ABSTRACT

A self-driving, fully automated, or “autonomous” vehicle (AV) revolution is imminent, with the potential to eliminate driver costs and driver error, while ushering in an era of shared mobility. Dynamic ride-sharing (or DRS, which refers to sharing rides with strangers en route) is growing, with top transportation network companies (TNCs) providing such services. This work uses an agent-based simulation tool called MATSim to simulate travel patterns in Austin, Texas in the presence of personal AVs, and shared AVs (SAVs), with DRS and congestion pricing policies in place. Fleet size, congestion pricing, and fare level impacts are analyzed in depth. Results indicate that the cost-effectiveness of traveling with strangers overcomes inconvenience and privacy issues at moderate-to-low fare levels. An Austin, Texas fleet of just 5000 SAVs serves more than 65% of all trips made during the day. The average vehicle occupancy (AVO) of this fleet was around 1.26 (after including the 10.5% of SAV vehicle-miles traveled (VMT) that is empty/without passengers), with negligible VMT savings, as compared to the base case. This same fleet size performs better when congestion pricing is enforced in the peak periods (4 hours a day), cutting VMT by 8%, however, reduces fleet manager revenue to about $30 per SAV per day after paying tolls.

Keywords: Shared autonomous vehicles; dynamic ride-sharing, congestion pricing; agent-based simulation; Austin, Texas
INTRODUCTION

Smartphone technology is widely available and used by people of all ages and income brackets. Internet-enabled smartphones are changing how we travel, shop and communicate in our daily lives (Shaheen et al., 2016b). In particular, on-demand services by Transportation Network Companies (TNCs), like Lyft and Uber, are easily summoned and regularly arrive within 10 minutes. On-demand bikes are also available in the central business districts of many major cities (Shaheen et al., 2016a), and many parking lots are becoming less relevant. A rather new service, in the form of en-route carpooling, or DRS, by TNCs enables travelers to share their rides with people they have not met before, thereby reducing travel costs further and making car ownership less attractive (Chan and Shaheen, 2012).

When AV technology eventually eliminates the driver’s role, big changes in travel behavior can be expected. AVs will be expensive to own in the early years of implementation, and SAVs will be the first economical alternative. DRS-enabled and fuel-efficient SAV systems will further reduce operating and thus access costs, while lowering congestion, emissions, and other negative externalities of driving one’s own car.

To reflect the details of car-sharing and ride-sharing, the multi-agent transport simulation (MATSim) framework (Horni et al., 2016) is used here, to track travelers and vehicles across the Austin 6-county region in 2035. MATSim uses a co-evolutionary algorithm to anticipate a convergent set of dynamic traveler choices (for departure times, modes and routes) and traffic assignment to the network. This analysis benefits from MATSim’s congestion feedback mechanism that uses queue-based links to employ microscopic dynamic traffic assignment, as compared to static assignment and aggregate zone-based and four-step demand modeling. MATSim’s agent-level utility scores are maximized to seek user equilibrium in all cases. Hörl’s (2017) recent DRS + SAV contributions to MATSim code allow for a base-case scenario consistent with that used in Simoni et al. (2018), for several congestion pricing scenarios. Policies like region-wide distance-based tolls and demand-dependent congestion pricing (variable tolls), along with different SAV+DRS fare assumptions, improve our understanding of how SAV fleets and travel demand management through road pricing will impact mode choices and traffic conditions, as well as traveler welfare.

The remaining sections of the paper are structured as follows: a brief literature review discusses the benefits of simulation and DRS, the model framework is described, and key assumptions and algorithms are presented. Subsequently, travel demand and traffic congestion results across different policy, fleet-size and fare-level scenarios are presented, along with recommendations for transportation planning and policy futures.

MOTIVATION

Dynamic ride-sharing or real-time carpooling in conventional vehicles has been studied for nearly two decades now, but DRS benefits are not so widely known. Levofsky and Greenberg’s (2001) case study of U.S. cities highlighted DRS’ operational and environmental benefits. Since then, numerous studies have analyzed DRS using different approaches and for cities with diverse land use patterns. More recent studies assume the use of SAVs.

Optimization-based studies have emphasized the potential of DRS (Agatz et al., 2011; Santi et al., 2014; Alonso-Mora et al., 2016; Hyland and Mahmassani, 2018). While they highlight the
viability of a ride-sharing system, they do so without considering the endogenous effects of
congestion and shifting mode choices. Recent survey-based research has examined mode choices
and willingness to pay (WTP) for DRS services inside SAVs, to get a statistical insight into how
the market may play out (see, Krueger et al., 2016; Haboucha et al., 2017; Gurumurthy and
Kockelman, 2018a, Quarles and Kockelman, 2018a & 2018b). These studies provide valuable
insights on DRS adoption rates and profitability possibilities, giving operators a sense of future
fleet sizes, but they lack the system perspective needed for managing the larger transport systems
at play. Fortunately, several simulation studies have been pursued. Some of these use more
realistic travel times (like Brownell and Kornhauser, 2014; Fagnant and Kockelman, 2015a;
Levin et al., 2017; and Loeb and Kockelman, 2018), while others employ big datasets to
understand travel on static networks (Gurumurthy and Kockelman, 2018b; Wang et al., 2018).
Both sets provide some system perspective, but congestion feedbacks for SAV activities been
attempted only by Bischoff and Maciejewski (2016), without DRS for Berlin, Germany.

Agatz et al. (2011) studied an optimization-based approach to understanding the potential of
DRS and optimization for Atlanta. They used data from a travel demand model and assessed
wait-times that such fleets can operate under. Santi et al. (2014) and Alonso-Mora et al. (2016)
used the New York City taxicabs dataset and graph-based optimization approach to show that
high trip-making density, like in New York City, significantly reduced fleet requirements by
nearly 75%. However, they did not comment on the system-wide VMT benefits it may or may
not have. More recently, Hyland and Mahmassani (2018) formulated an optimization problem to
simultaneously assign incoming trip-requests as well as those waiting in queue. They used small
fleet-sizes to capture half of the Chicago taxicabs dataset under fast computation times but had to
rely on static networks.

Alternatively, survey-based research has been used to study mode-choice and willingness to pay
(WTP) to use DRS services. Krueger et al. (2016) used a stated preference survey to study the
market group which was most likely to adopt such a service. The authors remarked that young
people and people with multimodal travel patterns were more like to take up DRS services.
Haboucha et al. (2017) studied the mode-choice behavior by comparing conventional car-use to
privately-owned AVs and SAVs and found that even freely available SAVs would only be used
by 75% of the respondents. In addition, Gurumurthy and Kockelman (2018a) found that travel
times played a significant part in WTP for DRS and many long-distance business trips were
likely to be shared. On the contrary, Quarles and Kockelman (2018b) have data that suggests that
only 10% of the people are actually interested in DRS but more may be willing to adopt if the
price of such a service is at a 40% discount to owning and operating a personal AV. Such studies
suggest that the perception on DRS is still evolving and simulation-based studies must be used to
take advantage of experienced travel times and their role in decisions to adopt DRS.

Simulation studies, on the other hand, have attempted to use experienced travel-times to get more
realistic travel behaviors and its impact on certain fleet metrics but have not fully considered
induced modal demand. Burns et al. (2013), compared DRS potentials in three cities with
spatially differing travel patterns: Ann Arbor, Michigan, Babcock Ranch, Florida and Manhattan,
New York. The study focused on trip costs and empty vehicle-miles and concluded that DRS
was economically viable under all three scenarios. Brownell and Kornhauser (2014) used travel
demand data and static travel times generated by the model for the state of New Jersey and used
a grid-based approach to study the efficiency of DRS over the entire state. A similar approach
was taken by Fagnant and Kockelman (2015a) but they used dynamic travel-times updated using
Gurumurthy, Kockelman and Simoni

MATSim to show more reliable operational benefits of DRS-enabled SAVs in Austin, Texas. System-wide VMT was reduced for wait-times under 10 min. Levin et al. (2017) used a cell-transmission network assignment approach to get accurate experienced travel times. Their study showed that DRS was needed to avoid the additional VMT that SAVs without DRS would bring to the system. Loeb and Kockelman (2018) studied the economics of DRS-enabled fleets with the context of electric AVs and charging-location decisions. Their DRS results showed promise in curbing empty VMT as well as system-wide VMT, as battery ranges improved, but used experienced travel time as observed after one run of the simulation, similar to Bösch et al. (2016). Javed and Chen (2018) also studied electric AVs and assessed the benefits of DRS using a 100 mi x 100 mi grid and solved a capacitated vehicle routing problem with a time window. The results suggested a high vehicle-replacement ratio of 13 conventional vehicles to 1 electric SAV and nearly 50% of all occupied VMT by the fleet is shared. Wang et al. (2018) also used taxi booking data in Singapore to understand trip-matching and fleet-sizing using a simulation tool they developed. Among only the taxi trips, nearly 30% of VMT savings including a higher rate of incoming requests could be met, especially during the peak times. Gurumurthy and Kockelman (2018b) used cellphone data for Orlando, Florida and static travel times from the Metroplan Orlando travel demand model to simulate SAVs with DRS. Empty VMT was maintained under 4% and nearly half of all 2.8 million trips were met with the SAV fleet with wait times under 15 min. Although these studies help garner support for DRS by depicting its numerous benefits (e.g., VMT reduction, low wait-times, minimal travel delay, high vehicle-replacement ratios), they do not wholly acknowledge induced demand for SAVs and DRS since they do not take into consideration congestion-feedback.

Only a few studies have tried to fill the gaps mentioned above. For example, Rodier et al. (2016) used the San Francisco Bay Area’s activity-based travel demand model to assess the benefits of DRS. With a focus on VMT, the authors examined how road-pricing scenarios compare to business-as-usual and transit-oriented scenarios, using existing trip patterns. Across scenarios, 10% to 30% VMT reductions were observed, thanks to moderate to high adoption of DRS. Martínez and Viegas (2017) used an agent-based model to study use of SAVs and DRS in Lisbon, Portugal and predicted a reduction of nearly 30% VMT, with the average SAV traveling about 155 mi per day. Their mode choice model was based on current, revealed-preference data, which can limit future-year mode splits across AV technologies, and they did not allow for changes in destination choice, which will come with making travel easier.

As alluded to above, the existing DRS literature has some important gaps. This study seeks to address those by: (1) Using real-time trip-matching with the option to share rides, (2) Using congested-travel-time feedbacks within MATSim for mode choice flexibility, (3) Simulating SAV + DRS fare sensitivities, and (4) Anticipating the impacts of congestion pricing, DRS, and variable SAV fleet sizes.

MODEL FRAMEWORK

MATSim’s general framework was developed by Horni et al. (2016), to simulate individual travelers’ (or “agents”) movements across networks, with flexibility in mode choice, departure-time choice and route choices. An initial set of activity or travel plans is fed into the system for all simulated agents (e.g., 10 percent of a region’s population, to moderate computing demands), and a co-evolutionary algorithm seeks to maximize the utility of all agents based on user equilibrium. Since engagement in activities is a key objective for each agent, activity
participation is given positive utility while travel and late arrivals are given a disutility. Re-planning of activities is done, as needed, to (approximately) maximize the utility of each agent.

Network assignment is done using a queue-based approach, and the entire iterative framework is summarized as Figure 1’s MATSim loop. The authors recommend that readers look through Simoni et al. (2018) for an in-depth explanation of the MATSim loop within the context of shared mobility.

Here, travel plans for 45,000 people residing in Austin, Texas, are used as the initial demand. This 2.2% sample was obtained from a 6-county regional population of roughly 2 million persons to limit computational burdens in tracking the shared use of large fleets of shared vehicles. The complete Austin roadway network was obtained from OpenStreetMap and consists of more than 148,000 links and 63,000 nodes. MATSim runs were done on the Texas Advanced Computing Center’s (TACC’s) Wrangler supercomputer, to enable 24-hour completion of most scenarios.

| FIGURE 1 The MATSim loop (Source: Horni et al., 2016) |

SAVs and Dynamic Ride-Sharing

In futuristic scenarios, it is important to recognize that AVs may be privately owned, by at least a small percent of the population - even with very high purchase prices. To address this, AV ownership was assumed for 10% of the simulated population, as suggested by Quarles and Kockelman (2018a) for early stages of U.S. adoption. The network benefits of AV and SAV use are realized during network assignment, with AVs and SAVs demonstrating a 50% higher flow rate than a stream of conventional (human-driven) vehicles in MATSim (Maciejewski and Bischoff, 2017).

SAVs are expected to be common modes of transport in urban settings in the long term, but DRS may not be popular if travelers are largely unwilling to share rides with strangers. Hörl’s (2018) work is an extension of Bischoff and Maciejewski’s (2016) code, and improves our understanding of how many trips can be shared, based on travelers’ utility scores in MATSim.

Fares assessed for SAV users are independent of whether or not trips are shared and depend only on distance traveled. Trips that are not shared will cost more than shared rides, but there may be a lower willingness to share rides the longer the trip’s duration (as found in Gurumurthy and Kockelman’s [2018] extensive survey work). Here, to facilitate trip-matching, all SAV trip requests are evaluated as candidates for DRS. A least-cost-path algorithm in MATSim identifies a subset of these trip requests to form an aggregated trip for a nearby SAV (i.e., an SAV available to the first user within a 10-min radius).

Table 1 provides travel disutility parameter assumptions (from Simoni et al. [2018]), with $\beta_{\text{mode}}$ serving as each model’s alternative-specific constant and $\beta_{\text{time}}$ serving as mode-specific marginal disutilities of travel time (in minutes). This disutility for using SAVs (where rides may
be shared) is derived based on a 25% increase with respect to solo travel in one’s own AV. This arises from the fact that traveling in personal AVs is likely to be cleaner and riders will not have to worry about coming in contact with strangers. Operating costs are captured for personal vehicles, whereas, fares are assessed for the shared fleet. Personal vehicles (both conventional and autonomous) have a nominal operating cost of $16/mi (AAA, 2017) for fuel and maintenance. SAV fares have a fixed-cost and a distance-dependent cost, as shown in Table 2. The reference fare level is based on Simoni et al.’s (2018) study: Compared to solo travel in one’s own AV, an SAV’s fixed cost component is assumed to be 50% lower, at $0.125 per trip, and an SAV’s distance-based costs also is 50% lower, at $0.1/mile. As mentioned previously, shared rides will accrue higher mileage, lowering the willingness to use DRS. These rates are lower than what popular TNC companies like Uber or Lyft charge for their DRS option, but with driver costs eliminated and high value of travel time (Fagnant and Kockelman, 2015b), fares are expected to be lower in the future. The impact of such lowered fares is captured. Transit and the non-motorized modes are not charged monetary values but the travel disutility captures the transit fares, unavailability of a vehicle for future legs and distance thresholds chosen for walking/biking.

<table>
<thead>
<tr>
<th>Travel Mode</th>
<th>$\beta_{mode}$</th>
<th>$\beta_{time}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional Vehicle</td>
<td>-0.1</td>
<td>0</td>
</tr>
<tr>
<td>Public Transit</td>
<td>-1.5</td>
<td>-0.36</td>
</tr>
<tr>
<td>Walk or Bike</td>
<td>-0.2</td>
<td>0</td>
</tr>
<tr>
<td>AV</td>
<td>0</td>
<td>+0.48</td>
</tr>
<tr>
<td>SAV with DRS</td>
<td>0</td>
<td>+0.38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Levels</th>
<th>Fixed Cost ($/trip)</th>
<th>Distance-based Travel Cost ($/mi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference Fare</td>
<td>0.125</td>
<td>0.10</td>
</tr>
<tr>
<td>50% Discount</td>
<td>0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>75% Discount</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

**FLEET-SIZING AND CONGESTION PRICING**

Most past studies replace all conventional-vehicle trips with shared-fleet trips to assess the benefits of SAVs. In the early adoption stages, however, conventional vehicles will continue to exist, along with public transit and non-motorized modes (biking and walking). Making motorized travel easier (through AV, SAV and DRS options) can result in a lot of extra VMT

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1. [https://uber.com](https://uber.com) and [https://lyft.com](https://lyft.com) report less than $1/mi, on average, for shared rides.
and congestion, so congestion pricing policies are tested here, along with changes in fleet sizes and SAV fare assumptions.

The no-toll scenario tested here is self-explanatory and provides insight into the viability of DRS, with different fleet sizing and fares. The pricing scenario is pretty straightforward: All major network links (functional class of arterial or higher) carry both distance-based and time-based tolls for all road users during the morning and evening peak periods (7-9 am and 5-7 pm), at $0.10/mile and $0.50/min. The metrics used to assess fleet performance are total vehicle-miles traveled (VMT), empty VMT (by SAVs without occupants), and average vehicle occupancy (AVO) of the SAV fleet. The daily net income of the fleet is also calculated as the difference between the revenue accumulated from fares and the toll paid by the operator.

**RESULTS**

The pricing and fleet scenarios examined here can be compared based on various performance metrics. In order to compare future travel behaviors to current travel trends, a 2% Austin population is simulated using parameters assessed by Simoni et al. (2018), but with Austin’s actual transit schedules to better understand system performance. In the base case, mode shares reflect current patterns (73.4% car users, 11.5% public transit users, and 15.1% for walking and biking). Tables 3 and 4 show system performance metrics for the various pricing and fare assumption scenarios, as described earlier.

Without tolls, the base SAV fare level attracts strong SAV use, but travelers do not have sufficient utility gains to elect ride-sharing. For smaller fleet sizes (1 SAV for 90 travelers), there was a high percentage of walking and biking trips arising from a lack of cars at activity locations for subsequent trip legs. In other words, those who were able to quickly catch one of the region’s relatively few SAVs for a morning trip from home were not quickly assigned such a vehicle for their return trip, so they had to shift to other available modes.

Regional VMT is predicted to fall about 25% with such SAV use, which is tremendous. A very large fleet size, of 25,000 vehicles, which is more than 1 SAV for almost 2 did not perform much better, than using only one-fifth of the fleet, with negligible VMT savings and similar mode shares. Personal AV use appears saturated at about 6% under most scenarios. When SAV service is priced 50% lower than the reference, more SAV trips are made, as expected, but large fleet sizes (5000 and 25,000 SAVs) seem to add 5-7% VMT. This was also observed at a 75% discount in fares, but the small fleet of 500 SAVs (that is, 1 for every 90 travelers) eliminated 24% VMT. Congestion pricing showed increased SAV use for higher fleet sizes but it remained nearly the same for low fleet sizes. This originates from not tolling SAV users directly, resulting in larger reductions in VMT from the widespread use of SAVs. Small fleets of 500 SAVs reduced VMT by 40% but larger fleets reduced VMT by only 6-8%.

**TABLE 3 System-Wide Impacts in terms of VMT Change**

<table>
<thead>
<tr>
<th>Policy</th>
<th>Fare Level</th>
<th>SAV Availability (1 SAV for every X persons)</th>
<th>Mode Split (Δ%)</th>
<th>VMT (Δ%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td></td>
<td></td>
<td>Car AV SAV PT W/B</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>73.4 0 0 11.5 15.1</td>
<td>-</td>
</tr>
</tbody>
</table>
The operational viability of the SAV fleet is also important to discuss. Small fleet sizes encourage sharing due to their lack of availability, so a relatively high AVO is observed for smaller fleets than larger ones. A maximum AVO of 1.32 is observed for the small SAV fleet (500 SAVs) when congestion pricing is implemented and fares are provided at a 75% discount compared to the reference fare level. However, this does not prove to be financially viable, making only about $8,500 in a day or $17 per SAV. Larger fleet sizes also stayed idle for longer each day (nearly 2 hours, on average). Congestion pricing does not seem to impact empty VMT of the fleets. Larger fleets have lower than 4% empty VMT which may be from waiting before servicing a single traveler. On average, the empty VMT stayed at around 10%. Large fleet sizes cannot be operationalized at very low fares as they are seen to lose money.

### TABLE 4 Fleet Performance Metrics

<table>
<thead>
<tr>
<th>Policy</th>
<th>Fare Level</th>
<th>SAV Availability (1 SAV for every X persons)</th>
<th>eVMT (% of VMT)</th>
<th>AVO*</th>
<th>Idle Time (hours/SAV/day)</th>
<th>Revenue ($/day/SAV)</th>
<th>Tolls Paid ($/day/SAV)</th>
<th>Net Revenue ($/day/SAV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Toll</td>
<td>Reference Fare</td>
<td>90</td>
<td>18.9</td>
<td>1.05</td>
<td>0.3</td>
<td>85.4</td>
<td>N/A</td>
<td>85.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9</td>
<td>10.3</td>
<td>1.04</td>
<td>0.6</td>
<td>36.3</td>
<td></td>
<td>36.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>3.8</td>
<td>1.04</td>
<td>1.9</td>
<td>7.8</td>
<td></td>
<td>7.8</td>
</tr>
<tr>
<td></td>
<td>50% Discount</td>
<td>90</td>
<td>11.1</td>
<td>1.21</td>
<td>&lt;0.1</td>
<td>78.8</td>
<td></td>
<td>78.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9</td>
<td>14.8</td>
<td>1.13</td>
<td>0.1</td>
<td>35.0</td>
<td></td>
<td>35.0</td>
</tr>
</tbody>
</table>
CONCLUSION

AVs and SAVs are imminent according to several experts and auto manufacturers. Smartphone technology is ushering in an era of easy-to-use shared mobility, making it important to understand well. DRS is picking up steam and this study utilizes agent-based tools to address some key gaps.

The study reveals that the use of SAVs with DRS is beneficial to the system, but more so with congestion pricing. Pricing improves shared-use uptake and helps reduce congestion by eliminating VMT by around 15%, on average, and up to as much as 40% for small fleets. If SAV operators are subsidized similar to public transit, there is hope for a congestion-free future.

The service was analyzed with fares set at $0.02/mi, $0.05/mi and $0.1/mi, and it was seen that lowering the fares to $0.02/mi may be detrimental to the fleet’s operation. Even though SAVs are tolled, the fleet continues to generate more than $30 a day per SAV. This revenue is relatively low compared to how much existing fleets with human drivers make but it is important to keep in mind that the fleet operators have no driver-related costs. Lower prices increased riders’ willingness to share rides and produced a higher AVO. Larger fleets promoted single-agent use and diminished the value of DRS. The revenue generated by these large fleets also fell per SAV.

In the future, there is a good chance that transport is replaced by SAVs with rides more likely to be shared. Future fleet operators must set fares such that the number of people served is high, but maintain a small fleet of SAVs to ensure a high rate of DRS. This in turn provides system-wide benefits such as reductions in congestion and shrinks the U.S. fleet size. Congestion pricing will help resolve travel delays further but it must be set in accordance with SAV fleets in use. Providing additional support in the form of subsidies to these SAV fleet operators will ensure that mobility is affordable, convenient, and delay-free.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm the contribution to the paper as follows: study conception and design: Gurumurthy, K.M and Kockelman, K., Simoni, M; Data analysis and interpretation of results:
Gurumurthy. K.M and Kockelman, K., and Simoni, M.; Draft manuscript preparation: Gurumurthy. K.M., Kockelman, K. All authors reviewed the results and approved the final version of the manuscript.

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