

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

3                                   Krishna Murthy Gurumurthy  
4                   Department of Civil, Architectural and Environmental Engineering  
5                   The University of Texas at Austin  
6                                   [gkmurthy10@utexas.edu](mailto:gkmurthy10@utexas.edu)

7                                   Kara M. Kockelman, Ph.D., P.E.  
8                                   (Corresponding Author)  
9           Professor and Dewitt Greer Centennial Professor of Transportation Engineering  
10           Department of Civil, Architectural and Environmental Engineering  
11           The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall  
12                                   Austin, TX 78712-1076  
13                                   [kkockelm@mail.utexas.edu](mailto:kkockelm@mail.utexas.edu)

14                                   Benjamin J. Loeb  
15                   Delaware Valley Regional Planning Commission  
16                   Philadelphia, PA 19106  
17                                   [bloeb@dvrpc.org](mailto:bloeb@dvrpc.org)

18                   Word Count: 7,087 words + 1 table x 250 words = 7,337 word equivalents.

19           Under review for presentation at the 99<sup>th</sup> Annual Meeting of the Transportation Research Board,  
20                                   to be held in Washington, D.C., 2020.

21     **ABSTRACT**

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

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

36  
37

## 1 BACKGROUND

2 Fully-automated or autonomous vehicles (AVs), referred to as Level 4 AVs according to SAE  
3 International<sup>1</sup>, are in an advanced testing phase in the U.S. states of Arizona, California,  
4 Pennsylvania, and Texas, among others. It will be no surprise if AVs are widely available for  
5 public use in the next five years. Technology companies, like Waymo (AV subsidiary of Alphabet  
6 Inc.) and Uber (Transportation Network Company, or TNC), are spearheading innovation in AV  
7 technology alongside original equipment manufacturers (OEMs), and significant progress has  
8 been made in as little as the last decade. Boasting benefits in several realms, such as travel time,  
9 energy and safety, AVs are geared to disrupt the market in the next decade (Kockelman et al., 2016  
10 & 2018). The benefits they have to offer, however, do come with a high price-tag. As in any  
11 industry, the cost of innovation is eventually burdened on the consumer, and, consequently, AVs  
12 are expected to be expensive to own, at least in the early stages of deployment. This chapter focuses  
13 on a particular near-term, and potential long-term, alternative to AV ownership – shared AVs  
14 (SAVs).

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

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

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

---

<sup>1</sup> 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](https://saemobilus.sae.org/content/j3016_201609)).

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

## 7 **FROM SHARING VEHICLES TO SHARING RIDES**

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

28 Brownell and Kornhauser (2014) explored the used of SAVs at a much larger level. Travel  
29 behavior for the entire state of New Jersey was aggregated in grids, arising from satellite feed  
30 pixels, due to the lack of a detailed road network. Their analysis tested SAVs as a paratransit  
31 service, and primarily showed that allowing O-D aggregation for pickup and dropoff (rather than  
32 fixed stops) increased average vehicle occupancy (AVO), i.e., number of travelers accommodated  
33 in one vehicle, due to increased convenience and comfort from closer pickup and dropoff points.  
34 Similar to Spieser et al. (2014), the entire state’s travel demand could be served by one-third of  
35 the personally-owned fleet, but it is important to note that Brownell and Kornhauser (2014)  
36 simulated a preliminary version of DRS. Burghout et al. (2015) was able to use a detailed network  
37 for Stockholm, Sweden but with a limitation of only zone level O-D available for personal-vehicle  
38 trips. They were able to test three subsets of DRS matched at the zone level, i.e., trips with common  
39 O-D pairs, trips with common O’s but different D’s, and trips with different O’s but common D’s.  
40 Owing to zone level information, intra-zonal travel time was assumed, and travel times were fixed  
41 at a fraction of the free-flow speed. An overall reduction in VMT was observed, thanks to DRS,

1 with a fleet just 5% the size of the private fleet serving all trips. Although a version of DRS was  
2 tested by Brownell and Kornhauser (2014) and Burghout et al. (2015), severe aggregation and use  
3 of static travel times may have led to optimistic results of AVO and replacement rate (in hindsight)  
4 for the scenarios tested. It was common consensus by now that realistic behavior using dynamic  
5 traffic assignment (DTA), i.e., a simulation-based analysis, was required to understand the impact  
6 of an SAV fleet, and especially that of DRS.

## 7 **Large-Scale Agent-Based Simulations**

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

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

1 near-term because of safety concerns and human drivers fearing tight headways to SAVs, at least  
2 initially.

### 3 **Simulating Dynamic Ride-Sharing**

4 An increase in VMT was a common conclusion in the literature at this point which would  
5 eventually lead to increased congestion, despite several personally-owned vehicles being replaced.  
6 With prior research supporting the benefits of DRS, albeit with limitations, a natural next step was  
7 to observe network-wide impacts when an SAV service is operated with DRS. Fagnant et al.'s  
8 (2015) model on the gridded-network for Austin, Texas was extended by Fagnant and Kockelman  
9 (2018) to include DRS capabilities. Several conditions for added travel time to riders were included  
10 to filter away unrealistic ride-matching (with travelers experiencing high wait times or added  
11 delays) and an overall increase in the SAV fleet's serviceability was observed. This study, which  
12 was published online in 2016, showed that the 8% increase in VMT that was previously observed,  
13 was at least partially mitigated, even with only a sample of the population using DRS. Adding  
14 more flexibility to the ride-matching procedure (like allowing greater than a 40% increase in travel  
15 time from DRS as opposed to direct O-D travel time, but with wait time constrained to  
16 approximately 10 min) capped rising VMT at 1%. When more travelers (11% of the region's  
17 demand) were simulated to use the service, the overall VMT decreased. DRS was, therefore, seen  
18 as a potential solution to the rising congestion.

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

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

1 comparable to that observed by Fagnant and Kockelman (2018) in their simulation with 11% of  
2 the region's demand.

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

12 Another study to include mode choice was Liu et al. (2017) who also studied SAV fare impacts,  
13 but without DRS. They modeled choice between conventional vehicles, transit and SAVs, and  
14 served requests using an SAV, with a wait time threshold of 10 minutes. Although they observed  
15 significant energy and emission savings by considering better drive cycles for AVs (Kockelman  
16 and Boyles, 2018), the increase in VMT from the absence of DRS, and resulting congestion, was  
17 found at all fare levels. However, this will depend on how AVs are priced in the future. Further,  
18 the authors highlighted the importance of modeling destination choices for future studies to capture  
19 changes in trip distribution whilst using low-cost SAVs. Heilig et al. (2017) solved this problem  
20 with a case study for Stuttgart, Germany. Their model allowed choices for walking, biking, transit  
21 and sharing rides in SAVs, along with destination choice. They found overall VMT in Stuttgart  
22 reduced by about 20% using a relatively small fleet, just 15% the size of the existing private vehicle  
23 fleet, but similar to Bösch et al.'s (2016) findings who did not simulate DRS. Interestingly, the  
24 walk, bike and transit modal shares in Liu et al.'s future scenario increased, similar to Heilig et al.  
25 (2017), although one might assume that low-cost alternatives of 50¢/mi for SAVs would prevent  
26 this. Zhao and Kockelman (2018), used a more familiar approach of a four-step demand model,  
27 and tested fare sensitivities when destination choice was modeled. Spanning 9 scenarios, they  
28 showed that VMT increased under different operating costs, parking costs, tolls.

## 29 **Operational Nuances**

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

33 An SAV fleet's operational efficiency and ride-matching rate were tested by Hörl et al. (2018) and  
34 Ruch et al. (2018) using a common framework. The studies focused on testing two ride-matching  
35 algorithms (a simple heuristics and a bipartite optimization routine) and two rebalancing  
36 techniques for case studies of Zurich and San Francisco using MATSim's traffic assignment  
37 module. Their results suggested that smart matching and rebalancing algorithms are able to quickly  
38 match travelers to their SAVs, and can give a competitive advantage in the market when several  
39 companies are competing for demand. However, from a single operator perspective, reduction in  
40 wait times proved to be beneficial. Hyland and Mahmassani (2018) tested six distinct dispatch

1 strategies for an SAV fleet without DRS simulated using the Manhattan, New York grid. Their  
2 study revealed that any future SAV fleet is better off with an optimization framework in order to  
3 either reduce fleet size or empty VMT, and that this also depends on the spatial structure (e.g.,  
4 dense or sprawling) of the region. Their research helps inform initial SAV operators dispatch  
5 strategies based on the region and their objective.

6 Large availability of travel data from cellphone records, prompted Gurusurthy and Kockelman  
7 (2018) to conduct a benchmark test for DRS. Their study, based on travel in Orlando, Florida,  
8 generated the region's demand and simulated them as served by an SAV fleet with DRS. The  
9 initial aggregate dataset was discretized temporally and spatially and DRS-based data analytics  
10 showed that around 60% of single-occupant trips in the region could be served by 60,000 SAVs,  
11 or 25 travelers per vehicle. This is lower than the 31 person-trips served per SAV in Fagnant and  
12 Kockelman (2018) but the discrepancy arose mainly from the sprawling region and special nature  
13 of recreational trips in Orlando. This study validated Hyland and Mahmassani's (2018) hypothesis  
14 on spatial structure with around 3% added VMT when ride-matches were maximized. However,  
15 it is important to note that even under sprawling conditions, DRS was found to be viable.

## 16 **ENERGY AND EMISSIONS**

17 Utilizing the SAV fleet better than existing personal vehicle fleet will lead to some emission  
18 improvements. Fagnant and Kockelman (2014) showed that reduction in cold and warm starts (to  
19 0.05 and 0.7, respectively, per person trip) from shifting to an SAV fleet can reduce CO<sub>2</sub> emissions  
20 and particulate matter in the air. These results stayed true even with a better simulation framework  
21 by Fagnant et al. (2015) showing an 85% reduction in cold starts. SAVs and aBuses offering DRS  
22 as in Martinez and Viegas (2017) were able to reduce CO<sub>2</sub> emissions by almost 40% across all  
23 road modes.

24 Electrification can mitigate some of the issues caused by SAVs with internal combustion engines.  
25 These include eliminating engine idling, lower emissions to counteract added VMT and a quieter  
26 experience for the customer. EVs are also well suited for the ultra-rigorous use of an SAV fleet  
27 with likely less maintenance needs without the complexity of an ICE powertrain. The idea of  
28 electrified SAVs (or SAEVs) has gained the interest of researchers lately with many conducting  
29 agent-based models to understand how these systems operate. Researchers' goal is generally to  
30 determine the feasibility of electrifying an SAV fleet, so the first step is looking at system  
31 performance. EVs are limited with relatively short range and slow charge times compared to  
32 gasoline-powered vehicles and their refuel times, so it is not obvious if they can deliver timely,  
33 on-demand transportation service without computer simulation. Chen et al. (2016), Kang et al.  
34 (2016), Yang et al. (2017) and Loeb et al. (2018), all simulate SAEV fleets, focusing on response  
35 times and necessary fleet sizes. These papers published between 2016 and 2018 have modeled  
36 SAEV fleets with increasing complexity.

37 Chen et al. (2016) modeled SAEVs in a generic grid imitating a large, metropolitan area with a  
38 dense, urban core. Trips were generated based on their proximity to the center of the area. The  
39 fleet and charging stations were generated based on demand through a "warm start" period to  
40 encourage reasonable vehicle start locations and charging station placement. Their goals were to

1 understand how charge time and vehicle range affected the fleet size and the number of charging  
2 stations needed to serve demand quickly. They found a fleet of 200-mile range vehicles could be  
3 20% smaller than one composed of vehicles with 80-mile range and 30-minute fast-charging  
4 reduced fleet size by 30% compared to 4-hour charge times. Combining fast-charging and long  
5 range gave a 44% decrease in fleet compared to lower ranges and slower charging. The number of  
6 charging stations needed to meet demand did not vary much based on these modeling settings, but  
7 the number of chargers at each station could be cut by 45% when upgrading from slow charging  
8 to fast charging for the short range case and cut by 86% for the long-range case. Vehicle response  
9 times for trip requests was 7 - 10 min on average, unoccupied travel accounted for 10 - 14% of  
10 SAEV VMT (a very small portion of which was for charging) and each vehicle could replace up  
11 to 6.8 privately owned vehicles based on daily trip-making rates.

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

24 Kang et al. (2016) took a slightly different approach by modeling an autonomous car-sharing  
25 service, where vehicles perform charging trips and meet passengers autonomously, but are human-  
26 driven when occupied by a user so as to more seamlessly emulate the experience of a traditional  
27 car-sharing service. Rather than simply borrow trip data from literature, Kang et al. estimate  
28 demand through an iterative process with a profit-maximizing objective. Their model is an in an  
29  $11 \times 11$  mile square simulating Ann Arbor, Michigan. Similar to Chen et al.'s findings, they  
30 determined that metrics like wait time are not effected by vehicle range and charge times so long  
31 as the vehicle fleet is sufficiently large. Charging stations were placed throughout the region at  
32 locations which minimize the average distance needed to travel to them. They assumed 30 minutes  
33 were needed to charge a 24 kWh (80-mile) battery to 80%. They found reasonable wait times of  
34 11.9 min, a bit slower than 9.7 minutes for a non-electrified fleet.

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

40 Loeb et al. (2018), inspired by Chen et al. (2016), used a detailed SAEV simulation environment,  
41 modeling the Austin, Texas region using a true network and zonal data as supplied by the local



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

15 Lu Miaoja et al. (2018) used Ann Arbor's travel demand model to quantify the energy use with  
16 SAVs and SAEVs, showing that both these fleets did not significantly help with curbing energy  
17 use or emissions compared to present-day vehicle fleets. There was an overall increase in energy  
18 use from empty VMT, and switching to electric propulsion increased SO<sub>2</sub> emissions (a toxic  
19 pollutant) due to the emission intensity observed in Michigan's electric-grid. However, the overall  
20 energy use decreased for SAEVs as compared to gasoline-powered SAVs. Another study by Lee  
21 and Kockelman (2019) used results from some of prior simulation studies mentioned here (Loeb  
22 et al., 2018; Loeb and Kockelman, 2019) and supported the positive effect that SAEVs will have  
23 in terms of energy and emissions reduction. Even though these vehicles will need to add charging  
24 trips to their itinerary, their research show that, overall, even with pessimistic estimates, the energy  
25 use was lower and emission reduction was higher when a fleet of SAEVs are used compared to  
26 non-electrified vehicles.

## 27 **COSTS OF SAV SERVICE**

28 Operational viability of a fleet of SAVs or SAEVs forms an important point of discussion in this  
29 field of research. However, it is equally important to understand the financial aspect of these  
30 services. Ride-hailing services by TNCs these days are not making a profit. A large percentage of  
31 the fare revenue goes to the driver. Those that cannot turn a profit will have no market to operate,  
32 especially without federal funding like in the case of public transit. Burns et al. (2013) included a  
33 cost analysis of the simplistic SAV service that they simulated. Low response times, in the order  
34 of seconds, combined with high conventional-vehicle replacement ratios in their study showed that  
35 SAVs were feasible at as little as \$0.30 – \$0.40 per mile. This is nearly one-tenth the fares that  
36 taxis charge (about \$3/mi). These results offer for more robust calculations. Spieser et al. (2014)  
37 compared SAVs to personal vehicles (both conventional and autonomous), taking into account the  
38 explicit yearly costs (operation, retrofitting, and maintenance included) and value of travel time.  
39 SAVs were viable at \$0.45 per mile, which was lower than both personal AVs and conventional  
40 vehicles. Fagnant and Kockelman (2018) showed that an assumed operating cost of \$0.50 per mile  
41 would require that the fleet's fare be assessed at about \$1.00 per mile for a profitable operation

1 when capital costs and traveler waiting costs were included. Bösch et al. (2018a) developed a  
2 detailed cost calculator to piece together the different contributions to the cost of an SAV service.  
3 Their study concluded an operational cost range of \$0.50 per mile, for SAVs with DRS, to \$0.70  
4 per mile for private ride in SAVs, which means that a profitable fare may be close to \$1.00 per  
5 mile that Fagnant and Kockelman (2018) predicted. Bösch et al. (2018b) further used MATSim to  
6 run costs assessed in Bösch et al. (2018a) but across different modes, such as personal rides, shared  
7 rides, and transit. They established the tradeoff between VMT and total delay arising from these  
8 services, and suggested that the high costs associated with increased VMT can still be offset by  
9 gains from reduced travel times observed with SAV services. This is assuming that AV technology  
10 is able to maintain smaller headways resulting in higher effective road capacity.

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

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

39 Kang et al. (2016) also looked carefully at a many of the same costs considered by Chen et al.  
40 (2016) and Loeb and Kockelman (2019), like charger costs, vehicle acquisitions, electricity cost  
41 and more. They used these figures to help understand SAVs' level of competition with existing

1 car-sharing service Zipcar. They found a market-based profit-maximizing price of \$2.50 per 10  
 2 minutes driving rate and a membership fee of \$6 per month. Zipcar’s prices vary by location, but  
 3 as of 2019, a typical base membership is \$6 - \$7 per month and about \$10 per hour (\$1.67 per 10  
 4 minutes), up to 180 miles per day.

5 **DISCUSSION**

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

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

16 **Future Directions**

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

29 **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	✓	✓	✓		✓		✓

1

## 2 AUTHOR CONTRIBUTION STATEMENT

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

## 1 REFERENCES

- 2 Auld, J., Hope, M., Ley, H., Sokolov, V., Xu, B., Zhang, K., 2016. POLARIS: Agent-based  
3 modeling framework development and implementation for integrated travel demand and  
4 network and operations simulations. *Transp. Res. Part C Emerg. Technol.* 64, 101–116.  
5 <https://doi.org/10.1016/j.trc.2015.07.017>
- 6 Bischoff, J., Maciejewski, M., 2016. Simulation of City-wide Replacement of Private Cars with  
7 Autonomous Taxis in Berlin. *Procedia Comput. Sci.* 83, 237–244.  
8 <https://doi.org/10.1016/j.procs.2016.04.121>
- 9 Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018a. Cost-based analysis of  
10 autonomous mobility services. *Transp. Policy* 64, 76–91.  
11 <https://doi.org/10.1016/j.tranpol.2017.09.005>
- 12 Bösch, P.M., Ciari, F., Axhausen, K.W., 2018b. Transport Policy Optimization with  
13 Autonomous Vehicles. *Transp. Res. Rec.* 0361198118791391.  
14 <https://doi.org/10.1177/0361198118791391>
- 15 Bösch, P.M., Ciari, F., Axhausen, K.W., 2016. Autonomous Vehicle Fleet Sizes Required to  
16 Serve Different Levels of Demand. *Transp. Res. Rec.* 2542, 111–119.  
17 <https://doi.org/10.3141/2542-13>
- 18 Brownell, C., Kornhauser, A., 2014. A Driverless Alternative: Fleet Size and Cost Requirements  
19 for a Statewide Autonomous Taxi Network in New Jersey. *Transp. Res. Rec.* 2416, 73–  
20 81. <https://doi.org/10.3141/2416-09>
- 21 Buehler, M., Iagnemma, K., Singh, S. (Eds.), 2009. *The DARPA Urban Challenge: Autonomous*  
22 *Vehicles in City Traffic*, Springer Tracts in Advanced Robotics. Springer-Verlag, Berlin  
23 Heidelberg.
- 24 Burghout, W., Rigole, P.-J., Andreasson, I., 2015. Impacts of Shared Autonomous Taxis in a  
25 Metropolitan Area. Presented at the 94th Annual Meeting of the Transportation Research  
26 Board.
- 27 Burns, L.D., Jordan, W.C., Scarborough, B.A., 2013. *Transforming Personal Mobility* 42.
- 28 Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric  
29 vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transp. Res.*  
30 *Part Policy Pract.* 94, 243–254. <https://doi.org/10.1016/j.tra.2016.08.020>
- 31 Clements, L.M., Kockelman, K.M., 2017. Economic Effects of Automated Vehicles. *Transp.*  
32 *Res. Rec.* 2606, 106–114. <https://doi.org/10.3141/2606-14>
- 33 Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities,  
34 barriers and policy recommendations. *Transp. Res. Part Policy Pract.* 77, 167–181.  
35 <https://doi.org/10.1016/j.tra.2015.04.003>
- 36 Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of  
37 shared autonomous vehicles in Austin, Texas. *Transportation* 45, 143–158.  
38 <https://doi.org/10.1007/s11116-016-9729-z>
- 39 Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared  
40 autonomous vehicles, using agent-based model scenarios. *Transp. Res. Part C Emerg.*  
41 *Technol.* 40, 1–13. <https://doi.org/10.1016/j.trc.2013.12.001>
- 42 Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of Shared Autonomous Vehicle  
43 Fleet for Austin, Texas, Market. *Transp. Res. Rec. J. Transp. Res. Board* 2536, 98–106.  
44 <https://doi.org/10.3141/2536-12>

- 1 Farhan, J., Chen, T.D., 2018. Impact of ridesharing on operational efficiency of shared  
2 autonomous electric vehicle fleet. *Transp. Res. Part C Emerg. Technol.* 93, 310–321.  
3 <https://doi.org/10.1016/j.trc.2018.04.022>
- 4 Gurumurthy, K.M., Kockelman, K.M., 2018. Analyzing the dynamic ride-sharing potential for  
5 shared autonomous vehicle fleets using cellphone data from Orlando, Florida. *Comput.*  
6 *Environ. Urban Syst.* 71, 177–185. <https://doi.org/10.1016/j.compenvurbsys.2018.05.008>
- 7 Heilig, M., Hilgert, T., Mallig, N., Kagerbauer, M., Vortisch, P., 2017. Potentials of Autonomous  
8 Vehicles in a Changing Private Transportation System – a Case Study in the Stuttgart  
9 Region. *Transp. Res. Procedia, Emerging technologies and models for transport and*  
10 *mobility* 26, 13–21. <https://doi.org/10.1016/j.trpro.2017.07.004>
- 11 Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand  
12 responses. *Procedia Comput. Sci.* 109, 899–904.  
13 <https://doi.org/10.1016/j.procs.2017.05.418>
- 14 Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2018. Fleet control algorithms for  
15 automated mobility: A simulation assessment for Zurich. Presented at the 97th Annual  
16 Meeting of the Transportation Research Board.
- 17 Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. *The Multi-Agent Transport Simulation*  
18 *MATSim*. Ubiquity Press. <https://doi.org/10.5334/baw>
- 19 Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations:  
20 Optimization-based strategies to assign AVs to immediate traveler demand requests.  
21 *Transp. Res. Part C Emerg. Technol.* 92, 278–297.  
22 <https://doi.org/10.1016/j.trc.2018.05.003>
- 23 Iacobucci, R., McLellan, B., Tezuka, T., 2018. The Synergies of Shared Autonomous Electric  
24 Vehicles with Renewable Energy in a Virtual Power Plant and Microgrid. *Energies* 11,  
25 2016. <https://doi.org/10.3390/en11082016>
- 26 Kang, N., Feinberg, F.M., Papalambros, P.Y., 2016. Autonomous Electric Vehicle Sharing  
27 System Design. *J. Mech. Des.* 139, 011402-011402–10.  
28 <https://doi.org/10.1115/1.4034471>
- 29 Kockelman, K., Boyles, S. (Eds.), 2018. Anticipating Emissions Impacts of Smoother Driving by  
30 Connected and Autonomous Vehicles Using MOVES Model, in: *Smart Transport for*  
31 *Cities & Nations: The Rise of Self-Driving & Connected Vehicles*.
- 32 Kockelman, K., Boyles, S., Avery, P., Claudel, C., Loftus-Otway, L., Fagnant, D., Bansal, P.,  
33 Levin, M.W., Zhao, Y., Liu, J., Clements, L., Wagner, W., Stewart, D., Sharon, G.,  
34 Albert, M., Stone, P., Hanna, J., Patel, R., Fritz, H., Choudhary, T., Li, T., Nichols, A.,  
35 Sharma, K., Simoni, M., 2016. Bringing Smart Transport to Texans: Ensuring the  
36 Benefits of a Connected and Autonomous Transport System in Texas (No. FHWA/TX-  
37 16/0-6838-2). TxDOT.
- 38 Kockelman, K., Boyles, S., Claudel, C., Stone, P., Loftus-Otway, L., Sturgeon, P., Sharon, G.,  
39 Gurumurthy, K.M., Huang, Y., Simoni, M., Lei, T., Patel, R., He, D., Mohamed, A., Liu,  
40 J., Yarmohammadi, S., Thorn, E., Wagner, W., Stewart, D., Albert, M., Hanna, J., 2018.  
41 Phase 2 - Bringing Smart Transport to Texans: Ensuring the Benefits of a Connected and  
42 Autonomous Transport System in Texas (No. FHWA/TX-18/0-6838-3). TxDOT.
- 43 Lee, J., Kockelman, K.M., 2019. Energy and Emissions Implications of Self-Driving Vehicles.  
44 Presented at the 98th Annual Meeting of the Transportation Research Board,  
45 Washington, D.C.

- 1 Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling  
2 shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing  
3 application. *Comput. Environ. Urban Syst.* 64, 373–383.  
4 <https://doi.org/10.1016/j.compenvurbsys.2017.04.006>
- 5 Liu, J., Kockelman, K.M., Bösch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous  
6 vehicles across the Austin, Texas network using agent-based simulation. *Transportation*  
7 44, 1261–1278. <https://doi.org/10.1007/s11116-017-9811-1>
- 8 Loeb, B., Kockelman, K.M., 2019. Fleet performance and cost evaluation of a shared  
9 autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transp. Res.*  
10 *Part Policy Pract.* 121, 374–385. <https://doi.org/10.1016/j.tra.2019.01.025>
- 11 Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV)  
12 operations across the Austin, Texas network with charging infrastructure decisions.  
13 *Transp. Res. Part C Emerg. Technol.* 89, 222–233.  
14 <https://doi.org/10.1016/j.trc.2018.01.019>
- 15 Lu Miaojia, Taiebat Morteza, Xu Ming, Hsu Shu-Chien, 2018. Multiagent Spatial Simulation of  
16 Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts.  
17 *J. Urban Plan. Dev.* 144, 04018033. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000469](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000469)
- 18  
19 Maciejewski, M., Bischoff, J., Hörl, S., Nagel, K., 2017. Towards a Testbed for Dynamic  
20 Vehicle Routing Algorithms, in: Bajo, J., Vale, Z., Hallenborg, K., Rocha, A.P., Mathieu,  
21 P., Pawlewski, P., Del Val, E., Novais, P., Lopes, F., Duque Méndez, N.D., Julián, V.,  
22 Holmgren, J. (Eds.), *Highlights of Practical Applications of Cyber-Physical Multi-Agent*  
23 *Systems, Communications in Computer and Information Science.* Springer International  
24 Publishing, pp. 69–79.
- 25 Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving  
26 urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *Int.*  
27 *J. Transp. Sci. Technol., Connected and Automated Vehicles: Effects on Traffic,*  
28 *Mobility and Urban Design* 6, 13–27. <https://doi.org/10.1016/j.ijtst.2017.05.005>
- 29 Ruch, C., Hörl, S., Frazzoli, E., 2018. AMoDeus, a Simulation-Based Testbed for Autonomous  
30 Mobility-on-Demand Systems, in: 2018 21st International Conference on Intelligent  
31 Transportation Systems (ITSC). Presented at the 2018 21st International Conference on  
32 Intelligent Transportation Systems (ITSC), pp. 3639–3644.  
33 <https://doi.org/10.1109/ITSC.2018.8569961>
- 34 Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a  
35 Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand  
36 Systems: A Case Study in Singapore, in: Meyer, G., Beiker, S. (Eds.), *Road Vehicle*  
37 *Automation, Lecture Notes in Mobility.* Springer International Publishing, Cham, pp.  
38 229–245. [https://doi.org/10.1007/978-3-319-05990-7\\_20](https://doi.org/10.1007/978-3-319-05990-7_20)
- 39 Yang, J., Dong, J., Wang, W., 2017. A Simulation Model for Performance Analysis of Electric  
40 Autonomous Taxi Systems. Presented at the 96th Annual Meeting of the Transportation  
41 Research Board.
- 42 Zhao, Y., Kockelman, K.M., 2018. Anticipating the Regional Impacts of Connected and  
43 Automated Vehicle Travel in Austin, Texas. *J. Urban Plan. Dev.* 144, 04018032.  
44 [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000463](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000463)