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, 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. 30,000 SAVs will be required to meet less than 45% of the demand due to the nature of trips (typically recreational) in Orlando.

INTRODUCTION
Traffic safety and congestion are key transportation issues for many regions around the world. Driver error remains the dominant 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 Uber Pool and Lyft Line. Ride-sharing is not a new concept (Chan and Shaheen, 2012), with carpooling often 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). Exploiting this feature, TNCs have designed user-friendly car-sharing 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. 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.*, 2017; 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 (including travel by persons who do not own cell phones or carry theirs with them, turned on).

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. 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.

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. 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. Thus, the original 30-day 24-hour dataset was disaggregated into 30 different sets of one-minute resolution trip-request files with higher spatial detail.

The departure times of these trips were not always 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. As hourly aggregations were made by AirSage, 30-minutes of overflow was permitted into the previous and next hour bin. Once a start time was assigned, 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 ± 2 minutes. The results were smooth, minute-by-minute trip-request files for each of the 30 days, and natural looking departure and arrival time patterns throughout each of the 30 days.

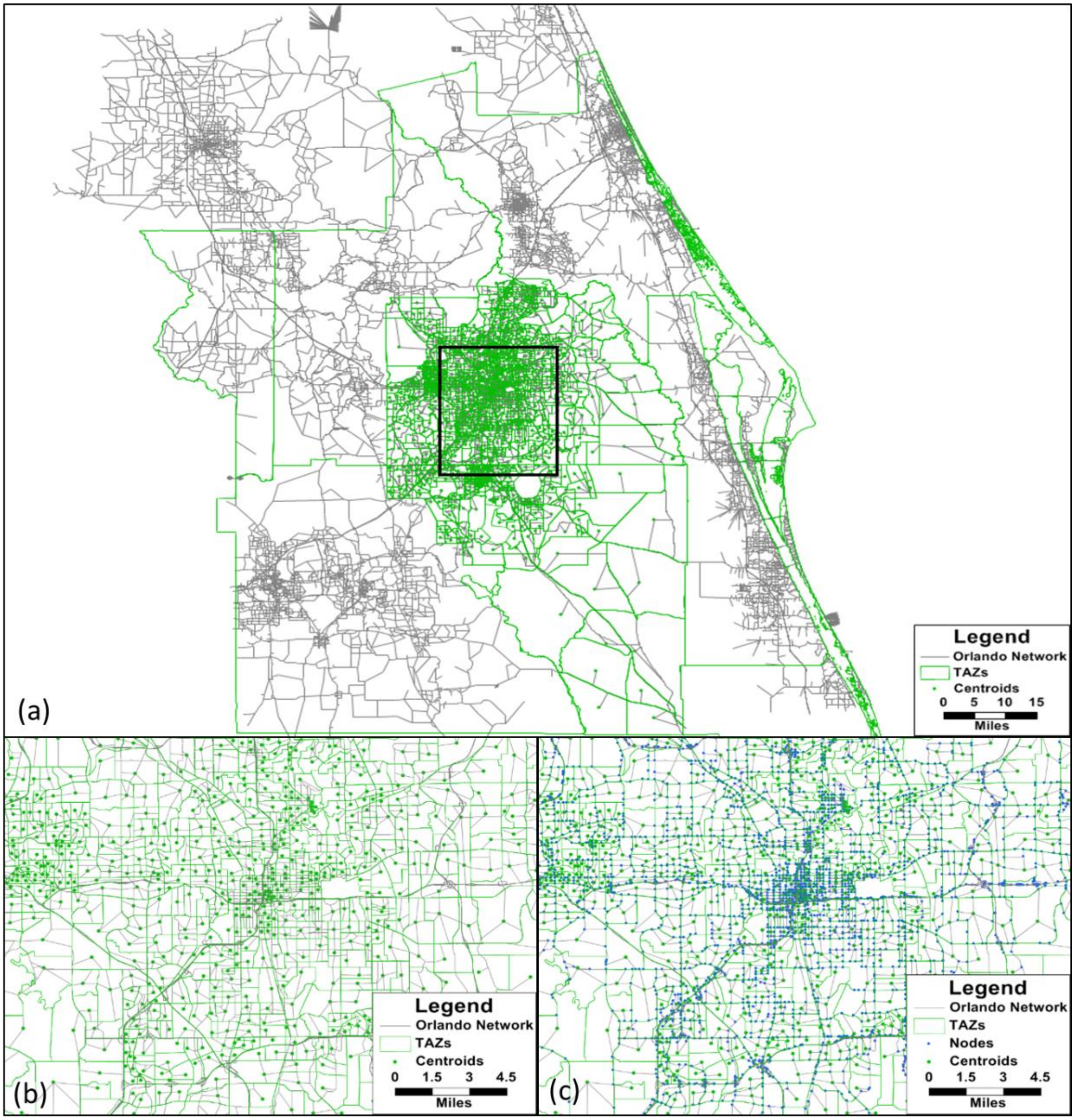

FIGURE 1 The Orlando network and nodes used for spatial disaggregation a) Orlando network separated by TAZ gridlines b) Centroids used in aggregated data c) Nodes available for spatial disaggregation.

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 . Variability, and consequently correlation, between each day was assessed using R software's statistical tool. 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.

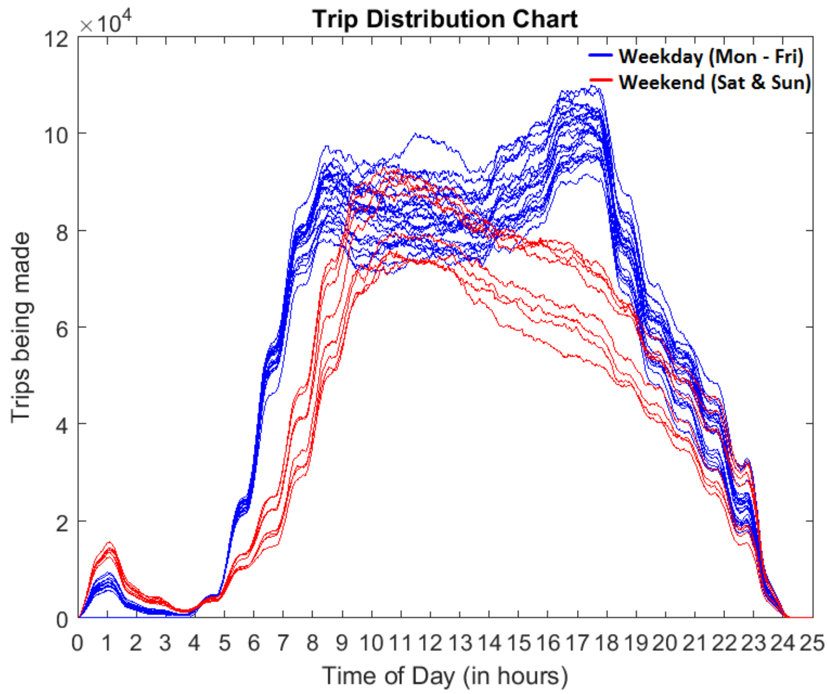

FIGURE 2 Orlando trip distribution differences, by time of day, between weekdays and weekends .

Trip Matching Results

An analysis of these trip patterns suggests how many 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).

illustrates how travel times under dynamic ride-sharing 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. 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. Thus, only 50% of the person-trips in the AirSage dataset were used here, to perform matching (of solo travelers with one another, rather matching those already in traveling parties).

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

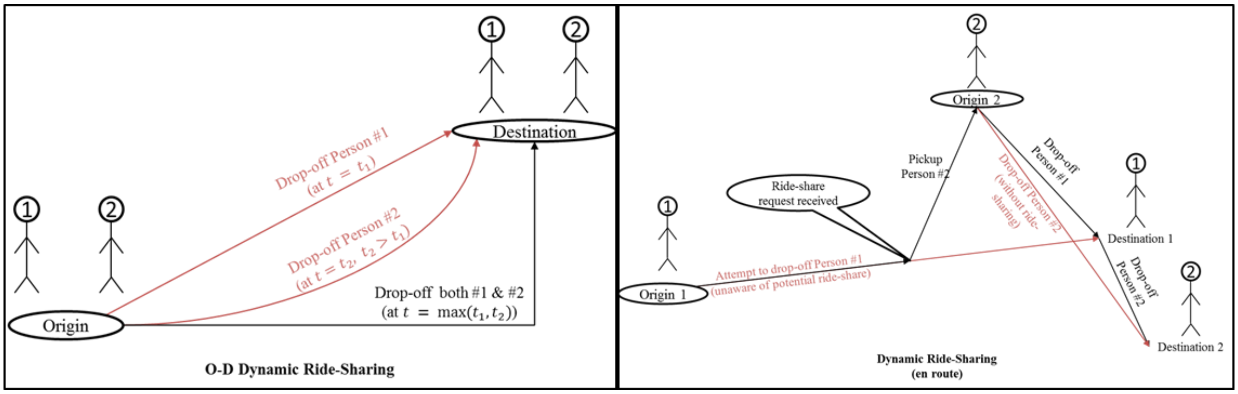

FIGURE 3 Illustrations of fleet-sharing of O-D DRS and DRS en route.

Fleet Simulation

A fleet simulation was carried out to assess the optimal SAV fleet requirement for the metropolitan region of Orlando to cater to all the trips with pre-specified service characteristics (such as, maximum waiting time or maximum additional in-vehicle travel time). 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. 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
noOfSAVs	Total number of SAVs used in the fleet
maxExtraTripTime	Minimum time imposed on travelers sharing their trips
maxWaitingTime	Maximum time that a passenger had to wait before an SAV reached them
maxSearchTime	Maximum time that a trip was stored on the waitlist before being rejected
unserviced	Total trips that could not be serviced under the above restrictions
ETA	Estimated time of arrival for an SAV to either pick up or drop off a passenger

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 . Fleet sizes varying from 5,000 - 25,000 SAVs, in intervals of 5,000 was used for these simulations and the results are discussed in the next section.

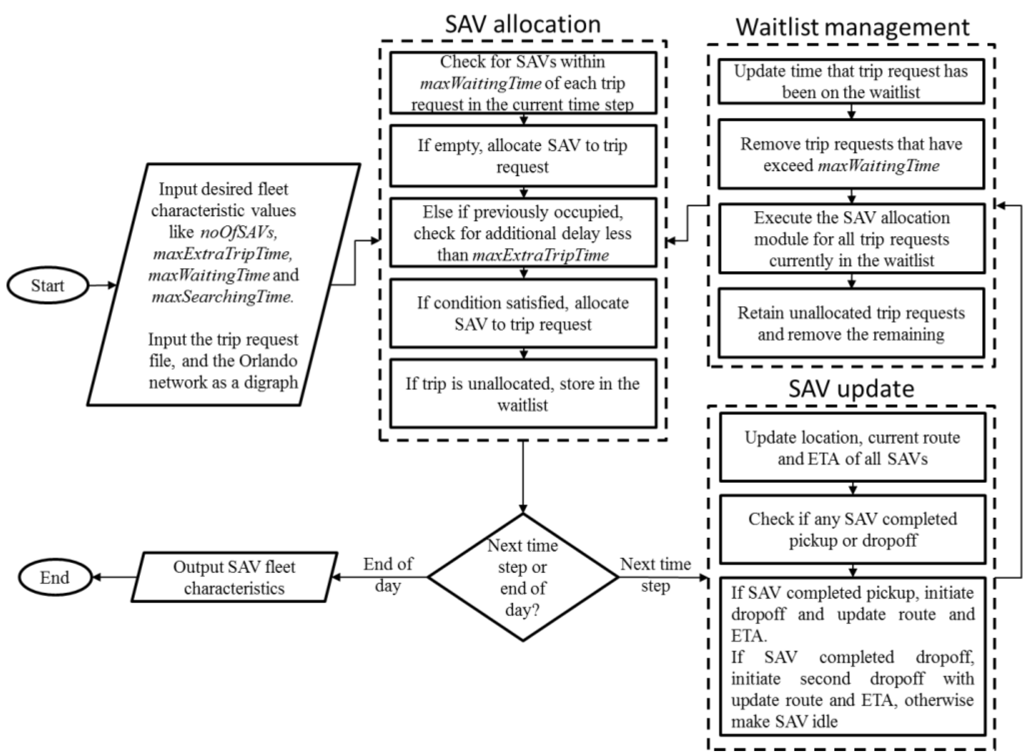

FIGURE 4 The flowchart describing the main modules of the simulation framework.

RESULTS

Infinite Fleet based Trip Matching

Trips matched assuming availability of an infinite fleet provided optimistic results. As shown in , 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 ready applicability. A simulation based on a fixed fleet size and given service characteristics were simulated to obtain optimal fleet sizes for each permutation and combination that was found to be practically valid. below shows the different fleet sizes assumed in different scenarios, as well as the different service characteristics. The number of trips that can be shared using DRS en route compared to the total number of trips ignored in the simulation have been shown as performance metrics of the given fleet to assess the best one.

TABLE 4 DRS Potential based on Fleet Size and Service Characteristic

Maximum Search Time	Maximum Waiting Time	Maximum Added Trip Time	No. Of SAVs	% trips unserviced (by SAVs)	% trips skipped (carpool)	% demand captured (by SAVs)
0 min	5 min	5 min	5,000	54.15%	43.55	4.07%
			10,000	53.55	43.55	5.14
			15,000	51.84	43.55	8.17
			20,000	46.20	43.21	18.65
			25,000	38.45	43.14	32.38
			30,000	32.59	43.25	42.57
0 min	5 min	10 min	5,000	54.92%	43.55%	2.71%
			10,000	53.07	43.55	5.99

			15,000	51.06	43.51	9.61
			20,000	49.35	43.55	12.58
			25,000	43.63	43.25	23.12
			30,000	39.20	43.17	31.02
0 min	5 min	15 min	5,000	54.78%	43.55%	2.96%
			10,000	52.81	43.55	6.45
			15,000	50.88	43.55	9.87
			20,000	48.97	43.55	13.25
			25,000	45.76	43.41	19.14
			30,000	40.29	43.21	29.05
1 min	5 min	5 min	5,000	55.16%	43.55%	2.29%
			10,000	53.57	43.55	5.10
			15,000	51.86	43.55	8.13
			20,000	46.16	43.22	18.70
			25,000	38.73	43.12	31.91
			30,000	33.24	43.23	41.45

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 day 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 opportunities for VMT reduction and 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 30,000 SAVs were sufficient to cater to less than 45% of the demand when not counting trips that are inherently classified as carpools. Under slightly relaxed trip delays and search times, such as a maximum of 15 and 2 minutes, the optimal fleet size required can be significantly reduced.

The main limitation arising from the methodology employed in this study is the disaggregation of trips. Since uniform temporal and spatial disaggregation was chosen, it can be argued that some trips may be more concentrated at particular locations or during a given time of day. This however, increases the likeliness of matching the trips during the peak time of the day and reduces the same during the off-peak time. The results mentioned in this study can be treated as an approximation of these values and, in any case, can drive future planners or fleet owners to employ a large-scale SAV fleet.

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