BENEFITS & COSTS OF RIDE-SHARING IN SHARED AUTOMATED VEHICLES ACROSS AUSTIN, TEXAS: OPPORTUNITIES FOR CONGESTION PRICING

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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 advanced pricing policies in place. Fleet size, pricing, and fare level impacts are analyzed in depth to provide insight into how SAVs ought to be introduced in a city. Results indicate that the cost-effectiveness of traveling with strangers overcomes inconvenience and privacy issues at moderate-to-low fare levels, with high fares being more detrimental than the base case. A moderately-sized Austin, Texas fleet (1 SAV serving 25 people) serves nearly 30% of all trips made during the day. The average vehicle occupancy (AVO) of this fleet was around 1.48 (after including the 12.7% of SAV vehicle-miles traveled [VMT] that is empty/without passengers), with a 4.5% increase in VMT. This same fleet performs better when advanced pricing is enforced in the peak periods (4 hours a day), moderating VMT by 2%, increasing SAV demand and in turn fleet-manager revenue. SAVs are able to earn around $100 per SAV per day even after paying tolls, but only at low-fare levels.

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 (*1*). 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 (*2*), 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 (*3*).

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 (*4*) is used here, to track travelers and vehicles across the City of Austin, Texas (Figure 1) 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. A recent DRS + SAV contribution (*5*) to MATSim code allows for a base-case scenario consistent with that used in (*6*), for several congestion pricing scenarios. Policies like advanced travel-time 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.

FIGURE 1 Map of the Region Modeled - Austin, Texas (Source: Google Maps)

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. The case study of U.S. cities (*7*) 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 ((*8*), (*9*), (*10*),(*11*)). 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, (*12*),(*13*), (*14*), (*15*),(*16*)). 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 (*17*), (*18*), (*19*), (*20*)), while others employ big datasets to understand travel on static networks ((*21*), (*22*)). Both sets provide some system perspective, but congestion feedbacks for SAV activities has been attempted only by (*23*), without DRS for Berlin, Germany.

Agatz et al. (*8*) 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. Two studies ((*9*), (*10*)) 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, (*11*) 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. A stated preference survey (*12*) was used 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. Other researchers (*13*) 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, (*14*) 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, (*15*) 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. DRS potentials in three cities with spatially differing travel patterns were studied (*24*), namely 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. (*17*) 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 (*18*) but they used dynamic travel-times updated using 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. A cell-transmission network assignment approach was used by (*19*) 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. (*20*) 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 (*25*). (*26*) 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. Another research (*22*) 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. A study based on Orlando, Florida (*21*) used cellphone data 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, (*27*) 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. An agent-based model was used to study SAV and DRS use in Lisbon, Portugal (*28*) 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 (*4*), 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 2's MATSim loop. The authors recommend that readers look through (*6*) for an in-depth explanation of the MATSim loop within the context of shared mobility.

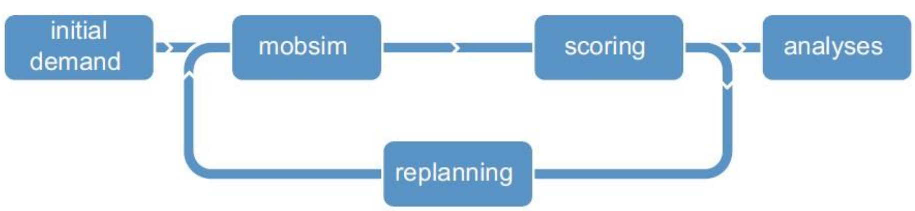

FIGURE 2 MATSim Loop (Source: (*4*))

Here, travel plans for 45,000 people residing in Austin, Texas, are used as the initial demand (*29*). This 5% sample for the City of Austin with about 900,000 people (https://www.austintexas.gov/)

was obtained by extracting city-specific trips dataset 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.

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 (*15*) for early stages of U.S. adoption. A higher or lower penetration rate for AVs can impact the outcome of this study but emphasis is placed here on SAVs. The benefits of AV and SAV use are realized from higher value of travel time associated with travel in these modes. This is taken into account in the travel disutility associated with each modes and is discussed later.

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 (*14*). Code developed by (*5*) is used and improves our understanding of how many trips can be shared, based on travelers' utility scores in MATSim. Fares assessed for SAV users are dependent of whether or not trips are shared, distance traveled and time taken to cover the distance. 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 (*14*)'s 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 30-min radius). An unmet trip request is assigned a high negative score so that in the convergent solution, each agent has learned whether using an SAV is a viable option for their trip.

Table 1 provides travel disutility parameter assumptions (from (*6*)), with β_{mode} serving as each model's alternative-specific constant and β_{time} serving as mode-specific marginal disutility of travel time (in minutes). Parking costs and transit fares are inherently modeled into the β_{mode} parameter. SAV fares are assessed separately and personal AVs are expected to travel empty (hypothetically) and not incur significant parking costs. The disutility for using SAVs (where rides may be shared) is maintained the same as that for solo travel in one's own AV. However, the opportunity cost of spending time in a shared ride is expected to reflect lower disutility in sharing. Operating costs are captured for personal vehicles, whereas, fares are assessed for the shared fleet. Personal conventional vehicles have a nominal operating cost of 30¢/mi (*30*) for fuel and maintenance averaged for different car-types. Personal AVs, on the other hand, are expected to run more efficiently and is unlikely to require frequent maintenance. To capture this, personal AVs have an operating cost of 20¢/mi (33% discount). SAV fares have a fixed-cost, a distance-dependent cost and a time-dependent cost, as shown in Table 2. The reference fare level is based on (*6*)'s study for 10% AV penetration: Solo travel in an SAV is assumed to be priced at 50¢ per trip, 40¢/mi, and 10¢/min. A shared ride in an SAV is expected to cost less and is assumed to cost approximately half as much as a solo trip in an SAV, i.e., 25¢, 20¢/mi and 5¢/min. As mentioned previously, shared rides will accrue higher mileage (and, consequently, time), lowering the willingness to use DRS. These rates are lower than what popular TNC companies like Uber or Lyft charge for their DRS option (less $1/mi, on average, for shared rides and, about, $2/mi for single-occupant rides), but with driver costs eliminated and high value of travel time (*31*), fares are expected to be lower in the future. The impact of such lowered fares is captured in stages. Transit and the non-motorized modes are not charged monetary values but the travel disutility from the opportunity cost of time captures the transit fares and unavailability of a vehicle for future legs. In addition, the transit network for Austin is replicated here with access thresholds of a quarter mile.

TABLE 1 Mode Choice Parameters (adjusted from (*6*))

Travel Mode	β_{mode}	β_{time}
Conventional Vehicle	-0.1	0
Public Transit	-1.7	-0.36
Walk or Bike	-0.2	0
AV	0	+0.48
SAV (***with DRS***)	0	+0.48

TABLE 2 SAV Fare Level Assumptions for Shared Rides

Levels	**Fixed Cost ($)**	**Distance-based Travel Cost ($/mi)**	**Time-based Travel Cost ($/min)**
Reference Fare	0.25	0.20	0.05
50% Discount	0.15	0.10	0.03
75% Discount	0.10	0.05	0.02

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 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 sizes and fares. The pricing scenario is straightforward: All major network links (functional class of arterial or higher) carry a toll based on travel time on the link for all road users during the morning and evening peak periods (7-9 am and 5-7 pm), at $0.05/min. This advanced travel-time based pricing policy was simulated and tested for welfare viability in a future with AVs and single-occupant SAVs (*6*).

RESULTS

In order to compare future travel behaviors to current travel trends, the 5% population sample for the City of Austin is simulated using parameters for current travel, along with existing transit schedule loaded in the Austin network, to better understand system performance. In the base case, mode shares reflect current patterns with cars dominating the streets as observed today (88.7% car users, 4.1% public transit users, and 7.2% for walking and biking (*32*)). The pricing and fleet scenarios examined here can be compared based on various performance metrics. These include 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.

Figure 3 shows the impact of fares, SAV availability and pricing on mode shares that are likely to be observed, and resulting changes to VMT. The reference level for SAV fares does not attract strong SAV use, even when the advanced pricing strategy is applied. SAVs are simply too expensive per mile, as compared to owning and operating a conventional vehicle for daily travel. Even when SAVs are widely available (1 for every 10 persons), the high fare only attracts about 3% mode share, with the shift from transit users and non-motorized modes. Mode share for travel in a personal AV remains nearly constant for all scenarios tested, and this is not surprising given the lower maintenance costs and lower travel disutility associated with AVs. Moderate-to-low fare levels does show a significant change in mode shares. Moderate fleet size (1 SAV for every 25 persons) shows the most promise capturing nearly 30% of all trips made in one day. At low-fare-levels, having SAVs available in abundance (1 SAV for every 10 persons) accounts for nearly half the trips made in the day, but is found to be detrimental to system VMT. This is expected as trips will likely be served without the need to ride-share and this will add a lot of empty VMT.

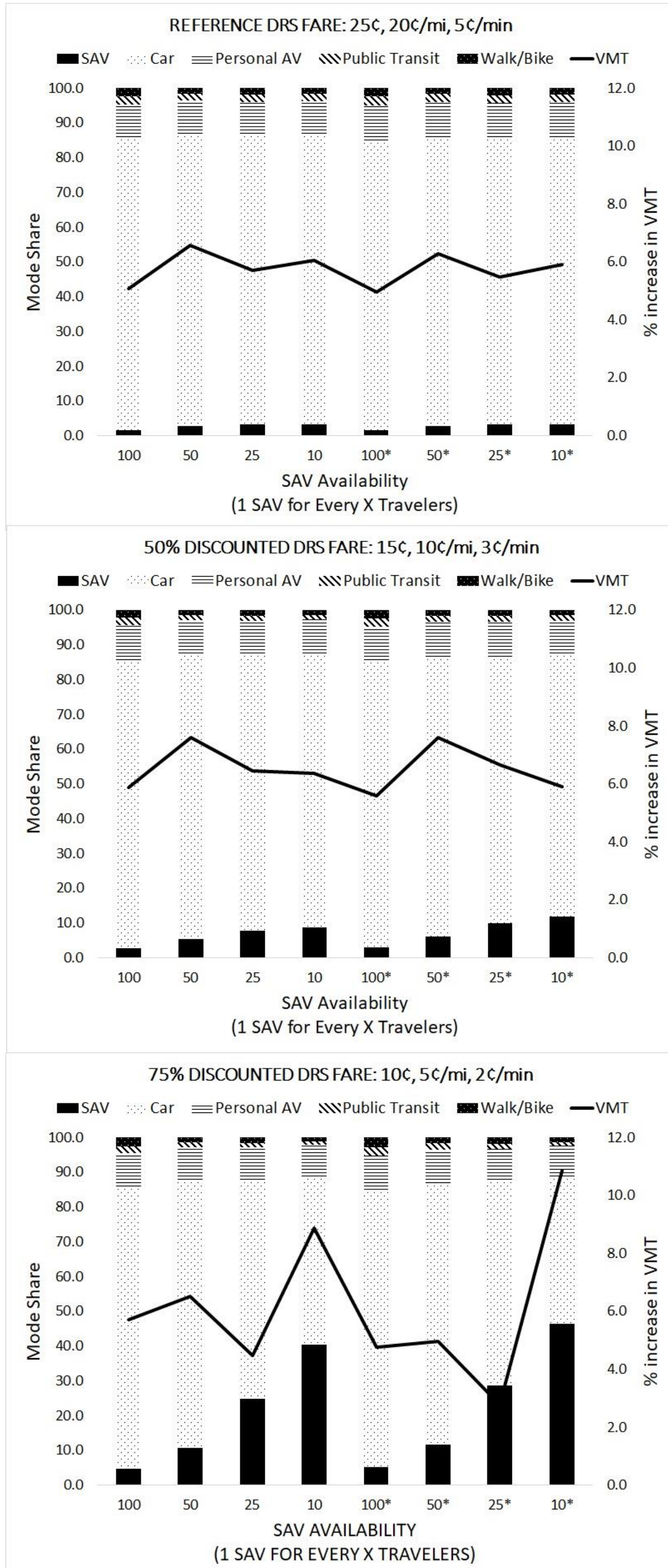

FIGURE 3 Mode Shares & Change in Vehicle-Miles Traveled (Note: * corresponds to results for the pricing scenario)

Regional VMT is predicted to increase by about 5% with the introduction of SAVs, largely arising from empty VMT when SAVs are operating with little-to-no demand. It is also unlikely that a pricing strategy will mitigate this increase. When the SAV service is priced 50% lower than the reference, more SAV trips are made, as expected, but the demand still seems to be insufficient for effective ride-sharing. Serving more trips also resulted in 6-7% increase in VMT. At a 75% discount, the competitive fares nearly tripled the SAV mode share. The effectiveness of pricing travel is seen when SAVs form a significant mode share. The rate of increase of VMT is reduced by about 2%. However, if SAVs are in abundance (1 for every 10 people), VMT is not effectively contained since more people are performing single-occupant trips.

The operational viability of the SAV fleet is also important to discuss and is illustrated in Figures 4 and 5. Small fleet sizes increase response times considerably, thus, limiting the number of people that are served within an acceptable response time. High response times drive the demand for SAVs down. Consequently, when 1 SAV is required to serve 100 travelers, even competitive fares do not capture the market well. The increase in ridership at low fares does mean that a higher AVO can be achieved, as travelers are more willing to ride longer as a tradeoff to paying lower. A maximum AVO of 1.56 is observed for a moderate fleet (with 1 SAV serving 25 people) when pricing is implemented and fares are provided at a 75% discount as compared to the reference fare level. Low mode shares arising from high fares, as well as reduced availability, greatly reduce fleet revenue. Operators are estimated to make $67 per SAV per day. Although reduced fare levels may imply lower revenue, the high mode shares and ride-sharing greatly improves operator revenue. Operators can make as much as $113 per SAV per day with moderate SAV availability (1 SAV every 25 persons) and after paying the tolls. Increased availability of SAVs beyond this threshold reduces revenue from lowered AVO. Empty VMT as a percentage of the fleet's VMT is exceptionally high for small fleets (arising from low demand), and very low for large fleets (arising from SAVs staying idle). A balance is struck for moderate fleet sizes (1 SAV for every 25 persons) charging competitive fares achieving a relatively low empty VMT, as well as maintaining low idle hours per SAV.

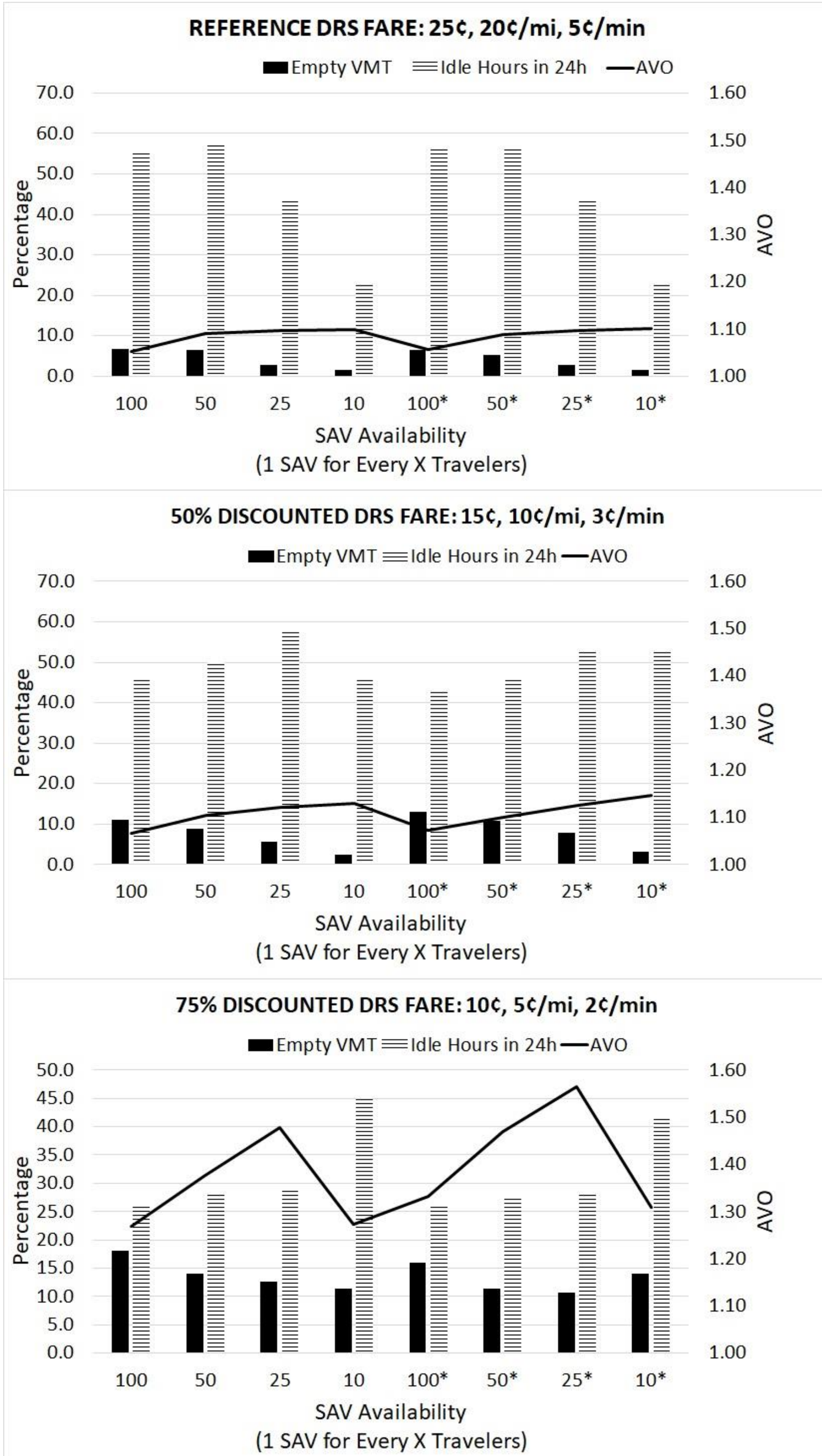

FIGURE 4 Empty VMT, Average SAV Idle Hours in a Day, and Average Vehicle Occupancy (AVO) [Note: * corresponds to results for the pricing scenario]

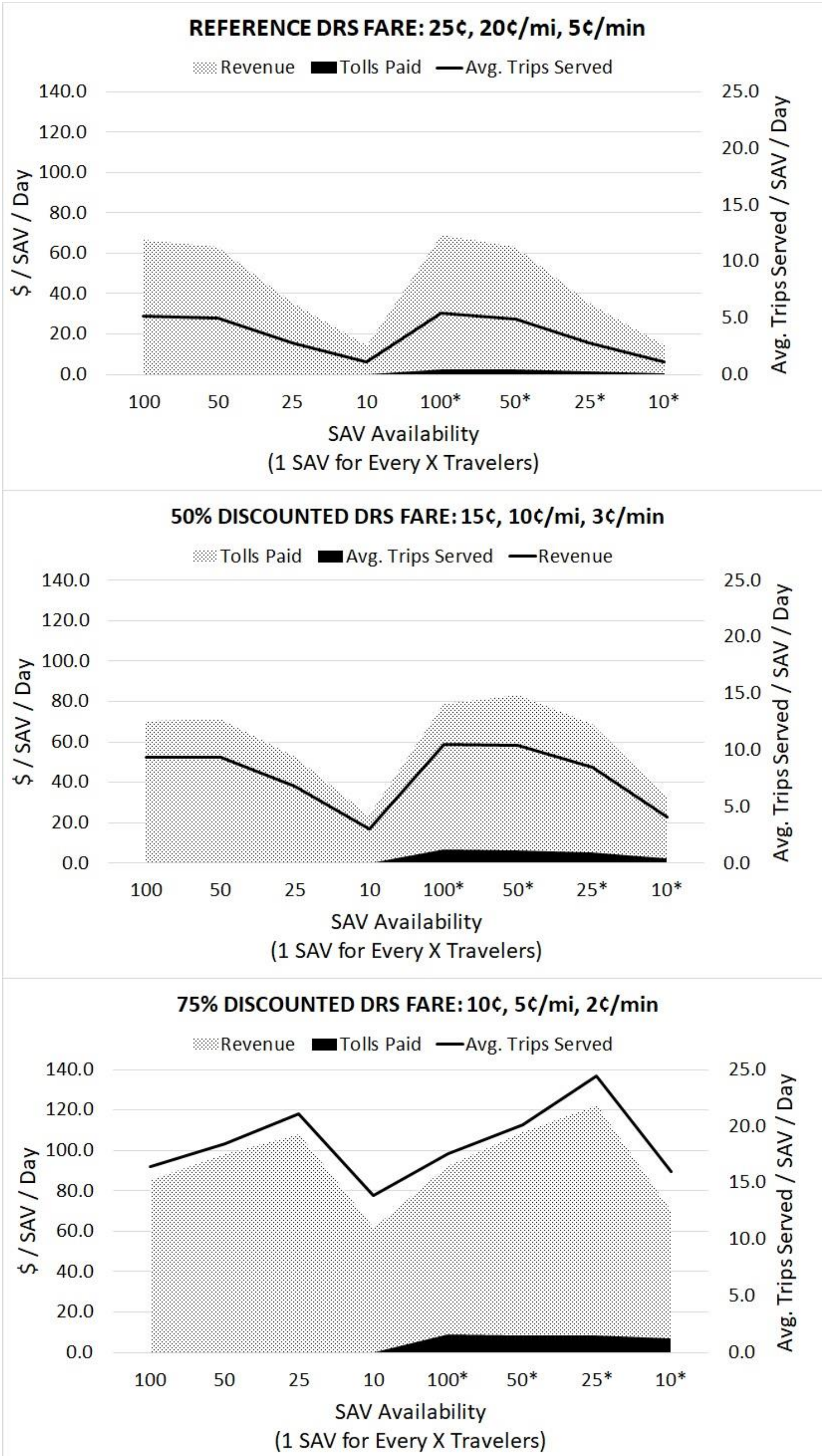

FIGURE 5 Revenue, Tolls and Average Trips Served (Note: * corresponds to results for the pricing scenario)

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 when available reasonably and priced competitively, especially with pricing schemes applied. Pricing improves shared-use uptake and helps moderate rising congestion by reducing added VMT as compared to not pricing. The service was analyzed for three fare levels for DRS, and it was seen that lowering the fares thoughtfully increases the fleet's revenue and demand. Even though SAVs are tolled, the fleet continues to generate more than $100 a day per SAV in the best setting. This revenue is comparable to how much existing fleets with human drivers make minus driver-related costs. Lower prices increases riders' willingness to share rides and produces a higher AVO. However, large fleets promote single-use and diminishes the value of DRS. The revenue generated by these large fleets also fall 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 moderate fleet of SAVs (on the order of 1 SAV for every 25 persons) to ensure a high rate of DRS. This in turn provides system-wide benefits such as moderating the rising congestion and shrinks the U.S. car fleet size. Congestion pricing will help resolve travel delays further, but it must be set in accordance with SAV fleets in use. Federal dollars reserved for an underutilized transit service can be used to provide an end-to-end service with SAVs ensuring that mobility is affordable, convenient, and delay-free. By introducing private fleet operators, it is then also possible to redirect accumulated tolls from fleets to individual drivers, thereby maintaining a revenue-neutral pricing policy.

There are some minor drawbacks in this study. One of them is not modeling induced demand by the elderly, children, and those without drivers' licenses. Computational limitations restricted simulations to a 5% population sample. Even if not explicitly considered, the results of this study will hold true for induced demand as well. Higher reliance on fully-automated modes will increase the viability of the service as demand served is key to a profitable service. Another aspect to note is that popular TNCs charge about $2/mi for single-occupant trips and about $1/mi for shared rides. Contrary to mode shares observed for SAVs here, TNCs enjoy nearly 5% mode share even at these high prices in places like Seattle. This stems primarily from modelers' assumption that an average conventional vehicles cost 30¢/mi, whereas, the majority of conventional vehicles cost upwards of 60¢/mi nowadays. They would then be readily willing to let go of their vehicles and share rides, thus, reinforcing the benefits SAVs and DRS have to offer.

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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