AGENT-BASED SIMULATIONS OF SHARED AUTOMATED VEHICLE OPERATIONS: REFLECTING TRAVEL-PARTY SIZE AND DAY-OF-YEAR DEMAND VARIATIONS

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ABSTRACT

This paper explores the effects of day of week and season of year demand variations for shared rides, along with realistic travel party sizes, on shared autonomous vehicle (SAV) services across the Austin, Texas region. Using the agent-based POLARIS program, annual averages for synthetic weekday person-trips were replaced with party-specific trips (from one to four persons) that also reflect passenger-trip variations over days and months, as evident in National Household Travel Survey data. Results show that realistic party sizes can bring considerable changes to SAV fleet performance, including up to 10% higher service rates (number of requests accepted within 15 minutes), 5-minute lower journey times (wait time + travel time), 28% higher vehicle occupancies, roughly 4 percentage-points lower empty fleet VMT, and fewer person-trips served per SAV (6.4% fewer on weekends). Weekend travels are most impacted by season of year, with weekday travel patterns looking more uniform (thanks to work and school trips). Various performance metrics for the Austin network, like total and empty VMT, are up to 30% different when considering realistic variations in party size and time of year. This paper underscores the value of recognizing day-to-day and month-to-month variations in travel demand, and the importance of agent-based model equations to reflect travel party size. Such realism can dramatically improve SAV seat occupancies but also create demand and supply issues for operators, who may wish to shift their fleet vehicles other regions for special events, to protect profits while offering reasonable wait times to customers throughout the year.

KEYWORDS

Shared automated vehicles, ride-sharing, agent-based simulation, travel party size, travel demand variability, seasonal travel shifts

INTRODUCTION

While travel party size and seasonal travel shifts are sometimes approximated in travel demand modeling research (Bradley et al., 2016; Grigolon et al., 2013; Miller, 2004; Stefan et al., 2016), newer, agent-based simulations have put more emphasis on individual travelers – their activity sequences, departures times, and route choices, as well as dynamic traffic assignment outcomes (Fagnant and Kockelman, 2018; Gurumurthy et al., 2019; Maciejewski and Bischoff, 2018). For systems of shared autonomous vehicle fleets or SAVs, a single 24-hr workday is typically synthesized, neglecting season and day or week, as well as party size. This paper conducts agent-based simulations of the 5-county Austin, Texas region to explore how key metrics differ as realism is added, in the form of variable party sizes (calling for SAV trips), day of week, and month of year.

Travel party size is a meaningful factor in both long- and short-distance travel demand models (see, e.g., Fakhrmoosavi et al. 2022). People can travel in a party of two or more in either personal vehicles or public transport (buses or TNCs). Many studies have demonstrated the interaction between other travel decisions like mode choice and destination choice (Hsieh et al., 1993; Rashidi and Koo, 2016). rJourney long-distance travel data for the year 2010 from FHWA shows an average party size of 2.18 (Federal Highway Administration, 2015), while a recent long-distance travel conducted by Huang et al. (2022) shows an average party size of 2.8 for both business and non-business travel. The national household travel survey (NHTS) 2016/2017 shows an average vehicle occupancy of 1.67 across all trip purposes (McGuckin and Fucci, 2018). Agent-based simulations can sometimes recognize multiple travel-party situations in family travel, like picking up children or dropping off household members at the airport; however, not all agent-based simulations can capture that, and they often lack the case when people travel with friends and colleagues. Moreover, almost all agent-based simulations allow a travel party of any size to occupy just one seat of a vehicle. It often makes no difference for a personal vehicle in terms of vehicle-trips simulated, but could be critical for ride-sharing service as it greatly alters the ride-sharing service patterns: 1) Trips made by a travel party over two can sometimes fail to be served due to limited seats in a TNC vehicle; 2) The average vehicle occupancy can be different because each person in the travel party should take one seat.

Seasonal travel shifts are another key factor that impacts the agent-based simulation analysis. Travel shifts over months of year and days of week are often failed to be captured, even in many traditional travel demand models (four-step models or activity-based models). In reality, Americans tend to make more trips over summer time instead of winter except for the holidays (e.g., Christmas and Thanksgiving), as indicated in NHTS 2016/2017 survey (McGuckin and Fucci, 2018). A 24-hour agent-based simulation (if not an analysis for just morning or afternoon peak times) often uses a synthetic population with corresponding travel behaviors (e.g., trip-making rates, destination choice, and mode choice) aggregated and averaged across a whole year. Capturing the fluctuations in travel demand (especially the peak demand) across a year can be important in identifying the bottleneck of network performance and the robustness of a service. This paper defines the seasonal travel shift as four seasons of a year, along with two types of days over a week: weekdays versus weekends. More importantly, party size can vary as well in different seasons. For example, people may travel solo in the summer time for leisure and business purposes, while in winter mostly family visiting trips could be in larger party size.

As emerging technologies, like AVs, penetrate future transportation, the ride-sharing service provided by shared automated vehicles (SAVs) is anticipated to become popular due to lower cost and improved safety (Bösch et al., 2018; Clements and Kockelman, 2017), and thus there is an urgent need to incorporate detailed party size distributions and seasonal shifts in coordination with agent-based simulations to reveal realistic ride-sharing service patterns. This paper aims to explore the answers to two questions: (1) How does the network performance vary in agent-based simulations of AVs' ridesharing service considering seasonal travel shifts? (2) What impacts can be brought by factoring travel party size in agent-based simulations? Since NHTS 2016/2017 survey offers a good annual pattern of seasonal travel shifts and travel party sizes, this dataset is leveraged to offer the related seasonal and travel party distributions, which are further used to adjust the demand tables for agent-based simulator POLARIS.

The paper is organized as follows. The next section reviews current literature about travel party size and seasonal travel shifts. The NHTS data is then described in detail regarding the travel party size and seasonal travel shifts, before introducing the methodology of generating realistic travel party size and seasonal travel shifts as inputs for agent-based simulator POLARIS. Scenario design and model results are then presented, before concluding the paper.

LITERATURE REVIEW

Travel party-size

Travel party size has been discussed in both short-distance and long-distance travel (Bradley et al., 2016; Stefan et al., 2016; Zhang et al., 2020) or tourism (Thrane and Farstad, 2011; Zhao et al., 2018). It is often considered a key step in traditional travel demand models and estimated jointly with other travel choices like mode choice, trip duration, and destination choice. Back in 2004, Miller (2004) suggested improving travel demand model specifications for inter-city travelers and trip attributes, including party size. Bradley et al. (2016) modeled long-distance tours across the whole US, considering three main party size categories in the choice model (one person traveling alone as the base case, commute and business purpose with party sizes from 2 to 4+, and other trip purposes with party size from 2 to 6+). Grigolon et al. (2013) considered simple travel party choices like alone, with partners, with family, with friends, other, and "not planned yet" in their binary mixed logit panel model for the vacation planning process.

Unlike the traditional travel party choices, Stefan et al. (2016) designed a logit model for three household travel party size alternatives: all household members travel, one household member travels, and part of the household travels. In addition, a solo household traveler is further selected through a logit choice model, while a primary traveler is selected first in the "part of the household" model before deciding the travel party size. However, this model considers the travel only for the household members, without considering the trips with colleagues and friends.

Party size models are often seen in long-distance or inter-city travel models. The party size is considered a more important factor for household travel, compared to regular commuting trips which are often made alone. The model methods focus on logit models with different design structures that reflect the trip-making decision process.

Seasonal shifts

Seasonality in travel varies by definition, such as four seasons of year, months of year, days of week, and weeks of year. They are sometimes incorporated as variables in models to differentiate the seasonal impact on travel shifts (see examples: Chakrabarti, 2018; Müller et al., 2020). Similarly to the use case of party size, the seasonal shifts are more closely related to tourism than normal day travel (Bar-On, 2002; Martínez et al., 2020).

Seasonal travel shifts are used for different travel demand forecast purposes. For example, Stamatiadis and Allen (1997) explored the use of seasonal adjustment factors to improve the estimation of daily volumes for each vehicle type. Dadashova and Griffin (2018) applied seasonal adjustment, which are monthly adjustment factors applied to short-duration counts for both pedestrian and bicyclist count data.

Elango et al. (2007) explored the demographic impact on trip-making under different seasons. They found that low-income, single-person, and zero-child households had no significant difference between annual and summer variability. Hasnine et al. (2021) leverage historical Uber data from 2016 to 2018 and revealed a positive correlation between seasonal effect (indicated by weather) and the TNC demand.

NHTS DATA SET

Various data sources and surveys revealed the party size of the travelers. In this paper, the NHTS 2016/2017 data was leveraged to explore and generate party size as well as seasonal travel shifts. The NHTS 2016/2017 data was deployed in 2016, which collected the daily travel of Americans over the whole year from April 2016 to April 2017. The survey provides detailed demographic information of surveyed households, along with their travel history on a particular day during the survey time horizon. The trip, person, vehicle, and household records are weighted to represent the annual travel pattern of the Americans. The NHTS 2016/2017 is a good source of data that can show the year-round travel shifts, with sufficient data records suitable for statistical analysis.

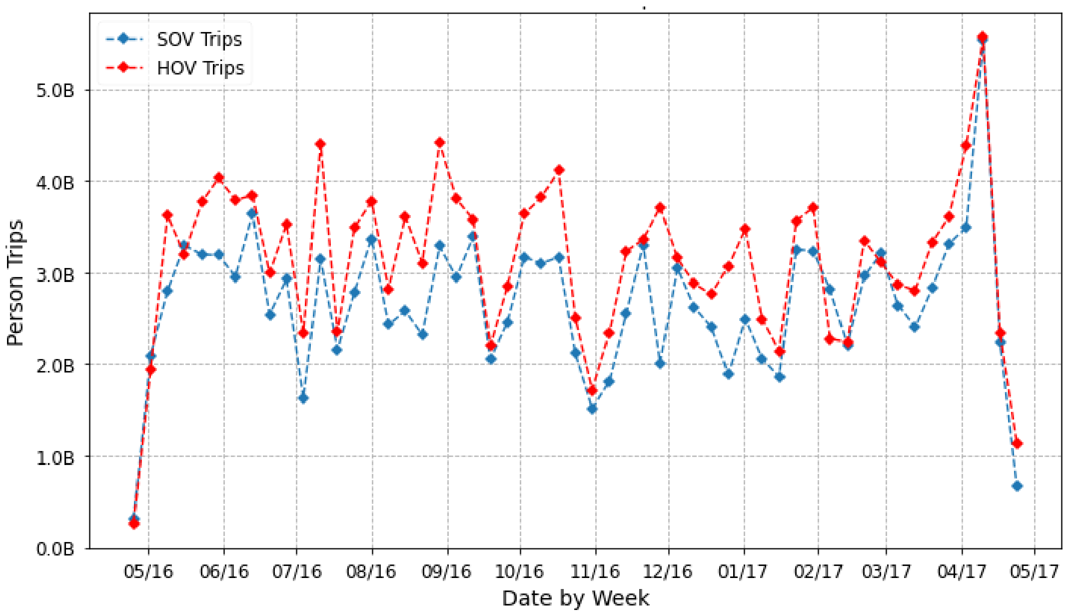

Figure 1. Number of person trips by the week of year

Figure 1 shows the number of total person trips made each week from April 2016 to April 2017. The travel shift fluctuates due to the occurrence of holidays and possible weather conditions, but the overall shift shows that people travel more during spring and summer in contrast to cold weather.

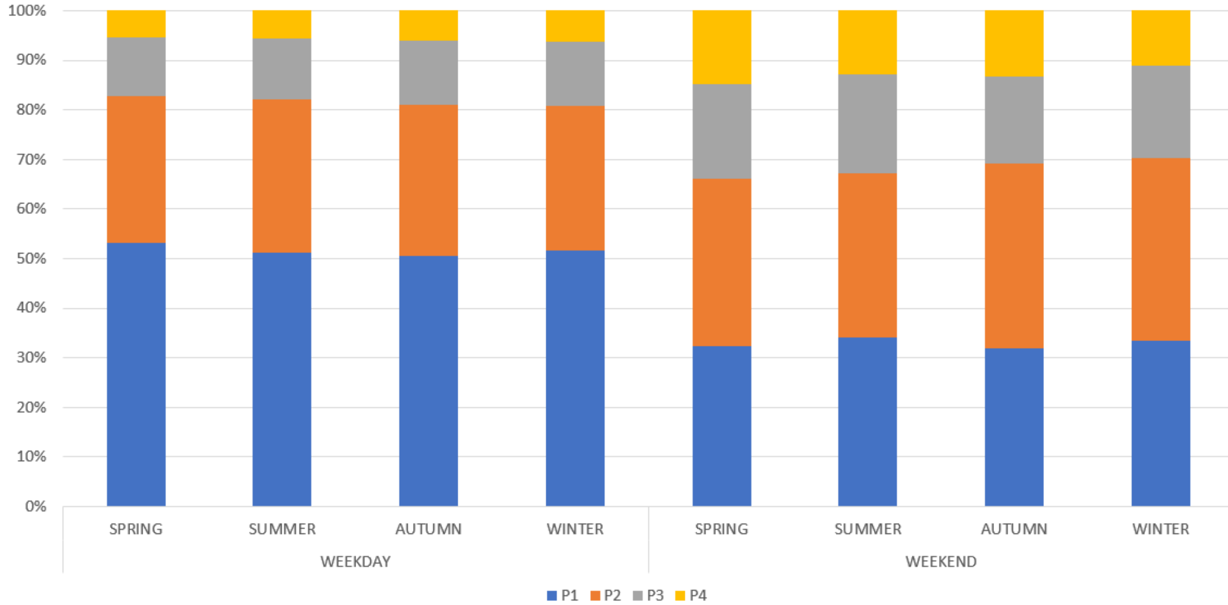

Figure 2. Share of person-trips by party sizes across four seasons

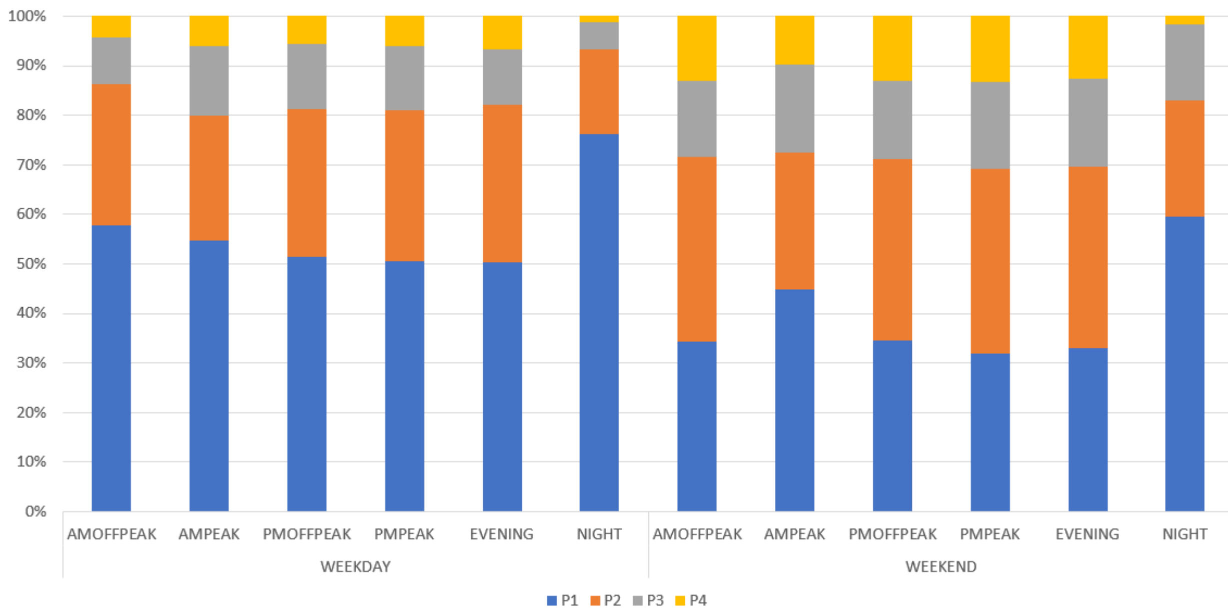

Figure 3. Share of person-trips by party sizes across six times of day

In terms of party size, NHTS 2016/2017 data shows an average party size of 1.43 across all automobile modes for party sizes smaller than four. Figures 2 and 3 show the share of person trips by party sizes for seasonal shifts and for different times of day, respectively. Figure 2 tells that the seasonal shifts do not vary much across seasons, especially on a weekday, with solo travelers more than 50% and 2-people travel parties over 15%. This figure shows the unit in “person-trips”, so solo travel parties account for a larger share of overall travel parties. Compared to weekday patterns, weekend patterns favor multiple-traveler parties, with person-trip accounts similar for solo travelers and two-people parties. Figure 2 also shows that 4-people travel parties happen more in spring than in other seasons, especially winter. Figure 3 demonstrates the shares of person-trips by party sizes across six times of day. To align with POLARIS time of day definitions, night, AM peak, AM off-peak, PM off-peak, PM peak, and evening are, respectively, "midnight to 6 am", "6 am to 9 am", "9 am to 12 pm", "12 pm to 4 pm", "4 pm to 7 pm", "7 pm to 12 am". The night is the time when solo travelers are most observed, accounting for 76% of person trips on weekdays and 59% on weekends. Similarly, people tend to travel solo on weekdays compared to weekends across the six times of day.

METHODOLOGY

Austin's POLARIS model

The agent-based travel demand simulator called POLARIS (Auld et al., 2016) is used to simulate travel in this study. An Austin regional case study is conducted to explore the variations in party-size and seasonal travel shifts on planning methods. POLARIS is an end-to-end travel demand simulator in that it has a population synthesizer that fits the agent population averages across several categories to the regional cross-tables iteratively. A series of activity models are executed on the synthetic population to generate, schedule, and plan for durations for each agent. Destination, mode, and route choice is then conducted to have a cogent 24-hr day plan for each person agent in the simulation. While the synthesizer allows scaling of person agents simulated, POLARIS is a powerful C++ framework that is able to simulate 100% of most regional populations in relatively low runtimes. Austin's 1.9M population making 530,500 person trips is simulated in under 2 hr on a supercomputer utilizing about 40 GB of memory.

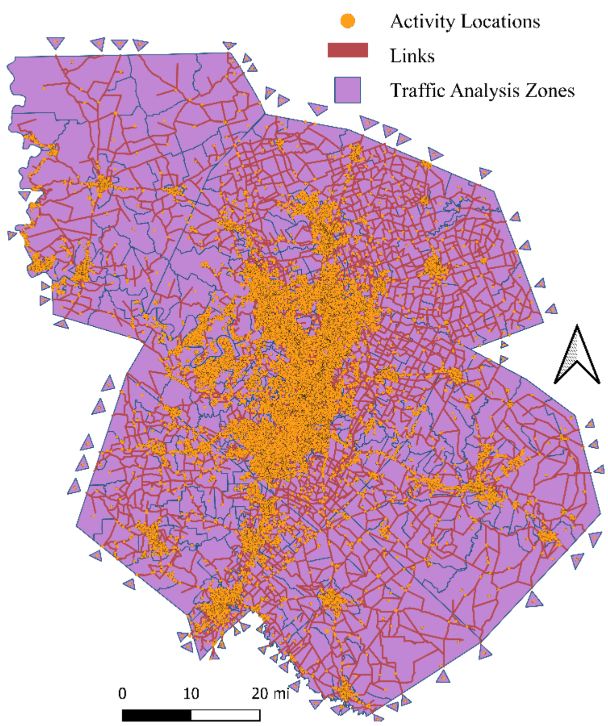

Figure 4. Austin 6-county POLARIS model

Austin is chosen for the analysis in this paper. The Austin network shown in Figure 4 comprises of over 22,863 bi-directional links and 17,231 nodes with different controls (two-way or four-way stop, or signal control). The 6-county region is spread over 5,480 sq. mi and the local MPO consolidates this region into 2,161 traffic analysis zones (TAZs). About 94% of all travel is made with an automobile (personal or TNC).

In order to isolate the effect of seasonality and party-size impacts on fleet operations, a fixed travel demand was used. Figure 5 illustrates the network loading from an Austin simulation, defining the clear bimodal peaks that are wider in the PM. The trip data from this simulation was converted as a fixed travel demand input for POLARIS. By using all travel demand, the speed profile for the region will remain consistent and reflect on routes chosen by SAVs that react on-demand in the simulation.

The SAV module (Gurumurthy et al., 2020) was extended to read in and execute party-size restrictions for shared trips. Since the focus was on party-size restrictions and seasonal variations, the default algorithm for dynamic ride-sharing (DRS) was used, with modifications to ensure the total parties involved in a shared trip are less than or equal to the vehicle's seated capacity. The default algorithm considers vehicle location and the directionality of a trip request, while trying to control for detours imposed on all traveling parties. When the trip request aligns with the direction of travel (if any) for the SAV, and the maximum detour for any parties already in the vehicle is not violated, a match is confirmed, and the SAVs find the shortest path to execute the series of pickup and drop-offs. For more details on the DRS ride-matching algorithm, refer to (Dean et al., 2022).

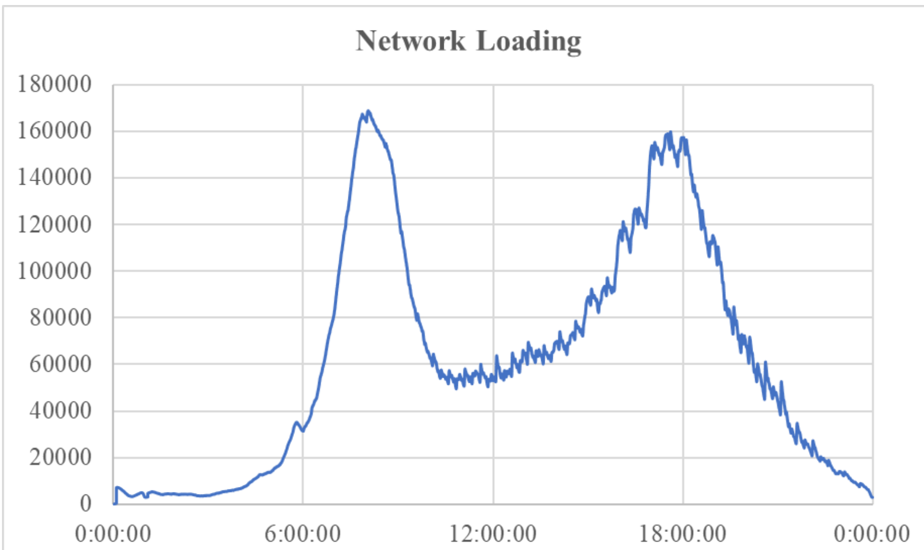

Figure 5. Network loading in Austin's 6-county region

Seasonal travel adjustments

The seasonal travel variations reflect the fluctuations of demand across the year. As mentioned in the NHTS summary statistics, travelers present different behaviors in reaction to weather and temperature. Setting up the season travel demand adjustment is based on the following considerations and assumptions:

1. The seasonal travel shifts are only reflected in the amount of travel demand. They do not distinguish between the trip purposes (home-based vs. non-home-based), destination choices (inter-city or intra-city), mode choices (car vs bus, under extreme weather conditions), since most of them have already been captured in agent-based simulations. The travel shifts aim to tackle the drawback of an "average" day that is often assumed in agent-based simulations.

2. The seasonal travel shifts are mainly revealed through four seasons of year (spring, summer, fall, and winter) and two types of days (weekday vs. weekend). This gives a lower resolution of the temporal picture compared to 12 months of a year and seven days of a week, but it provides relatively clear distinctions among the demand patterns. Four seasons of a year can better represent the temperature and

activity changes across a whole year, while a weekday-weekend setup can often tell the commuting trips of a weekday pattern from the leisure trips of a weekend activity pattern.

3. It is assumed that the NHTS 2016/2017 data can represent the seasonal shift and party size distributions. This indicates another average in the spatial pattern because the travel shifts are different between the Northern states and the Southern states. A Southern state like Austin would likely see more trips in winter compared to the Northern states. However, the US pattern is assumed to be suitable for the Austin area, due to the lack of datasets that can present seasonal shifts and party size distributions within the Austin area.

4. The travel demand level is reflected at a daily level, since the 24-hour simulation is usually the time horizon for most agent-based simulations. This is achieved by comparing the seasonal average with the annual average to obtain the adjustment factor for both weekdays and weekends. Weekday is usually the assumption for most agent-based simulations, as they incorporate commuting trips. Therefore, the weekday is set as the base, and adjustment factors are applied for weekends across four seasons. The average person-trips for weekdays and weekends are divided by 5 and 2, respectively, for a reasonable level of daily travel comparison to get the daily person-trip ratio of a weekend to a weekday.

5. Factors for seasonal shifts (similarly to the party size) are calculated based on the “auto” mode in NHTS 2016/2017, which consists the modes of car, SUV, van, pickup truck, rental car, and TNCs. This can help properly adjust the level of total demand and the party size simultaneously. In terms of the adjustment factors from weekdays to weekends, only TNC data was explored. This offers a better distinction for the use of TNCs on weekdays and weekends.

Table 1 shows the adjustment factors that incorporate the demand change for four seasons of year (f_w) and two types of days (f_s). People make more daily TNC trips on weekends compared to regular workdays except in summer. Winter is the season that people tend to use TNC service more often during the weekends since they are less likely to drive personal cars or use public transit due to weather conditions, although the overall reduction in trips occurs generally in fall and winter in contrast to spring and summer, which have about 5% more trips.

Table 1. Adjustment factors for seasonal travel shifts, by weekday vs weekend

Adjustment Factors	Weekday → Weekends (f_w)	Annual Avg → Season Avg (f_s)	
		Weekends	Weekdays
Spring	1.39	1.04	1.05
Summer	0.86	1.04	1.06
Fall	1.15	1.00	0.96
Winter	1.91	0.92	0.93

Party size generation

Party size distribution is obtained to reflect a realistic party-trip instead of a person-trip, so that the true vehicle occupancy is simulated. The party size distribution in this paper considers the variation in seasonal travel shifts (four seasons plus two types of day) as well as the departure time of day. This means that travel party sizes are assumed unaffected by trip distance, purpose, and destinations, although the trip purpose and destination choice could be partially captured by the departure time of day. For example, an afternoon trip could be a family trip while a commuting trip in the morning is more likely to be a solo trip.

A few papers have discussed the potential of different SAV sizes for different services (Huang et al., 2022, 2021), but many agent-based simulations still introduce SAVs as a vehicle of four seats. The NHTS

2016/2017 has trips made by a travel party of over four, but the situation is rarely observed, and those trips often happened in other modes, like bus or school bus. In addition, more than 4 people using a dynamic ride-sharing service could lead to more detours unless their routes align very well. Therefore, this paper follows the commonly used vehicle size as four, while party size over four (the request of which can never be served) is considered outside the scope of this paper.

In addition, the party size of TNC users is considered to have the same distribution as other automobile modes, like SUVs, vans, pickup trucks, and rental cars, as mentioned in the seasonal shift section. Although these vehicles are distinct in the number of seats designed, variations in traveling party size using different vehicles remain an unclear picture. Due to insufficient data on the party size distribution of TNC users, the automobile mode in NHTS 2016/2017 is used as a proxy to generate party size distributions.

This paper leverages the existing Austin POLARIS model's person-trip records to adjust the travel demand to factor in the seasonal travel shifts and party size distributions. The existing person-trip data comes from a robust run of dynamic traffic assignment in Austin's POLARIS model. Like other agent-based simulations, this person-trip data, or called the demand table, can be read in to serve as input in POLARIS for other scenarios or testing purposes. One important advantage of adjusting based on a fixed demand table is to mitigate the randomness out of most agent-based simulation models, especially the population synthesis and land use simulations, which often alter the demand and spatial pattern from scenario to scenario. The fixed demand table for the Austin network has been well-tested in previous work (Dean et al., 2022) and offers balanced origin-destination pairs across the whole of Austin's 6-county area.

The original Austin's TNC service accounts for 1.5% of the total 5.36 billion person-trips per day, representing a full level of Austin's travel demand. Considering the use of SAVs in a future scenario, the original mode share of TNC (in person-trips) was adjusted to be 10% based on existing studies, which indicates the annual average mode share. This mode share was further tuned by applying the two factors shown in Table 1 to the original number of person-trip records (N_0), i.e., from annual average to seasonal average (f_w), and from weekday to weekend (f_s). This provides the number of person-trips after considering the seasonal shifts ($N_s = N_o \times f_w \times f_s$). Moreover, Figure 3 is used to scale down person-trip records to reflect actual party sizes. In this way, the number of party-trips for each party size (P_n) relies on total number of person trips $N_{n,t}$ of party size *n* at time-of-day *t* divided by party size *n*:

$$P_n = \sum_t \frac{N_{n,t}}{n} \qquad \forall n = 1, 2, 3, 4$$

where $N_{n,t}$ is calculated based on the shares ($p_{n,t}$) of person-trips by party sizes *n* and time of day *t* (as shown in Figure 3):

$$N_{n,t} = N_s \times p_{n,t} \qquad \forall n, \forall t$$

Therefore, the total number of party-trips will be:

$$N_p = \sum_n \sum_t \frac{N_s \times p_{n,t}}{n}$$

New party-trips are defined by adding a travel party size feature to existing person-trip records. However, the final number of person-trips probably does not align with the number of party-trips needed. After processing the seasonal shift and the party size, if the overall number of person-trip falls (i.e., if $N_p < N_o$), redundant person-trips are discarded randomly. However, if total person-trips rises (so $N_p > N_o$), the extra person-trips are complemented by duplicating existing person-trip records by random selection.

RESULTS

This section discusses Austin POLARIS simulation results as a comparison of the seasonal shifts and the incorporation of party size. The seasonal shifts are compared among the four seasons of year and between weekdays and weekends. The party-size scenarios are compared with the non-party-size scenarios to see the true impact of SAVs' ride-sharing service when considering party-trips. Austin's base case, which assumes an annual average of population synthesis and trip-making patterns, gives a service rate of 93.5% for 530,500 total TNC requests, using an SAV fleet of about 21 thousand vehicles (assuming one SAV for 25 requests). The average trip service time is 28.74 minutes, including an average 6.75-minute wait time. The average vehicle occupancy (AVO) is 1.61 in terms of person-miles traveled (per revenue VMT by SAVs). The same fleet size was used for all seasonal shift scenarios and party size scenarios for a fair comparison, as shown in Table 2.

Table 2. SAV fleet performance metrics

Scenarios		**Party-size scenario**				**Non-party-size scenario**			
		Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter
Week-ends	Service rate	93.5%	95.0%	94.2%	92.6%	88.7%	94.1%	93.2%	84.1%
	Avg travel time per party-trip	25.5	25.3	25.4	26.0	30.0	28.7	29.4	30.6
	Avg wait time per party-trip	6.0	5.5	5.8	6.4	7.8	6.5	7.1	8.2
	empty VMT (million)	1.20	0.79	0.98	1.46	1.86	1.27	1.56	2.11
	VMT (million)	3.63	2.55	3.04	4.25	5.02	3.66	4.33	5.59
	% eVMT	33%	31%	32%	34%	37%	35%	36%	38%
	AVO	2.15	2.09	2.12	2.16	1.68	1.61	1.65	1.71
	Party-trips per SAV per day	21.5	14.3	17.5	25.9	34.2	22.9	28.0	40.5
	Person-trips per SAV per day	31.9	21.7	26.3	37.5	34.2	22.9	28.0	40.5
	Total person-trips (thousands)	680	462	559	797	647	458	555	726
Scenarios		**Party-size scenario**				**Non-party-size scenario**			
		Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter
Week-days	Service rate	94.4%	93.9%	94.8%	94.9%	93.1%	93.3%	94.0%	94.0%
	Avg travel time per party-trip	26.8	26.7	26.7	26.4	29.3	29.3	28.8	28.8
	Avg wait time per party-trip	6.1	6.1	6.0	5.9	7.0	6.9	6.6	6.6
	empty VMT (million)	1.10	1.07	1.00	0.97	1.36	1.45	1.33	1.30
	VMT (million)	3.27	3.21	3.02	2.96	3.75	4.09	3.81	3.73
	% eVMT	34%	33%	33%	33%	36%	36%	35%	35%
	AVO	1.92	1.94	1.92	1.91	1.66	1.64	1.62	1.61
	Party-trips per SAV per day	19.4	19.1	17.6	17.3	24.6	26.2	24.0	23.5
	Person-trips per SAV per day	24.5	24.5	22.6	22.2	24.6	26.2	24.0	23.5
	Total person-trips (thousands)	521	523	482	472	488	520	481	469

Inclusion of party size

This table provides clear insights into how simulations would differ when the travel party comes into play. The service rate increased under all seasonal shifts, from 0.64% (summer weekdays) up to 8.5% (winter weekends). The leading reason is that there are not as many requests as the case when the party size is always assumed to be one, since two persons as a party size of two only make one request. Fewer requests are also revealed from the improvement in passenger travel and wait times: about 5 minutes saving in total journey time and more than 1 minute wait time on weekends. In addition, the SAVs in the party-size scenarios rarely have to accommodate 4 different travel parties when a portion of the travel parties already take two or more seats. Although the available seats in SAVs may lead to some rejections of requests (e.g., a vehicle with one seat can not serve a party of two travelers), this situation avoids long detours for every travel party and demonstrate a more efficient ride-sharing than agent-based simulations that are commonly seen.

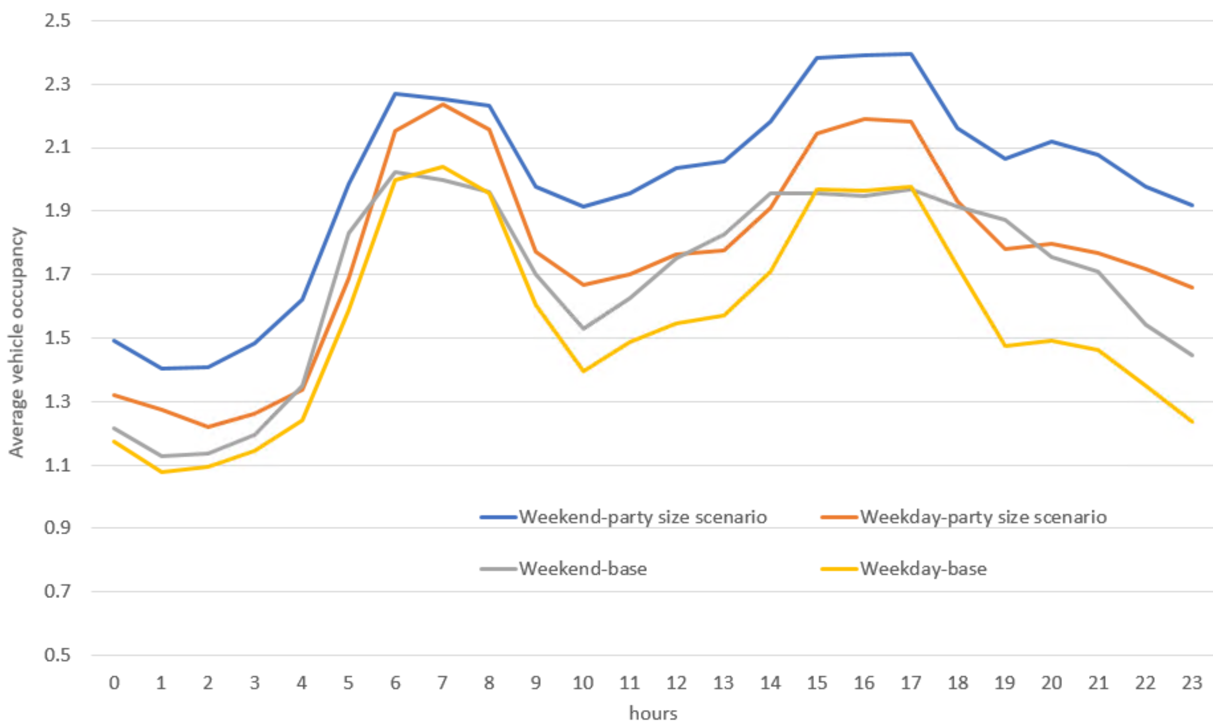

Figure 6. Average vehicle occupancies across a day in winter

Similarly, party-size variations enable better use of vacant seats, so the share of empty vehicle-miles traveled (eVMT) also falls, by as much as 37.4% (on summer weekends). Interestingly, due to larger weekend party sizes, the average eVMT reduction is 35.2% (averaged across four seasons), versus 23.8% across weekdays - when more Americans travel solo. More balanced use of the available seats is also demonstrated in the AVO result. AVO rises 28.3% on weekends (from 1.66 to 2.13 persons, averaged over four seasons), and 17.8% on weekdays (from 1.63 to 1.92). Again, weekday AVO improvements are less notable, due to more solo travelers, leading to lower overall seat utilization.

However, since SAVs do not take as many requests as the case when the party size is always assumed to be one (due to roughly 38% fewer total ride requests), the average number of requests met (within 15 minutes of wait time) by SAVs falls. Moreover, when a request failed to be served eventually, the number of unserved person-trips in party-size scenario is also greater than in the non-party-size scenario. For weekends, party-size scenarios serve 6.4% fewer person-trips than the non-party-size scenario, and this number drops to 4.5% when looking at weekdays.

Figure 6 shows AVO shifts due to use of realistic party sizes, with the winter season for illustration. The overall shifts are similar between weekdays and weekends, and between seasonal and annual averages: the morning peak and afternoon peak enjoy higher AVOs, as compared to other times of day. Weekend AVOs are much higher than those on weekdays (thanks to fewer work and school focused trip-making), enabling better SAV fleet use across weekend hours. This is not only due to higher ride-sharing demand over the weekend, but also larger party sizes. In the base case scenario (when party sizes are all 1 person), the weekend still shows higher AVOs due to higher travel demand (thanks to more destinations or activities per person, as well as longer-distance excursions, thanks to avoidance of long work and school days).

Therefore, fewer total requests, lower average travel and wait times, more efficient DRS services, less eVMT, higher AVO, and fewer person-trips served per SAV are the key impacts from incorporating party size, as compared to past simulations.

Seasonal shifts

Table 2 also presents the seasonal shifts between the seasons and between weekdays and weekends. Summer turns out to be the season when people are less likely to use SAVs, as seen from fewer person-trips and higher service rate, which aligns with Table 1 assumptions. The performance across four seasons is mainly impacted by the total number of requests or person-trip, as more requests under a fixed SAV fleet size leads to lower service rate, longer travel and wait times, and higher AVOs. The relative shifts among the four seasons are also similar between party-size scenarios and non-party-size scenarios. In addition, the seasonal shift across the four seasons is more distinct on weekends rather than on weekdays, because weekday travel demand is stable, and travel patterns are uniform.

Table 3. Comparisons between the base case and the boundary values in seasonal shift scenarios

	Base	Party-size scenario					
		Max	Source	%	Min	Source	%
Service rate	93.5%	95.0%	Summer-Weekend	1.6%	92.6%	Winter-Weekend	-1.0%
Average travel time per party-trip	28.7	26.8	Spring-Weekday	-6.8%	25.3	Summer-Weekend	-11.9%
Average wait time per party-trip	6.8	6.4	Winter-Weekend	-5.5%	5.5	Summer-Weekend	-18.2%
empty VMT (million)	1.4	1.5	Winter-Weekend	7.7%	0.8	Summer-Weekend	-41.4%
VMT (million)	4.0	4.3	Winter-Weekend	7.6%	2.6	Summer-Weekend	-35.4%
percentage of eVMT	34.22%	0.342	Winter-Weekend	-0.1%	0.31	Summer-Weekend	-9.4%
AVO	1.6	2.2	Winter-Weekend	34.4%	1.9	Winter-Weekday	18.9%
Party-trips per SAV per day	24.9	25.9	Winter-Weekend	4.0%	14.3	Summer-Weekend	-42.4%
Person-trips per SAV per day	24.9	37.5	Winter-Weekend	50.3%	21.7	Summer-Weekend	-12.9%
Total person-trips (thousands)	496	797	Winter-Weekend	60.8%	462	Summer-Weekend	-6.8%

One particular insight from the seasonal shifts is to explore how the system performance would change compared to the agent-based simulation results that have been demonstrated so far. Table 3 shows the comparison between the base case scenario and the extreme values (maximum and minimum values) from seasonal shift scenarios with party size incorporated. The source column shows the particular season and day of week for that value. One can see that many network performance metrics can be more than 30%

off, like eVMT, VMT, and the number of person-trips and party-trips served per SAV per day. And some of the metrics do not even fall within the maximum and minimum value that we expect from scenarios with party-size consideration. For example, the base case has biased-high average travel time and wait time, biased-high percentage of eVMT, and biased-low AVOs.

Figure 7 is an illustration of the seasonal shifts regarding the service rate across different party sizes. It is straightforward that small party sizes (i.e., one or two) can be served more easily, because they can fill in the vacant seats quickly, in contrast to large party sizes. Due to a similar reason, there is not much of a difference in the service rate between party sizes of one and two. Summer is the season when the service rates are robust to party sizes for various days, as they are all above 92%. Despite the seasonal discrepancy, the overall service rate is acceptable, because the lowest rate is still near 90% for party size four on weekdays in the fall.

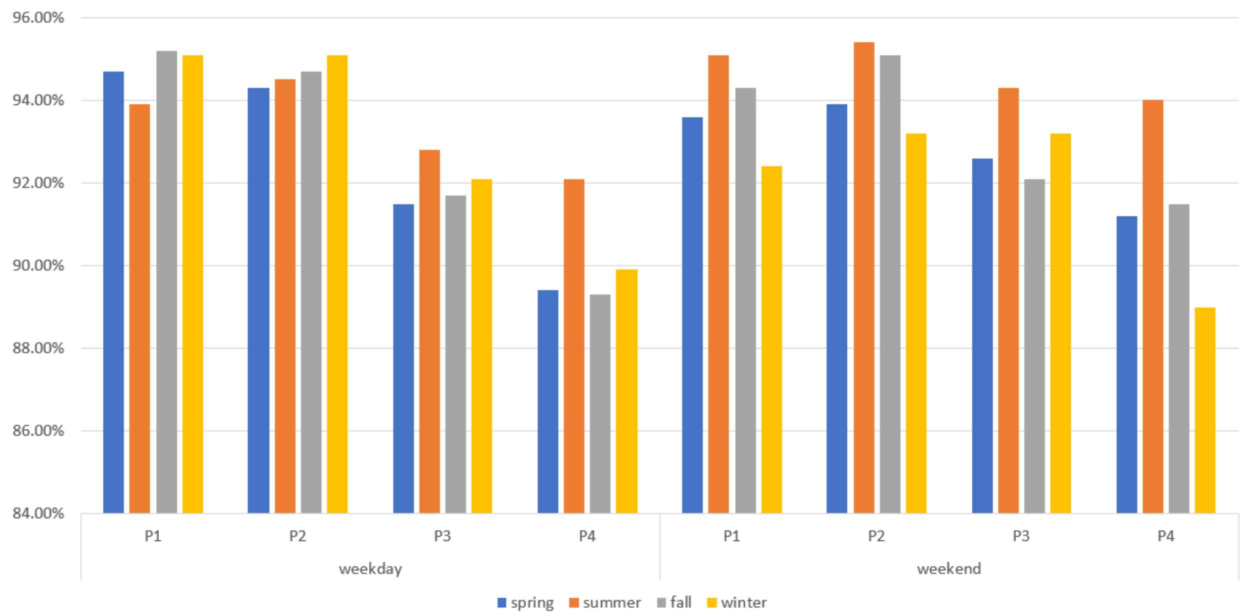

Figure 7. Service rates by party size

CONCLUSION

This paper explores the inclusion of realistic day of year demand variations and travel party sizes in agent-based simulations of SAV fleet performance. The NHTS 2016/2017 data was leveraged to offer detailed demand variations and travel party size distributions to simulate SAV operations, including dynamic ride-sharing among strangers, across the Austin area. Using POLARIS code, annualized averages were compared to variable counts and party sizes that mimic demand across four seasons (spring, summer, fall, winter), both weekday and weekend.

If SAVs are assumed to capture 10% person-trips in the region, on any given day, a fleet size of 21,000 SAVs can serve 93.5% of single-person calls within 15 minutes for 530,500 total ride requests on a typical day, with an average ride-service time of 28.7 minutes (from call placed to drop off at destination), and an average vehicle occupancy (AVO) of 1.61 persons during revenue service. Reflecting realistic party sizes while keeping fleet size constant increased service rate by up to 8.5% (in case of weekends in winter, from 84.1% to 92.6%), and lowered travel and wait times (resulting in 5 min total journey time savings), more efficient dynamic ride-sharing service, roughly 30% less eVMT, and 28% higher AVOs on weekends (averaging 2.13 persons per revenue-mile). While SAV seats can be more efficiently used when persons are already traveling in groups of 2 or 3 or more, there are also more rejected requests for those in bigger parties, since large-size travel parties are sometimes not able to be served by remaining seats of SAVs.

Fleet performance differences are also notable across seasons, and day of week. Summer and weekdays offer less demand, so fleets are more idle and able to offer higher service-completion rates. But high demand in other seasons means less demand served (within 15 minutes of wait times) overall, once demand variability is explicitly recognized.

Future work can explore more local demand variations, rather than relying on the national NHTS sample. For example, Texans may travel more in winter months than those in snowy states, and those in hot southern latitudes may head to cooler zones for summertime vacations. Special events like Austin City Limits, UT Austin football games, South by Southwest (SxSW) and other within-region demand variations can make a big difference in how well a single-sized fleet can serve demand while avoid being idle on other days of the year. Or fleets must be shared across regions, much like rental cars move with travelers, to meet demand at a wider scale: over time and space. Holidays are also special, and should be explicitly simulated. Finally, behavioral models with endogenous demand equations to directly estimate party size, trip-making, destination and scheduling choices can be valuable in POLARIS and other agent-based systems.

AUTHOR CONTRIBUTIONS

The authors confirm their contributions to the paper as follows: study conception and design: Y. Huang, K. Kockelman; Establishment of simulation models: Y. Huang and K.M. Gurumurthy; analysis and interpretation of results: Y. Huang; draft manuscript preparation: Y. Huang, K.M. Gurumurthy and K. Kockelman. All authors reviewed the results and approved the final version of the manuscript.

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