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 1267 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 min of added travel time (to arrive at their destinations), and this value climbs to 80% for 15 to 30 min of added wait or travel time. 60,000 SAVs will be required to meet nearly 50% of Orlando’s 2.8 million single-traveler trips each day. With maximum ride-sharing delays of 15 minutes, and when focused on serving solo travelers, the average SAV is able to serve 25 person-trips per day, reducing parking demands while filling up passenger vehicle seats.

1. 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, Cohen, and Zohdy, 2016). 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, Cohen, Zohdy, and Kock (2016) 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.

2. 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 (Lebovsky and Greenberg, 2001; Berbeglia et al., 2010; Ma et al., 2013; Farhan and Chen, 2018; 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) overcome 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 2000 vehicles and low waiting times (averaging just 2.8 min), backing DRS capabilities. Bhat (2016) confirmed those New York City taxi results, and added a vehicle repositioning algorithm. Tao (2007) also used a taxi dataset, 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 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).

3. 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 1267 TAZs (with 1261 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 1261 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.

MetroPlan Orlando, the region’s metropolitan planning organization (MPO), provided a detailed network (Fig. 1a), 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.