# ANALYZING THE DYNAMIC RIDE-SHARING POTENTIAL FOR SHARED AUTONOMOUS VEHICLE FLEETS USING CELLPHONE DATA FROM ORLANDO, FLORIDA

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**ABSTRACT**

Transportation network companies (TNCs) are regularly demonstrating the economic and operational viability of dynamic ride-sharing (DRS) to any destination within a city (e.g., uberPOOL or Lyft Line), thanks to real-time information from smartphones. In the foreseeable future, fleets of shared automated vehicles (SAVs) may largely eliminate the need for human drivers, while lowering per-mile operating costs and increasing the convenience of travel. This may dramatically reduce private vehicle ownership resulting in extensive use of SAVs. This study anticipates DRS matches across different travelers and identifies optimum fleet sizes required using AirSage's cellphone-based trip tables across 1,267 zones over 30 days. Assuming that the travel patterns do not change significantly in the future, the results suggest significant opportunities for DRS-enabled SAVs. Nearly 60% of the single-person trips could be shared with other individuals traveling solo and with less than 5 minutes added travel time (to arrive at their destinations), and this value climbs to 80% for 15 to 30 minutes of added wait or travel time. 120,000 SAVs will be required to meet less than 43% of Orlando's 2.8 million single-traveler trips. In other words, just 1 SAV per 22 person-trips, on average, is able to serve almost half the region's demand, helping reduce congestion while filling up passenger vehicle seats.

## INTRODUCTION

Traffic safety and congestion are key transportation issues for many regions around the world. Driver error remains the predominant reason for vehicle crashes (NHTSA, 2015), and rising vehicle-miles traveled (VMT) is worsening traffic congestion (FHWA, 2017). The introduction of autonomous vehicles (AVs) for personal use may dramatically reduce vehicle collisions by eliminating driver error. AVs will also improve mobility options for many travelers, especially those without driver's licenses.

Several transportation network companies (TNCs) offer a dynamic ride-sharing (DRS) option, like uberPOOL and Lyft Line. These TNC services attempt to match riders with similar trip plans so that overall travel costs are reduced for riders, without compromising driver wages and TNC profits. Some delay is added for travelers, as they wait to accommodate other riders (in their pickups and/or drop-offs). This also has been referred to as "ridesplitting" (Shaheen *et al*. 2016b). DRS is used here, since it is more widely used in the literature. Ride-sharing is not a new concept (Chan and Shaheen, 2012), with carpooling often being feasible for those with common origins and destinations, and stable, similar departure times on both ends of a round-trip (e.g., for many school trips within a neighborhood and for certain work trips). In practice, only casual carpooling or 'slugging' tends to serve real-time demands of flexible departure times (Ma and Wolfson, 2013; Dai, 2016), and is limited to very special corridors (where high toll and time savings induce many drivers to open their doors to different, unknown passengers every day).

Smartphone technology is fundamental to more widespread use of DRS, since it enables real-time access to traveler (and vehicle) locations (Amey *et al*., 2014). Shaheen *et al*.'s (2016a) FHWA report notes how important smartphone technology has been in improving travel information

access for transit (Transit App), providing shortest paths in real time for many modes (Waze and Google Maps), and increasing carpool-use (Carma). Exploiting this feature, TNCs have designed user-friendly ridesourcing platforms that interface passengers and drivers, at any time of day and in any region the TNCs serve. By selecting the DRS option, travelers' costs (but not travel times) are lowered, thanks to TNCs working to match two or more travelers with overlapping real-time routes. Such matches add some travel time, but deliver significant trip-cost savings and often good conversations among those sharing the ride, who had been strangers (alongside a TNC driver also on board).

AVs will be expensive, at least initially, and not be available for personal ownership for many years (Bansal and Kockelman, 2017). Fleet operators may profitably invest in a fleet of AVs, and manage them as TNCs currently manage their (driver-supplied) fleets, but with lower labor costs and complete control of plans and routes. Safer technologies should eventually bring down insurance costs, making shared AVs, or SAVs, more economically viable. In terms of congestion, SAVs offering DRS can increase average vehicle occupancy (AVO) and reduce regional VMT (Fagnant and Kockelman, 2016; Rodier *et al.*, 2016). It is useful to quantify the level of opportunity for such services, across a range of settings.

This paper studies the DRS potential for trip-making across the Orlando metropolitan area in Florida, as serviced by a fleet of SAVs. It relies on trip tables derived from cellphone data, as provided by AirSage across a period of 30 consecutive days, to provide a sense of day-to-day trip-making variations. The remaining paper summarizes related work, describes the AirSage dataset, and then explains the methodology used to match distinct vehicle trips or traveling parties and simulate a fleet of SAVs. All simulation results are presented, along with various conclusions.

**RELATED LITERATURE**
Over the past 10 years, several contributions have been made to optimize and/or implement DRS, with various researchers suggesting that DRS is a key method for reducing future roadway congestion (Levofsky and Greenberg, 2001; Berbeglia *et al.,* 2010; Ma *et al.,* 2013; Farhan and Chen, 2017; Levin *et al.*, 2017). More recently, DRS has been successfully demonstrated using agent-based models (see, e.g., Fagnant and Kockelman, 2016; Bischoff *et al.,* 2016; Loeb *et al*., 2018; and Hörl, 2017), such as MATsim (Horni *et al*., 2016) and a synthetically generated dataset of people and journeys to simulate dynamic traffic conditions.

When it comes to actual trip-making, mode choices, and traffic patterns, DRS has been investigated for cities like Atlanta, Georgia, Taipei, Taiwan, and New York City. DRS applications include the entire U.S. state of New Jersey and the nation of Singapore, using travel demand model trip-making predictions, publically available taxi datasets, and/or synthetically generated itineraries. Investigations demonstrate system feasibility and/or assess the computational efficiency of different methods for assigning vehicles and/or matching travelers in shared rides. (See Agatz *et al*., 2011; Santi *et al.,* 2014; Alonso-Moro *et al.*, 2016; Brownell and Kornhauser, 2014; Bhat, 2016; Tao, 2007; and Spieser *et al.*, 2014)

Agatz *et al.* (2011) developed a sophisticated algorithm to match riders to their drivers and conducted a simulation using person-trip data obtained from Atlanta's travel demand model. Their

results suggest that DRS works well not only in high-density, high-use settings, but also in sprawling suburbs and at low rates of utilization. However, they focused on driver (and thus TNC vehicle) unavailability, which can hamper sharing and dilute DRS opportunities. Brownell and Kornhauser (2014) focused on SAV system performance for the state of New Jersey. Employing a gridded-network for the entire state, along with synthetic trip-making data, valuable precision, accuracy, and applicability may have been lost in assessing optimal fleet requirements.

Santi *et al.* (2014) and Alonso-Moro *et al.* (2016) overcame both these issues by using publicly available taxi datasets for New York City and real networks (via OpenStreetMaps, an open-source platform for map data). Alonso-Moro *et al.* observed that 98% of the City's 3 million taxi trips could be served with just 2,000 vehicles and low waiting times (averaging just 2.8 minutes), backing DRS capabilities. Bhat (2016) confirmed those New York City taxi results, and added a vehicle repositioning algorithm. Tao (2007) also used a taxi data set, but for the city of Taipei. He developed a heuristic DRS algorithm using real-time taxi movements (not just trip calls by travelers) to test its efficiency in a realistic network setting. Tao (2007) achieved 60% ride matches and concluded that a higher matching rate could be obtained across larger networks with greater density of trip-making.

Of course, taxis do not represent all person-trips in any region. Such trips tend to be shorter than household-vehicle trips (due to their cost), more often for business reasons or those without parking access (again due to their cost), and for visitors (due to their unfamiliarity with the region). DRS investigations of more representative trip-making are desired. By using a population-weighted cellphone dataset, as done here, one overcomes the drawbacks of faked or taxi-based trip patterns. However, certain details are lost (such as trip-to-trip connections throughout the day), in order to protect travelers' privacy, over space and time. Thus, cell-phone-based trips or other forms of extensive diary data tend to be aggregated by traffic analysis zones (TAZs) or neighborhoods, to obscure home and work addresses. To keep data size manageable (for dataset sharing), trips are often aggregated into hourly or multi-hour time-of-day bins as well. More detailed trip ends and trip schedules can be simulated/faked and disaggregated, while preserving the population's basic trip patterns. This process ensures that matches are less obvious (with trips coming from all over a zone and hour, rather than from its centroid or mid-point, for example), and so was used here. But it comes at the expense of some accuracy and precision (versus the reality of actual trip locations and times, which are rarely available to anyone, for any large population).

**CELLPHONE DATASET**
The cellphone-based dataset employed here was generated by AirSage for the month of April 2014 and for travel across the Orlando metropolitan area in Florida. AirSage uses the regular location pings of cell phones that are turned on and carried by customers of its partner companies (like Verizon and Sprint). Cellphone trips observed were aggregated based on six factors: each trip's inferred origin and destination TAZs, the hour and day in which *most* of the trip was made (e.g., 0100-0200 on April 4 or 1600-1700 on April 20), inferred trip purpose, and cell-phone subscriber class. All trips (and basic demographics) inferred from phone pings (of the carriers' cell towers) were then expanded to reflect all trip-making in the region using population-weighted trip counts (including travel by persons who do not own cell phones or carry theirs, turned off). This type of cellphone data has been proven to represent origin-destination flows to a reasonably high-degree

of accuracy by capturing individuals' activity-based data (Calabrese *et al.,* 2011 and Alexander *et al.*, 2015). Of course, limitations remain when researchers do not have access to all cell phone records and/or zone sizes are large.

The Orlando region's metropolitan planning agency models travel across 1,267 TAZs (with 1,261 of them representing metropolitan area and the remaining 6 representing external TAZs). External-zone trips can be very long, with ambiguity in their true destination or origin, so all external trips were removed from the dataset before seeking matches. The remaining 1,261 TAZs have a mean area of 2.22 sq. mi., a standard deviation of 9.92 sq. mi., and a median of 0.53 sq. mi. Traveler type based on work-type (such as, someone who works from home, works within the study area, commutes to the study area for work, or commutes away from the study area for work) also is not relevant, so it is not used here, in making matches. The population-weighted dataset obtained from AirSage lacks mode-specific classification, but since this study attempts to prove the viability of DRS considering all trips, this information can be neglected for the purposes of this study.

MetroPlan Orlando, the region's metropolitan planning organization (MPO), provided a detailed network, with nearly 24,000 nodes and around 61,000 links. Shortest-path travel times between each TAZ were used while disaggregating the trips, as discussed in the next section.

## METHODOLOGY
### Data Disaggregation
Since AirSage provided an anonymized, spatially and temporally aggregate dataset (with trips classified into hourly bins and their origins and destinations by TAZs), smaller time steps and more detailed locations (instead of centroids) were needed for a DRS application of intra-regional trips. Also, the departure times of these trips need not always be in the hourly bin that AirSage indicated for each trip, because trips (within this region) can begin many minutes earlier (or can end many minutes later). This is because only the majority of the trip's duration had to have occurred in the hour bin to which the trip was assigned by AirSage. Keeping these in mind, the data was disaggregated as explained below.

A time-step of one minute was used here, to facilitate computation while preserving dataset integrity, and origins and destinations were randomly sampled from within the origin and destination TAZs. To simplify the process, the trips occurring within an hourly bin was uniformly distributed within the bin. Then, to account for the variability in departure time as mentioned above, 30-minutes of overflow was permitted into the previous and next hour bin, obtained by randomizing the minute-level departure time. The O's and D's for these trips, with varying departure times, were then sampled with equal probability from within their respective TAZs. Once a start time was assigned for these spatially disaggregated trips, the shortest-path travel times for that time of day, as obtained via Caliper Corporation's TransCAD software, a travel-demand modeling tool, were used to sample individual trip travel times from a normal distribution, whose mean equaled this shortest-path travel time and had a standard deviation of $\pm2$ minutes.

Thus, the original 30-day 24-hour dataset was disaggregated resulting in smooth, minute-by-minute trip-request files for each of the 30 days, with higher spatial detail and natural looking departure and arrival time patterns throughout each of the 30 days. The uniform disaggregation in

time and space employed here would serve as conservative estimates of the actual DRS capabilities. One day in this disaggregated dataset contains nearly 6.2 million person-trips.
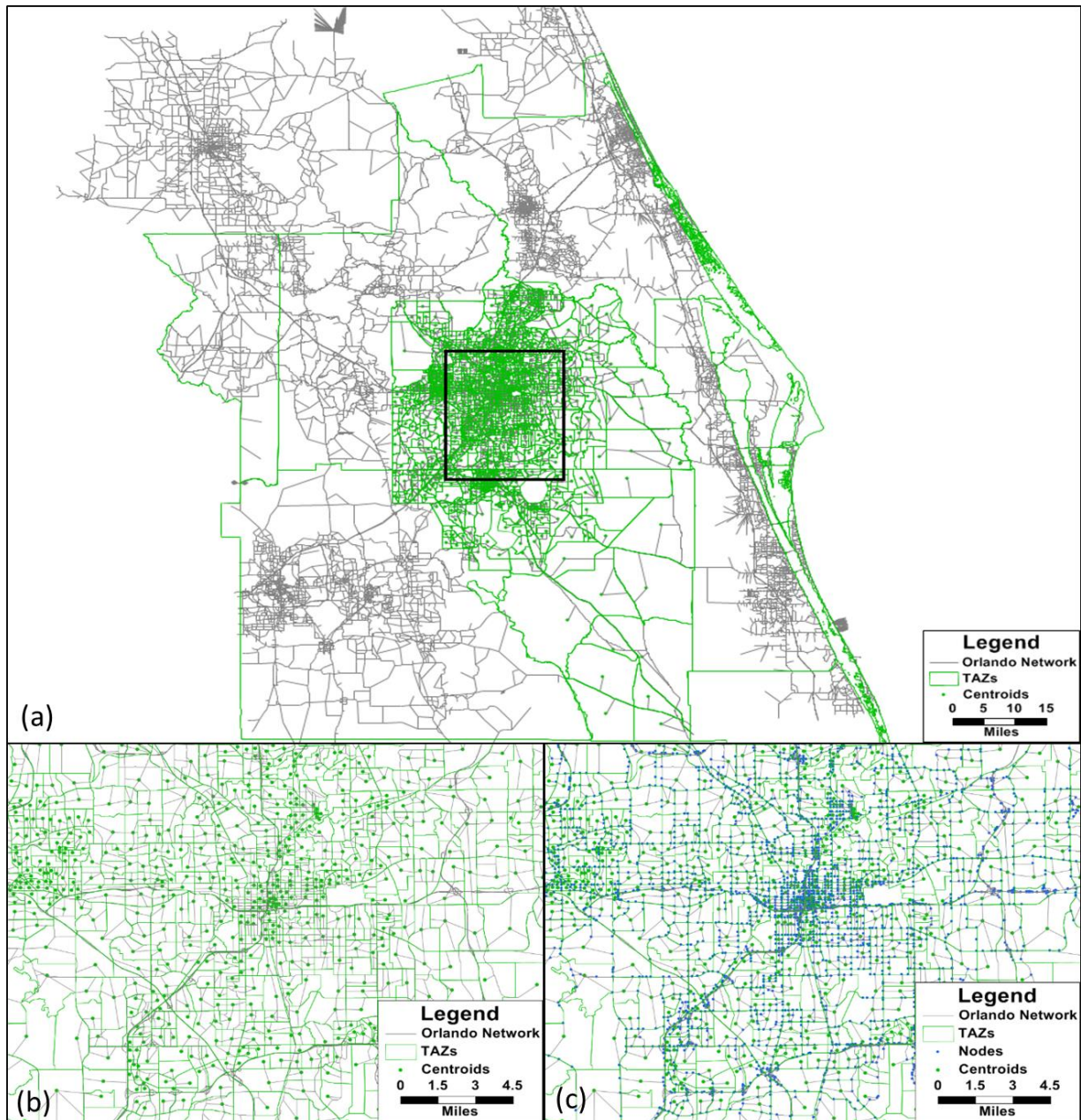


**FIGURE 1  The Orlando network and nodes used for spatial disaggregation a) Orlando network separated by TAZ gridlines b) Centroids used in aggregated data c) Nodes available for spatial disaggregation.**

**Day to Day Variability in Travel Patterns**
The cumulative trip distribution for each of the 30 days was obtained by time of day, as shown in Figure 2. It is evident that trip patterns are similar between weekdays and weekends. Variability, and consequently correlation, between each day was assessed using R software's statistical tool.

Table 1 shows correlation coefficients for trip counts across all origin-destination pairs and across all 30 days of the month, with shading to highlight correlation patterns. Table 1 indicates that high correlation exists for trip patterns on Saturdays and Sundays, and for those made on weekdays, as one would expect (since weekdays have high shares of work and school trips, starting early in the day, while weekends have more flexible departure times and more recreational trip-making). Given these similarities, the following results are presented for a single weekday and a single weekend day. Results are very similar for other days of the 30-day dataset.
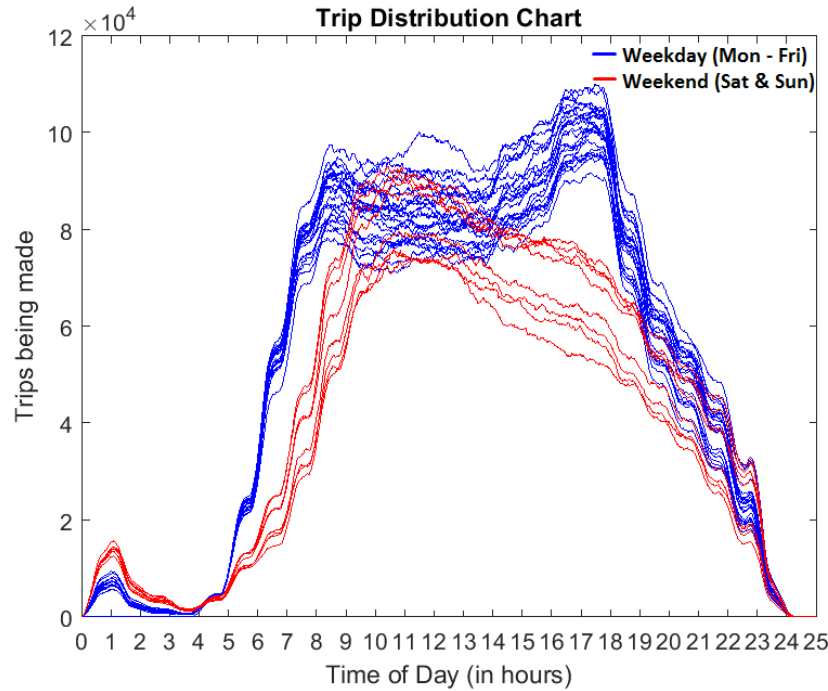


**FIGURE 2  Orlando trip distribution differences, by time of day, between weekdays and weekends.**

**Trip Matching**

An analysis of these trip patterns suggests how many single-person trips can be matched with other trips, enabling ride-sharing, under different trip-delay and re-routing assumptions. A MATLAB code was developed to identify trips whose rides (in an SAV, for example) can be shared. An assumption of 4-person maximum vehicle occupancy was made, along with various travel delay thresholds, before running the code, for various maximum-delay scenarios (ranging from 5 minutes of extra travel time, to a maximum of 30 minutes).

**Error! Reference source not found.** illustrates how travel times under DRS conditions is calculated for this exploratory analysis, with ride-sharing en-route, as compared to those sharing an origin zone and a destination zone and having similar departure times. As noted above, the O-D DRS program matches individual trip-makers so that the earliest departing traveler (in a group of matched travelers, all having the same O and D zone pair) does not experience a wait time greater than the pre-determined limit. The en-route DRS program approach is more complex, in that it matches travelers with potentially different O's and D's such that they have an intersecting

path where each of their wait times (between each traveler's pick-up and drop-off time) are within the same pre-determined limits. This en-route approach is more in line with services currently available, though many uberPOOL and Lyft Line travelers probably share a general origin or destination (e.g., different airlines' gates at the same airport).

Including the entire dataset of trips would mean that trips that are already shared/performed together, like family members travelling together for dinner, inflate the trip-sharing percentages. Florida DOT (2013) estimates that over 50% of all automobile trips in that state are driven alone and 90% of all person-trips are driven in an automobile. Thus, only the portion of the person-trips in the AirSage dataset that may have been a single occupancy vehicle trip were used here, to perform matching (of solo travelers with one another, rather matching those already in traveling parties). This was found to be nearly 2.8 million single occupancy vehicle trips.
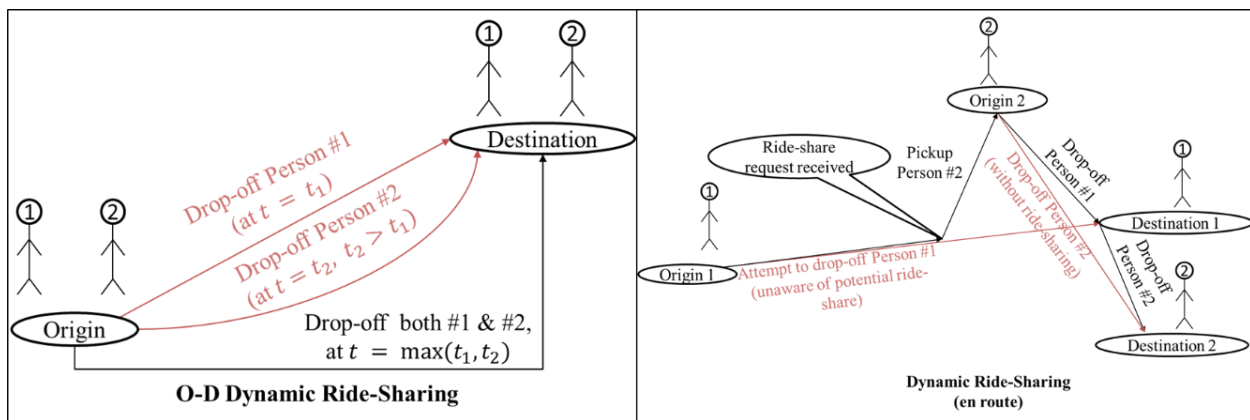


**FIGURE 3  Illustrations of fleet-sharing of O-D DRS and DRS en-route.**

**TABLE 1  Correlation between Hourly Trip-Count Vectors between all Days for the Month of April**

| | Tue | Wed | Thu | Fri | Sat | Sun | Mon | Tue | Wed | Thu | Fri | Sat | Sun | Mon | Tue | Wed | Thu | Fri | Sat | Sun | Mon | Tue | Wed | Thu | Fri | Sat | Sun | Mon | Tue | Wed |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tue | 1.0000 | 0.9979 | 0.9984 | 0.9955 | 0.9346 | 0.9143 | 0.9979 | 0.9942 | 0.9986 | 0.9988 | 0.9954 | 0.9410 | 0.9248 | 0.9984 | 0.9972 | 0.9976 | 0.9974 | 0.9832 | 0.9351 | 0.9166 | 0.9979 | 0.9987 | 0.9988 | 0.9986 | 0.9953 | 0.9450 | 0.9235 | 0.9972 | 0.9961 | 0.9977 |
| Wed | 0.9979 | 1.0000 | 0.9991 | 0.9980 | 0.9476 | 0.9305 | 0.9984 | 0.9956 | 0.9989 | 0.9989 | 0.9978 | 0.9526 | 0.9394 | 0.9982 | 0.9984 | 0.9985 | 0.9988 | 0.9889 | 0.9482 | 0.9305 | 0.9982 | 0.9977 | 0.9989 | 0.9990 | 0.9976 | 0.9563 | 0.9382 | 0.9972 | 0.9943 | 0.9971 |
| Thu | 0.9984 | 0.9991 | 1.0000 | 0.9984 | 0.9451 | 0.9262 | 0.9979 | 0.9955 | 0.9987 | 0.9995 | 0.9982 | 0.9500 | 0.9357 | 0.9982 | 0.9980 | 0.9980 | 0.9990 | 0.9879 | 0.9452 | 0.9258 | 0.9982 | 0.9978 | 0.9986 | 0.9996 | 0.9982 | 0.9536 | 0.9342 | 0.9966 | 0.9940 | 0.9967 |
| Fri | 0.9955 | 0.9980 | 0.9984 | 1.0000 | 0.9534 | 0.9356 | 0.9963 | 0.9958 | 0.9963 | 0.9971 | 0.9997 | 0.9567 | 0.9436 | 0.9956 | 0.9975 | 0.9958 | 0.9978 | 0.9918 | 0.9537 | 0.9319 | 0.9962 | 0.9943 | 0.9958 | 0.9979 | 0.9989 | 0.9597 | 0.9424 | 0.9949 | 0.9908 | 0.9938 |
| Sat | 0.9346 | 0.9476 | 0.9451 | 0.9534 | 1.0000 | 0.9941 | 0.9411 | 0.9415 | 0.9423 | 0.9419 | 0.9531 | 0.9986 | 0.9966 | 0.9432 | 0.9467 | 0.9526 | 0.9541 | 0.9768 | 0.9990 | 0.9917 | 0.9414 | 0.9287 | 0.9384 | 0.9445 | 0.9531 | 0.9981 | 0.9955 | 0.9352 | 0.9218 | 0.9296 |
| Sun | 0.9143 | 0.9305 | 0.9262 | 0.9356 | 0.9941 | 1.0000 | 0.9258 | 0.9292 | 0.9227 | 0.9220 | 0.9341 | 0.9896 | 0.9989 | 0.9244 | 0.9311 | 0.9353 | 0.9370 | 0.9683 | 0.9958 | 0.9952 | 0.9261 | 0.9096 | 0.9195 | 0.9254 | 0.9332 | 0.9910 | 0.9990 | 0.9201 | 0.9061 | 0.9128 |
| Mon | 0.9979 | 0.9984 | 0.9979 | 0.9963 | 0.9411 | 0.9258 | 1.0000 | 0.9975 | 0.9970 | 0.9976 | 0.9961 | 0.9453 | 0.9344 | 0.9984 | 0.9992 | 0.9975 | 0.9973 | 0.9886 | 0.9422 | 0.9266 | 0.9996 | 0.9980 | 0.9977 | 0.9980 | 0.9946 | 0.9505 | 0.9342 | 0.9995 | 0.9979 | 0.9979 |
| Tue | 0.9942 | 0.9956 | 0.9955 | 0.9958 | 0.9415 | 0.9292 | 0.9975 | 1.0000 | 0.9933 | 0.9944 | 0.9950 | 0.9436 | 0.9361 | 0.9934 | 0.9977 | 0.9935 | 0.9949 | 0.9908 | 0.9441 | 0.9253 | 0.9970 | 0.9943 | 0.9945 | 0.9959 | 0.9935 | 0.9487 | 0.9367 | 0.9976 | 0.9956 | 0.9965 |
| Wed | 0.9986 | 0.9989 | 0.9987 | 0.9963 | 0.9423 | 0.9227 | 0.9970 | 0.9933 | 1.0000 | 0.9993 | 0.9963 | 0.9489 | 0.9330 | 0.9978 | 0.9968 | 0.9986 | 0.9982 | 0.9849 | 0.9427 | 0.9252 | 0.9970 | 0.9983 | 0.9995 | 0.9989 | 0.9970 | 0.9524 | 0.9313 | 0.9959 | 0.9935 | 0.9974 |
| Thu | 0.9988 | 0.9989 | 0.9995 | 0.9971 | 0.9419 | 0.9220 | 0.9976 | 0.9944 | 0.9993 | 1.0000 | 0.9970 | 0.9477 | 0.9321 | 0.9983 | 0.9974 | 0.9983 | 0.9986 | 0.9857 | 0.9420 | 0.9234 | 0.9980 | 0.9986 | 0.9992 | 0.9995 | 0.9976 | 0.9513 | 0.9307 | 0.9966 | 0.9944 | 0.9972 |
| Fri | 0.9954 | 0.9978 | 0.9982 | 0.9997 | 0.9531 | 0.9341 | 0.9961 | 0.9950 | 0.9963 | 0.9970 | 1.0000 | 0.9568 | 0.9424 | 0.9958 | 0.9973 | 0.9957 | 0.9976 | 0.9910 | 0.9529 | 0.9310 | 0.9957 | 0.9942 | 0.9957 | 0.9978 | 0.9988 | 0.9595 | 0.9411 | 0.9945 | 0.9905 | 0.9934 |
| Sat | 0.9410 | 0.9526 | 0.9500 | 0.9567 | 0.9986 | 0.9896 | 0.9453 | 0.9436 | 0.9489 | 0.9477 | 0.9568 | 1.0000 | 0.9939 | 0.9494 | 0.9508 | 0.9586 | 0.9586 | 0.9768 | 0.9974 | 0.9907 | 0.9456 | 0.9349 | 0.9448 | 0.9498 | 0.9574 | 0.9988 | 0.9921 | 0.9394 | 0.9269 | 0.9354 |
| Sun | 0.9248 | 0.9394 | 0.9357 | 0.9436 | 0.9966 | 0.9989 | 0.9344 | 0.9361 | 0.9330 | 0.9321 | 0.9424 | 0.9939 | 1.0000 | 0.9345 | 0.9395 | 0.9451 | 0.9457 | 0.9730 | 0.9977 | 0.9970 | 0.9349 | 0.9202 | 0.9296 | 0.9351 | 0.9421 | 0.9952 | 0.9993 | 0.9290 | 0.9155 | 0.9224 |
| Mon | 0.9984 | 0.9982 | 0.9982 | 0.9956 | 0.9432 | 0.9244 | 0.9984 | 0.9934 | 0.9978 | 0.9983 | 0.9958 | 0.9494 | 0.9345 | 1.0000 | 0.9981 | 0.9986 | 0.9977 | 0.9861 | 0.9430 | 0.9281 | 0.9984 | 0.9977 | 0.9980 | 0.9985 | 0.9951 | 0.9535 | 0.9334 | 0.9973 | 0.9956 | 0.9963 |
| Tue | 0.9972 | 0.9984 | 0.9980 | 0.9975 | 0.9467 | 0.9311 | 0.9992 | 0.9977 | 0.9968 | 0.9974 | 0.9973 | 0.9508 | 0.9395 | 0.9981 | 1.0000 | 0.9974 | 0.9974 | 0.9907 | 0.9477 | 0.9309 | 0.9988 | 0.9967 | 0.9973 | 0.9983 | 0.9960 | 0.9550 | 0.9393 | 0.9984 | 0.9962 | 0.9972 |
| Wed | 0.9976 | 0.9985 | 0.9980 | 0.9958 | 0.9526 | 0.9353 | 0.9975 | 0.9935 | 0.9986 | 0.9983 | 0.9957 | 0.9586 | 0.9451 | 0.9986 | 0.9974 | 1.0000 | 0.9986 | 0.9894 | 0.9531 | 0.9390 | 0.9974 | 0.9966 | 0.9983 | 0.9984 | 0.9961 | 0.9621 | 0.9437 | 0.9961 | 0.9931 | 0.9962 |
| Thu | 0.9974 | 0.9988 | 0.9990 | 0.9978 | 0.9541 | 0.9370 | 0.9973 | 0.9949 | 0.9982 | 0.9986 | 0.9976 | 0.9586 | 0.9457 | 0.9977 | 0.9974 | 0.9986 | 1.0000 | 0.9914 | 0.9543 | 0.9374 | 0.9976 | 0.9962 | 0.9978 | 0.9988 | 0.9974 | 0.9621 | 0.9445 | 0.9956 | 0.9925 | 0.9953 |
| Fri | 0.9832 | 0.9889 | 0.9879 | 0.9918 | 0.9768 | 0.9683 | 0.9886 | 0.9908 | 0.9849 | 0.9857 | 0.9910 | 0.9768 | 0.9730 | 0.9861 | 0.9907 | 0.9894 | 0.9914 | 1.0000 | 0.9787 | 0.9647 | 0.9886 | 0.9809 | 0.9841 | 0.9877 | 0.9892 | 0.9807 | 0.9736 | 0.9866 | 0.9804 | 0.9825 |
| Sat | 0.9351 | 0.9482 | 0.9452 | 0.9537 | 0.9990 | 0.9958 | 0.9422 | 0.9441 | 0.9427 | 0.9420 | 0.9529 | 0.9974 | 0.9977 | 0.9430 | 0.9477 | 0.9531 | 0.9543 | 0.9787 | 1.0000 | 0.9930 | 0.9425 | 0.9297 | 0.9392 | 0.9447 | 0.9531 | 0.9976 | 0.9972 | 0.9368 | 0.9237 | 0.9313 |
| Sun | 0.9166 | 0.9305 | 0.9258 | 0.9319 | 0.9917 | 0.9952 | 0.9266 | 0.9253 | 0.9252 | 0.9234 | 0.9310 | 0.9907 | 0.9970 | 0.9281 | 0.9309 | 0.9390 | 0.9374 | 0.9647 | 0.9930 | 1.0000 | 0.9273 | 0.9125 | 0.9215 | 0.9259 | 0.9306 | 0.9931 | 0.9969 | 0.9212 | 0.9084 | 0.9141 |
| Mon | 0.9979 | 0.9982 | 0.9982 | 0.9962 | 0.9414 | 0.9261 | 0.9996 | 0.9970 | 0.9970 | 0.9980 | 0.9957 | 0.9456 | 0.9349 | 0.9984 | 0.9988 | 0.9974 | 0.9976 | 0.9886 | 0.9425 | 0.9273 | 1.0000 | 0.9982 | 0.9975 | 0.9981 | 0.9948 | 0.9511 | 0.9346 | 0.9990 | 0.9973 | 0.9974 |
| Tue | 0.9987 | 0.9977 | 0.9978 | 0.9943 | 0.9287 | 0.9096 | 0.9980 | 0.9943 | 0.9983 | 0.9986 | 0.9942 | 0.9349 | 0.9202 | 0.9977 | 0.9967 | 0.9966 | 0.9962 | 0.9809 | 0.9297 | 0.9125 | 0.9982 | 1.0000 | 0.9988 | 0.9980 | 0.9942 | 0.9402 | 0.9191 | 0.9981 | 0.9972 | 0.9983 |
| Wed | 0.9988 | 0.9989 | 0.9986 | 0.9958 | 0.9384 | 0.9195 | 0.9977 | 0.9945 | 0.9995 | 0.9992 | 0.9957 | 0.9448 | 0.9296 | 0.9980 | 0.9973 | 0.9983 | 0.9978 | 0.9841 | 0.9392 | 0.9215 | 0.9975 | 0.9988 | 1.0000 | 0.9990 | 0.9963 | 0.9485 | 0.9283 | 0.9969 | 0.9952 | 0.9985 |
| Thu | 0.9986 | 0.9990 | 0.9996 | 0.9979 | 0.9445 | 0.9254 | 0.9980 | 0.9959 | 0.9989 | 0.9995 | 0.9978 | 0.9498 | 0.9351 | 0.9985 | 0.9983 | 0.9984 | 0.9988 | 0.9877 | 0.9447 | 0.9259 | 0.9981 | 0.9980 | 0.9990 | 1.0000 | 0.9980 | 0.9533 | 0.9339 | 0.9970 | 0.9946 | 0.9976 |
| Fri | 0.9953 | 0.9976 | 0.9982 | 0.9989 | 0.9531 | 0.9332 | 0.9946 | 0.9935 | 0.9970 | 0.9976 | 0.9988 | 0.9574 | 0.9421 | 0.9951 | 0.9960 | 0.9961 | 0.9974 | 0.9892 | 0.9531 | 0.9306 | 0.9948 | 0.9942 | 0.9963 | 0.9980 | 1.0000 | 0.9595 | 0.9403 | 0.9929 | 0.9884 | 0.9928 |
| Sat | 0.9450 | 0.9563 | 0.9536 | 0.9597 | 0.9981 | 0.9910 | 0.9505 | 0.9487 | 0.9524 | 0.9513 | 0.9595 | 0.9988 | 0.9952 | 0.9535 | 0.9550 | 0.9621 | 0.9621 | 0.9807 | 0.9976 | 0.9931 | 0.9511 | 0.9402 | 0.9485 | 0.9533 | 0.9595 | 1.0000 | 0.9941 | 0.9454 | 0.9333 | 0.9401 |
| Sun | 0.9235 | 0.9382 | 0.9342 | 0.9424 | 0.9955 | 0.9990 | 0.9342 | 0.9367 | 0.9313 | 0.9307 | 0.9411 | 0.9921 | 0.9993 | 0.9334 | 0.9393 | 0.9437 | 0.9445 | 0.9736 | 0.9972 | 0.9969 | 0.9346 | 0.9191 | 0.9283 | 0.9339 | 0.9403 | 0.9941 | 1.0000 | 0.9291 | 0.9161 | 0.9222 |
| Mon | 0.9972 | 0.9972 | 0.9966 | 0.9949 | 0.9352 | 0.9201 | 0.9995 | 0.9976 | 0.9959 | 0.9966 | 0.9945 | 0.9394 | 0.9290 | 0.9973 | 0.9984 | 0.9961 | 0.9956 | 0.9866 | 0.9368 | 0.9212 | 0.9990 | 0.9981 | 0.9969 | 0.9970 | 0.9929 | 0.9454 | 0.9291 | 1.0000 | 0.9988 | 0.9981 |
| Tue | 0.9961 | 0.9943 | 0.9940 | 0.9908 | 0.9218 | 0.9061 | 0.9979 | 0.9956 | 0.9935 | 0.9944 | 0.9905 | 0.9269 | 0.9155 | 0.9956 | 0.9962 | 0.9931 | 0.9925 | 0.9804 | 0.9237 | 0.9084 | 0.9973 | 0.9972 | 0.9952 | 0.9946 | 0.9884 | 0.9333 | 0.9161 | 0.9988 | 1.0000 | 0.9976 |
| Wed | 0.9977 | 0.9971 | 0.9967 | 0.9938 | 0.9296 | 0.9128 | 0.9979 | 0.9965 | 0.9974 | 0.9972 | 0.9934 | 0.9354 | 0.9224 | 0.9963 | 0.9972 | 0.9962 | 0.9953 | 0.9825 | 0.9313 | 0.9141 | 0.9974 | 0.9983 | 0.9985 | 0.9976 | 0.9928 | 0.9401 | 0.9222 | 0.9981 | 0.9976 | 1.0000 |

**Fleet Simulation**

A fleet simulation was carried out to assess a practical SAV fleet requirement for the metropolitan region of Orlando to cater to the trips with pre-specified service characteristics (such as, maximum waiting time or maximum additional in-vehicle travel time). Here, practicality is defined from an operator's perspective: a practical fleet is one with fewest vehicles able to serve the most (single-person) trips possible while adhering to these pre-specified characteristics. A framework was developed in MATLAB to simulate a fleet of SAVs for a typical day. The trip request file generated from data disaggregation served as an input to the framework, along with the characteristics that are expected of the fleet. This included: fleet size, maximum allowable waiting time before an SAV is assigned to a passenger, maximum allowable time an SAV can take to reach the passenger, maximum additional time that is imposed on passengers who will be detoured for a new pickup and maximum additional time that a newly picked-up passenger has to wait while the previous occupants are dropped off. Table 2 states all these variables along with their abbreviations and this will stay consistent in definition for the remaining sections of the paper. In addition to this, Orlando's network was converted into a MATLAB directional graph (digraph) and used to analyze shortest-path routes and times taken by SAVs.

**TABLE 2 List of Abbreviations Used in Reference to the Simulation Framework**

| Abbreviation | Description | Values Considered |
|---|---|---|
| *#SAVs* | Total number of SAVs in the fleet | 5,000 , 10,000 , … 30,000 , 60,000 , 120,000 |
| *maxExtraTripTime* | Minimum time imposed on travelers sharing their trips | 5 minutes and 10 minutes, … 30 minutes |
| *maxWaitingTime* | Maximum time that a passenger has to wait before an SAV reaches him/her | 5 minutes, 10 minutes |
| *maxSearchTime* | Maximum time that a trip is stored on the waitlist before being rejected | 0 minutes, 1 minute, 3 minutes, 10 minutes |
| *unserviced* | Total trips that cannot be serviced under the above restrictions | *Internally calculated* |
| *ETA* | Estimated arrival time for an SAV to either pick up or drop off a passenger | *Internally calculated* |

The framework was composed of three distinct blocks: SAV allocation, SAV update and waitlist management. The SAV allocation block allocates the nearest SAV to a trip request based on the *maxWaitingTime* criterion. If no SAV was found satisfying this criterion, the trip request is stored in the waitlist. If an SAV with an existing occupant is located, the *maxExtraTripTime* criterion is checked prior to allocation, to minimize delays imposed on the travelers. After all the trips in a particular time step are either allocated to an SAV or stored in the waitlist, the SAV update block for the next time step is executed. In the SAV update block, the current location, destination and *ETA* of an SAV is monitored. If the SAV has not reached its destination for either a pickup or a dropoff operation, then its current location and *ETA* are updated. If the SAV has reached its

destination for pickup, the dropoff operation is initiated. If a dropoff was executed, the second destination for dropoff of shared rides is processed, or the SAV stays idle, waiting for the next request. Once the update block has executed, all previously waitlisted trip requests are checked for SAV allocation before moving on to the next time step of trip requests. If the trip requests have been on the waitlist for more than *maxSearchTime*, they are removed from the waitlist and *unserviced* is updated to reflect the same. The flowchart for the process described is shown in Figure 4. Fleet sizes varying from 5,000 - 120,000 SAVs, in intervals of 5,000 up to 30,000 and two sizes of 60,000 and 120,000, was used for these simulations and the results are discussed in the next section.
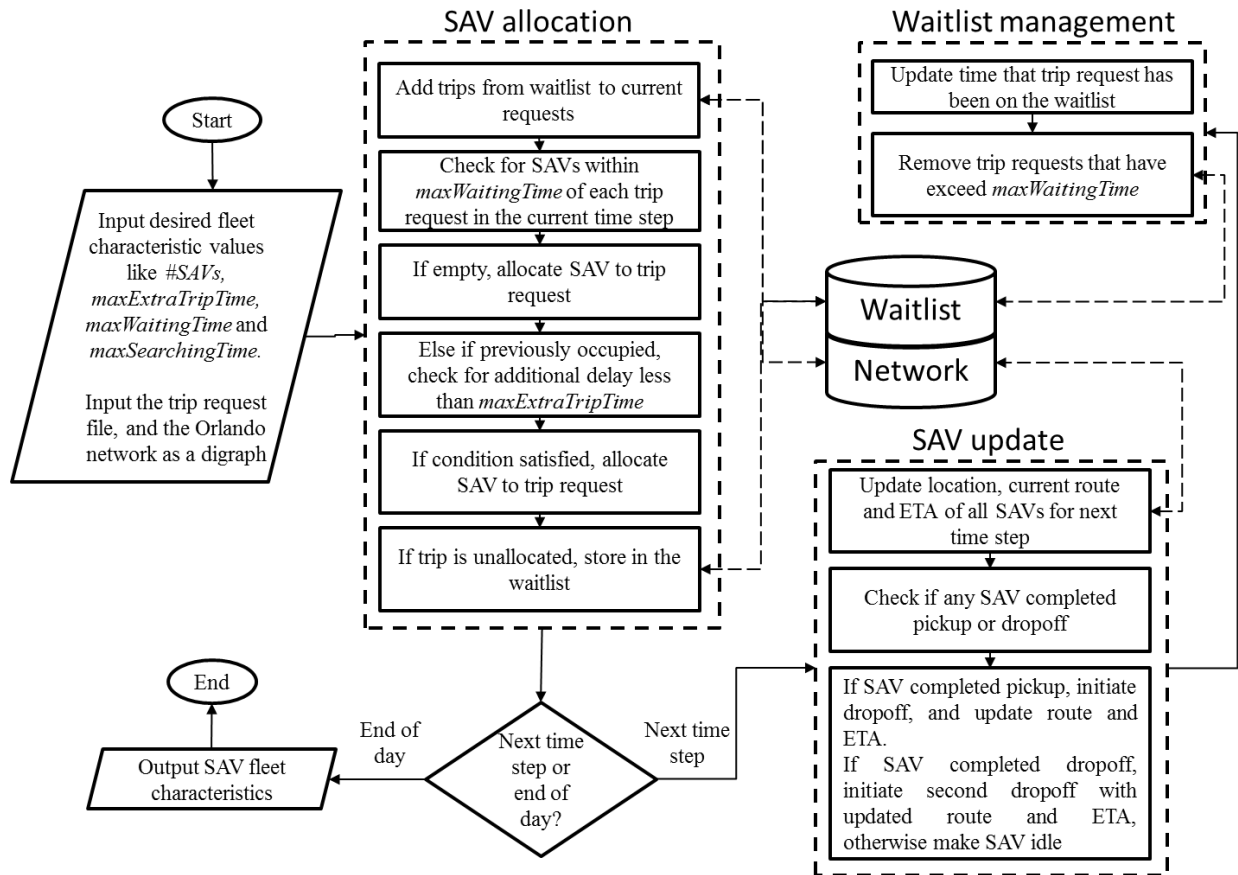


**FIGURE 4  The flowchart describing the main modules of the simulation framework.**

## RESULTS

### Infinite Fleet based Trip Matching

Trips matched assuming availability of an infinite fleet provided optimistic results. As shown in Table 3, even after removing a large share of trips that reflect traveling parties (and thus focusing only on Orlando trips undertaken by a single person), nearly 60% of all such single-person trips can be shared with less than 5 minutes of added total travel (for each of the ride-sharing travelers, including any wait time added). This percentage reaches 86% matching or shared when travelers are willing to wait (or delay their destination arrivals, for example) up to 30 minutes. Of course, not all travelers need to be willing to wait that long; most of the matches are made with added

delays of under 5 minutes. It is interesting to note that O-D DRS remains almost a constant for trips with maximum allowed travel time greater than 10 minutes. This is due to the spatial constraint on these trips which restricts scope for matches after a point in temporal flexibility.

**TABLE 3  Percentage of Orlando Trips That Can Be Shared With O-D DRS and DRS en-route for a 4-Passenger SAV under Different Maximum-Delay Assumptions**

| Maximum Added Travel Time (including wait time) | Percentage of Trips that Can be Shared (O-D DRS) | Percentage of Trips that Can be Shared (DRS en-route) |
|---|---|---|
| 5 min | 18.48% | 56.82% |
| 10 | 20.56 | 74.15 |
| 15 | 20.55 | 80.56 |
| 20 | 20.57 | 83.57 |
| 25 | 20.65 | 85.29 |
| 30 | 20.65 | 86.23 |

**Fixed Fleet based DRS Simulation**

A fixed fleet assumption offers reliable results in terms of ready applicability. A simulation based on a fixed fleet size and given service characteristics were simulated to obtain fleet sizes for each permutation and combination that was found to be practically valid. Figure 5 below shows the different fleet sizes assumed in different scenarios, as well as the different service characteristics. The percentage demand served, percentage VMT reduction observed, percentage empty VMT and the average number of trips served by an SAV have been shown as metrics to assess the best fleet. A vehicle replacement ratio is also calculated, as done by Loeb and Kockelman (2017) and Fagnant and Kockelman (2016). The average number of trips made by a conventional vehicle in one day is 3.02 (NHTS, 2009). Since the average SAV focused on solo travelers in the Orlando region serves 22.05 person-trips/day, it appears that more than 7 conventional vehicles can be replaced by 1 SAV. The average trip-length per person-trip for all the scenarios was found to be 14.4 miles with a standard deviation of $\pm$ 1.29 miles. The change in VMT was calculated relative to the VMT observed by all the trips on the network without the fleet. Surprisingly, the use of such fleets added VMT to the network from as little as 4% (by poorly performing fleets) to as much as 49% (by well performing fleets). On average, each SAV travels nearly 329 miles in one day and this intensive use explains the rise in VMT. SAVs can be expected to go through quick transitions from acquisition to being salvaged or sold.
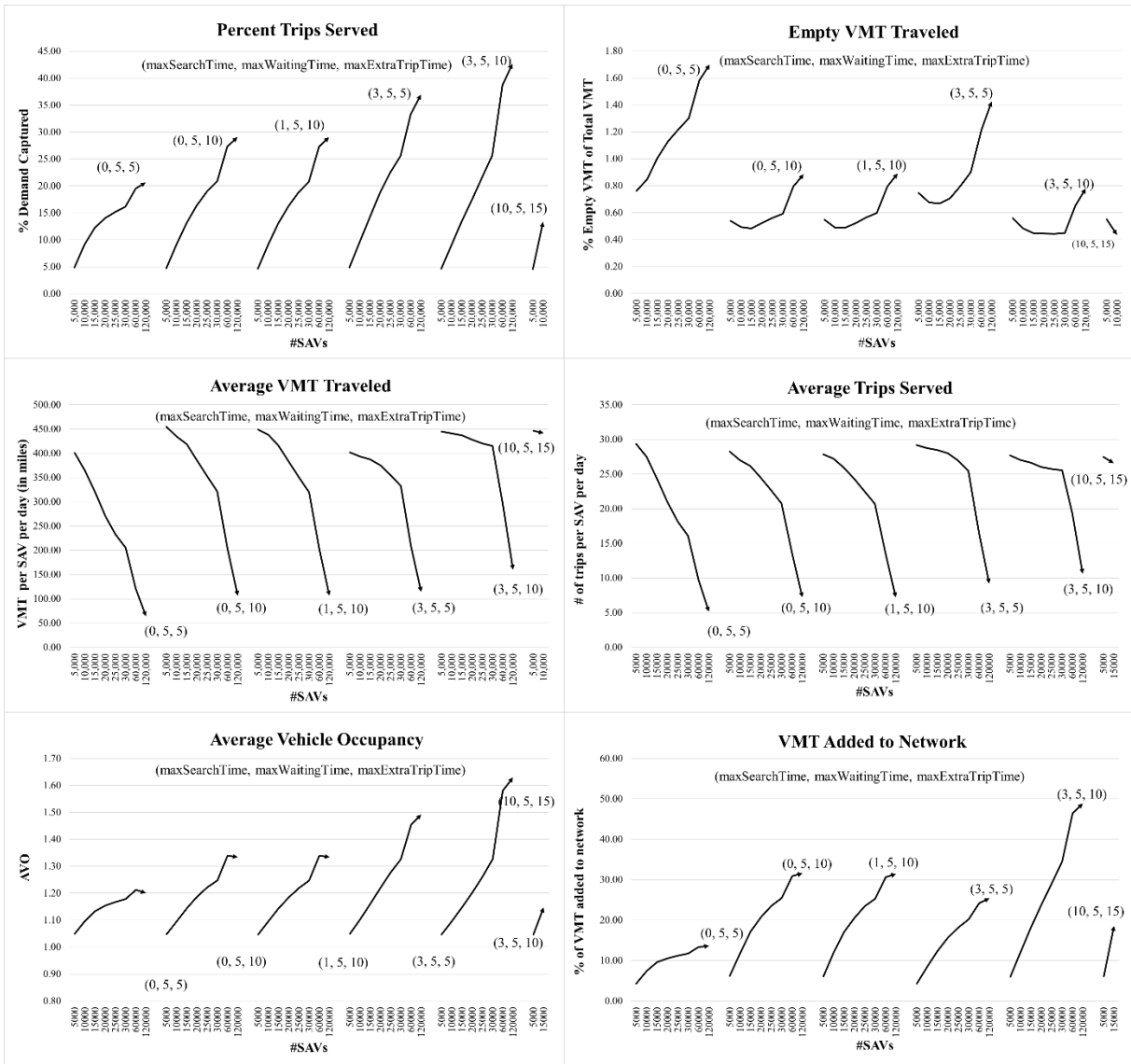
**FIGURE 5  DRS potential based on fleet sizes and service characteristics.**

High average trip-lengths for each SAV was observed for each scenario. To understand this, the trip-length distributions were visualized and as seen in Figure 6, Orlando has a heavy tail of high trip-lengths. This is consistent with the millions of tourists who make shopping and recreational trips in the region.

**Distribution of Trip-Lengths**
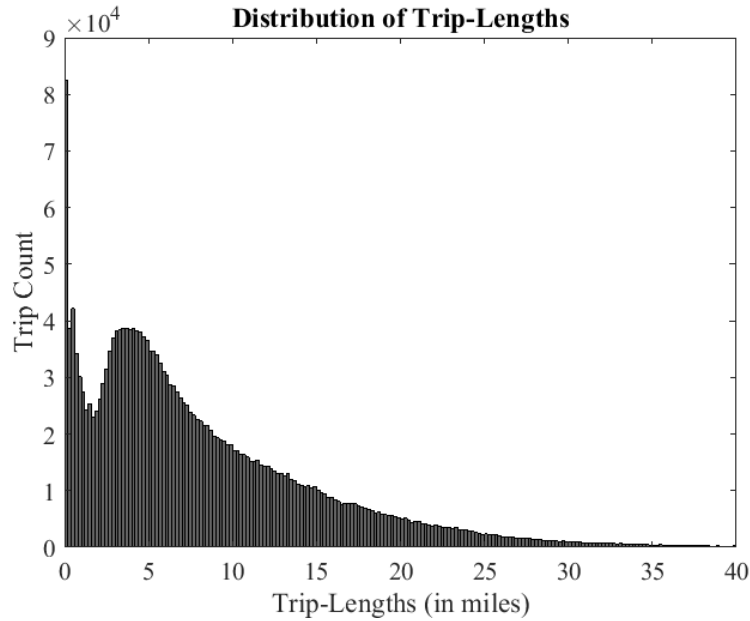
**FIGURE 6  Trip-length distribution for the disaggregated data for one day.**

**CONCLUSIONS**

This study anticipates the fraction of single-person trips that appear easily matched with one another, making them excellent candidates for dynamic ride-sharing across the Orlando metropolitan area. Several studies have simulated the operations of SAV fleets but without the comprehensive nature of this cellphone-based dataset (e.g., taxi datasets do not reflect other modes of travel) and/or without other key data (e.g., actual travel times). With such data in hand, and a new setting for simulation (a Florida city and major destination for many vacationers), the results obtained here may be relevant for many interested in encouraging SAV use and DRS, to keep travel costs, VMT, emissions, and congestion down, as self-driving vehicles start making travel easier.

The trip-matching algorithm employed here suggests that nearly 60% of all single-person trips occurring each weekday in Orlando appear matchable to other trips taking place (for those traveling solo), with less than 5 minutes of added total travel time (including any wait time). Any added willingness to wait (up to 10 minutes or 15 minutes, maximum, for example) brings this percentage up (to 74.2% and 80.6%, respectively), suggesting substantial shared-fleet activities in many (and probably all) cities around the U.S. and presumably around the world.The second part of the paper used a fleet simulation algorithm to gauge the fleet size requirements to achieve the above predicted levels of ride-sharing. Results indicated that a fleet size of around 120,000 SAVs were needed to cater to less than 43% of Orlando's 2.8 million single-traveler trip demands (i.e., not counting existing carpools by family, friends, and colleagues). On average, one SAV can replace a little more than 7 conventional vehicles or in the best demand-capture case, almost 4 conventional vehicles. The practical fleet size required can be significantly reduced, if one uses more complex matching algorithms, thus increasing the replacement ratio. It also worthy to note

that Orlando's unique trip patterns, shopping trip count and above-average person-trip lengths may be negatively biasing the results.

One important limitation arising here is the assumed disaggregation of trips, over space and time. Uniform temporal and spatial disaggregation was used to spread AirSage cellphone trip ends over time and space. In reality, many trips may be more concentrated, increasing the likelihood of trip-matching, especially during peak times of day. Real-world implementations may be even more successful. In other words, the vehicle-replacement ratio obtained in this study serves as a lower bound to practically observable values. Similar frameworks, with simulated data, have shown that replacement ratios between 6 and 9 (Burns *et al.*, 2013), 10.8 (Fagnant and Kockelman, 2016), and between 3.75 and 11.5 (Loeb and Kockelman, 2017).

In addition, average vehicle occupancies form an integral part of determining how effective the fleet is at matching and sharing trips. In this analysis, average AVO over all scenarios was found to be 1.21 with a maximum of 1.63. With the right policy being implemented, the rise in VMT can be countered by being able to remove every other SOV currently driven in Orlando. All it requires is travelers' willingness to share rides with people they do not yet know. Hopefully, that will not pose a challenge long-term, so that our cities and nations can reduce fossil fuel reliance, emissions, congestion, and travel costs.

**REFERENCES**

Agatz, Niels, Erera, Alan, Savelsbergh, Martin and Wang, Xing. (2011). Dynamic ride-sharing: A simulation study in metro Atlanta. *Procedia Social and Behavioral Sciences* 17: 532-550.

Alexander, L., Jiang, S., Murga, M., and Gonzalez, M. C. 2015. Origin-Destination Trips by Purpose and Time of Day Inferred from Mobile Phone Data. *Transportation Research Part C: Emerging Technologies* 58:240-250.

Alonso-Mora, Javier, Samaranayake, Samitha, Wallar, Alex, Frazzoli, Emilio and Rus, Daniela. (2016). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences of the United States of America* 114(3): 462-467.

Amey, A., Attanucci, J. and Mishalani, R. 2014. Real-time Ridesharing: Opportunities and Challenges in Using Mobile Phone Technology to Improve Rideshare Services. *Transportation Research Record* 2217: 103-110. DOI: 10.3141/2217-13.

Bansal, Prateek and Kockelman, Kara. 2017. Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies. *Transportation Research Part A* 95: 49-63. Retrieved from:
http://www.caee.utexas.edu/prof/kockelman/public_html/TRB16CAVTechAdoption.pdf (June 30, 2017).

Berbeglia, Gerardo, Cordeau, Jean-Francois, and Laporte, Gilbert. (2010). Dynamic pickup and delivery problems. *European Journal of Operational Research* 202(1): 8-15.

Bhat, Suraj. 2016. Quantifying the Potential for Dynamic Ride-Sharing of New York City's Taxicabs (Undergraduate Thesis). Retrieved from:

http://orfe.princeton.edu/~alaink/SmartDrivingCars/Papers/Bhat,Suraj_Final_Thesis2016.pdf (June 30, 2017).

Bischoff, J., Soeffker, N. and Maciejewski, M. (2016). A framework for agent based simulation of demand responsive transport systems. Retrieved from: http://dx.doi.org/10.14279/depositonce-5760 (June 30, 2017).

Brownell, Chris and Kornhauser, Alain. (2014). A Driverless Alternative: Fleet Size and Cost Requirements for a Statewide Autonomous Taxi Network in New Jersey. *Transportation Research Record* 2416: 73-81.

Burns, Lawrence D., Jordan, William C. and Scarborough, Bonnie A. 2013. Transforming personal mobility. *The Earth Institute-Columbia University.* Retrieved from: http://sustainablemobility.ei.columbia.edu/files/2012/12/Transforming-Personal-Mobility-Jan-27-20132.pdf (April 16, 2018)

Calabrese, F., Di Lorenzo, G., Liu, L., and Ratti, C. 2011. Estimating Origin-Destination Flows using Opportunistically Collected Mobile Phone Location Data from One Million Users in Boston Metropolitan Area. *IEEE Pervasive Computing* 10(4):36-44.

Chan, N. and Shaheen, S. 2012. Ridesharing in North America: Past, present, and future. *Transport Reviews 32*(1): 93-112. Retrieved from: http://tsrc.berkeley.edu/sites/default/files/Ridesharing%20in%20North%20America%20Past%20%20Present%20%20and%20Future.pdf (July 20, 2017).

Dai, Chengcheng. 2016. Ridehsaring Recommendation: Whether and Where Should I Wait? Proceedings of the International Conference on Web-Age Information Management, Nanchang, China. Retrieved from: https://link.springer.com/content/pdf/10.1007%2F978-3-319-39937-9_12.pdf (July 20, 2017).

Fagnant, Daniel J. and Kockelman, Kara M. (2016). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles. *Transportation* 45: 1-16.

Farhan, Javed and Chen, T. Donna. (2017). Impact of Ridesharing on Operational Efficiency of Shared Autonomous Electric Vehicle Fleet. Under review for publication in *Transportation Research Part C: Emerging Technologies*.

Federal Highway Administration (2009). National Household Travel Survey. U.S. Department of Transportation. Washington, D.C. Retrieved at http://nhts.ornl.gov/index.shtml.

FHWA. *Document on Traffic Volume Trends*. U.S. Department of Transportation, 2017. Retrieved at: https://www.fhwa.dot.gov/policyinformation/travel_monitoring/17maytvt/17maytvt.pdf (July 15, 2017).

Florida Department of Transportation, 2013. 2009 National Household Travel Survey – Florida Data Analysis. Retrieved from: http://www.fdot.gov/planning/trends/special/nhts.pdf (June 20, 2017).

Hörl, Sebastian. (2017). Agent-based simulation of autonomous taxi services with dynamic demand responses. *Procedia Computer Science* 109C: 899-904.

Horni, A. *et al*. 2016. Multi-Agent Transport Simulation MATSim. London: Ubiquity Press. DOI: https://doi.org/10.5334/baw

Levin, Michael., Li, Tianxin, Boyles, Stephen, and Kockelman, Kara. (2017). A General Framework for Modeling Shared Autonomous Vehicles with Dynamic Network-Loading and Dynamic Ride-Sharing Application. *Computers, Environment and Urban Systems* 64: 373-383.

Loeb, Benjamin, Kockelman, Kara M. and Liu, Jun. 2018. Shared Autonomous Electric Vehicle (SAEV) Operations Across the Austin, Texas Network with a Focus on Charging Infrastructure Decisions. *Transportation Research Part C: Emerging Technologies* 89: 222-233.

Loeb, Benjamin, Kockelman, Kara M. 2017. Fleet Performance & Cost Evaluation of a Shared Autonomous Electric Vehicle (SAEV) Fleet: A Case Study for Austin, Texas. Accepted for publication in *Transportation Research Part A – Policy and Practice*.

Ma, S., Zheng, Y. and Wolfson, O. (2013). T-share: A large-scale dynamic taxi ridesharing service. Proceedings of the 2013 IEEE 29th International Conference on Data Engineering (ICDE 2013). Brisbane, Australia.

Ma, Shuo and Wolfson, Ouri. 2013. Analysis and evaluation of the slugging form of ridesharing. Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, Orlando, Florida. Retrieved from: http://dl.acm.org/citation.cfm?id=2525365 (July 20, 2017).

NHTSA. Document on Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey. Publication DOT-HS-812-115, U.S. Department of Transportation, 2015.

Rodier, C., Alemi, F. and Smith, D. 2016. Dynamic Ridesharing: An Exploration of the Potential for Reduction in Vehicle Miles Traveled. Proceedings of the 95th Annual Meeting of the Transportation Research Board, Washington, D.C.

Santi, Paolo, Resta, Giovanni, Szell, Michael, Sobolevsky, Stanislav, Strogatz, Steven and Ratti, Carlo. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences of the United States of America* 111(37): 13290-13294.

Shaheen, S., Coehn, A., Zohdy, I., and Kock B. *Smartphone Applications to Influence Travel Choices: Practices and Policies.* Publication FHWA-HOP-16-023. FHWA, U.S. Department of Transportation, 2016a. Retrieved at: https://ops.fhwa.dot.gov/publications/fhwahop16023/fhwahop16023.pdf (January 24, 2018).

Shaheen, S., Cohen, A., and Zohdy, I. *Shared Mobility: Current Practices and Guiding Principles.* Publication FHWA-HOP-16-022. FHWA, U.S. Department of Transportation,

2016b. Retrieved at: https://ops.fhwa.dot.gov/publications/fhwahop16022/fhwahop16022.pdf (January 24, 2018).

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D. and Pavone, M. 2014. Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore. *Road Vehicle Automation* 229-245.

Tao, C. C., 2007. Dynamic taxi-sharing service using intelligent transportation system technologies. *Wireless Communications, Networking and Mobile Computing* 3209-3212. DOI: 10.1109/WICOM.2007.795.