehicle automation, chargers, insurance, maintenance, electricity, and replacement batteries. They found SAEVs would cost about $0.60 to $0.67 per occupied mile to operate when including 10% profit margins. These vehicles would be used an estimated 131 – 241 miles per day or 47,000 to 88,000 miles per year assuming minimal downtime for weekends, maintenance, etc. This is compared to $0.58 per occupied mile for non-EV SAVs with approximately 94,000 annual miles under the same assumptions. Loeb and Kockelman (2019) followed up Chen et al.'s cost estimates with their more detailed model and a few more cost considerations, such as cleaning, land acquisitions for charging stations and demand-based electricity costs. They estimated a cost of about $0.59 per occupied SAEV mile compared to $0.45 per occupied mile for a gasoline SAV fleet. This served to provide a rigorous validation of Chen et al.'s estimates.

Kang et al. (2016) also looked carefully at a many of the same costs considered by Chen et al. (2016) and Loeb and Kockelman (2019), like charger costs, vehicle acquisitions, electricity cost and more. They used these figures to help understand SAVs' level of competition with existing car-sharing service Zipcar. They found a market-based profit-maximizing price of $2.50 per 10 minutes driving rate and a membership fee of $6 per month. Zipcar's prices vary by location, but as of 2019, a typical base membership is $6 - $7 per month and about $10 per hour ($1.67 per 10 minutes), up to 180 miles per day.

DISCUSSION

This chapter covers the body of literature generated from 2010 to present in the realm of SAVs. SAVs are almost here and researchers around the world have studied several aspects of SAV usage. Table 1 shows a comprehensive list of articles relevant to this review laid out in chronological order. The different aspects of SAVs covered so far in this chapter are listed across the table.

Several frameworks have been developed from scratch to analyze SAV use in different regions. To date, the most widely applied model for SAV simulations (tracking travelers and vehicles) appears to be MATSim. MATSim is open-source and able to run large-scale simulations. Recent code contributions by researchers around the world have enabled simulation of DRS, SAEVs, and advanced pricing policies. Another emerging agent-based modeling tool for SAVs is POLARIS (Auld et al., 2016), as developed by the US Department of Energy's Argonne National Laboratory.

Future Directions

In the near term, AVs and human-driven vehicles will share the same infrastructure. Some driver apprehension may exist and these interactions need to be studied. Gaps in the rapidly evolving SAV literature also exist for replacing or complementing traditional transit services, including provision of first-mile and last-mile services. Large-vehicle SAVs with DRS is an important area that can be explored further and use of SAVs for commercial applications is largely missing in the literature. Other areas that merit further examination include congestion and parking impacts from SAV services, in combination with strategic SAV-stop placement (for pickups and drop-offs, especially in dense downtowns or other popular destinations), smart road tolling and microtolling (using AVs' smart GPS systems), and vehicle design, to facilitate relatively private travel during DRS services, and route design, to enable deviations for relatively personalized aBus services. The behavioral response to data privacy from connectivity and data generation in AVs may also impact trip outcomes. These are some of the most immediate future research directions.

Table 1: Features and contributions of all relevant articles on SAVs

Relevant Articles (chronological)	Region	Dyn. Ride-Share	Electric Vehs.	Large-Scale (> 1M trips)	Emissions	Simulation	Optimization	Cost Analysis
Burns et al. (2013)	3 U.S. cities					✓		
Spieser et al. (2014)	Singapore						✓	
Brownell and Kornhauser (2014)	New Jersey			✓			✓	

Fagnant and Kockelman (2014)	10 mi grid				✓	✓		
Fagnant et al. (2015)	Austin, TX					✓		
Burghout et al. (2015)	Stockholm, Sweden	✓					✓	
Bösch et al. (2016)	Zurich, Switzerland			✓		✓		
Bischoff and Maciejewski (2016)	Zurich, Switzerland			✓		✓		
Chen et al. (2016)	100 mi grid		✓			✓		✓
Kang et al. (2016)	Ann Arbor, MI		✓			✓		
Fagnant and Kockelman (2018) [published online in 2016]	Austin, TX	✓				✓		✓
Maciejewski et al. (2017)	-	✓		✓		✓		
Yang et al. (2017)	Shanghai, China		✓			✓		
Hörl (2017)	Sioux Falls, SD	✓		✓		✓		
Heilig et al. (2017)	Stuttgart, Germany	✓		✓		✓		
Martinez and Viegas (2017)	Lisbon, Portugal	✓		✓	✓	✓		
Levin et al. (2017)	Austin, TX	✓				✓		
Liu et al. (2017)	Austin, TX			✓		✓		
Hörl et al. (2018)	Zurich, Switzerland	✓		✓		✓	✓	
Loeb et al. (2018)	Austin, TX		✓	✓		✓		
Bösch et al. (2018a)	Zurich, Switzerland							✓
Hyland and Mahmassani (2018)	Chicago, IL					✓	✓	
Iacobucci et al. (2018)	Tokyo, Japan		✓				✓	
Farhan and Chen (2018)	Austin, TX	✓	✓			✓	✓	
Bösch et al. (2018b)	Zurich, Switzerland	✓				✓		✓
Gurumurthy and Kockelman (2018)	Orlando, FL	✓		✓		✓		
Ruch et al. (2018)	San Francisco, CA	✓		✓		✓	✓	
Lu Miaojia et al. (2018)	Ann Arbor, MI		✓			✓		
Zhao and Kockelman (2018)	Austin, TX			✓				✓
Lee and Kockelman (2019)	Austin, TX				✓			
Loeb and Kockelman (2019)	Austin, TX	✓	✓	✓		✓		✓

AUTHOR CONTRIBUTION STATEMENT

The authors confirm equal contribution to the paper for this literature review. All authors reviewed the document and approved the final version of the manuscript.

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