AGENT-BASED SIMULATIONS OF SHARED AUTOMATED VEHICLE OPERATIONS: REFLECTING TRAVEL-PARTY SIZE, SEASON AND DAY-OF-WEEK 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, synthetic person-trips that reflect travel-party size (from one to four persons) and demand variations over days and months, as evident in the National Household Travel Survey data were simulated in each scenario over a 24-hour travel day. Results show that realistic party sizes can bring considerable changes to SAV fleet performance, including up to 8.5% higher service rates (number of requests accepted within 15 minutes), 5-minute shorter journey times (wait time + travel time), 28% higher vehicle occupancies on weekends, and roughly 4% lower empty fleet VMT. Weekend travel is 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, change by up to 30% 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 help quantify SAV seat occupancies more accurately, highlighting the importance of shared mobility. However, it also creates demand and supply issues for operators that now need more information on party size to manage dynamic ride-sharing, or those that may wish to shift their fleet vehicles to other regions for special events to protect profits while offering reasonable wait times to customers throughout the year.

KEYWORDS

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

STATEMENTS AND DECLARATIONS

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.

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, departure 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 (SAV) fleets, a single 24-hr workday is typically synthesized, neglecting seasonality and travel day or week, as well as party size (Dean et al., 2022; Nahmias-Biran et al., 2021; Winter et al., 2021). Given the general situation of lacking travel party size and demand variations over time in many current studies, this paper conducts agent-based simulations on the 6-county Austin, Texas region to explore how key metrics differ as realism is added, in the form of variable party sizes (that request SAV rides), day of week, and season 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 using either personal vehicles or public transport, e.g., buses or transportation network companies (TNCs). In agent-based simulation, it often makes no difference for a personal vehicle in terms of vehicle-trips simulated, but could be critical for ride-sharing services as it greatly alters the ride-sharing service patterns: 1) Trips made by a travel party greater than 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 occupy one seat. Seasonal travel shifts are another key factor that impacts the agent-based simulation analysis. In reality, Americans tend to make more trips over the summer than in the winter, except during the holidays (e.g., Christmas and Thanksgiving), as indicated in NHTS 2016/2017 survey (McGuckin and Fucci, 2018). Travel variations over months of a year and days of a week are often failed to be captured, even in many traditional travel demand models (four-step models or activity-based models). 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 also vary in different seasons. For example, people may travel solo in the summer for leisure and business purposes, while in the winter, many people travel to visit family and have larger party sizes.

As emerging technologies, like AVs, penetrate future transportation, the ride-sharing service provided by 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 efficacy and service patterns. This paper aims to explore the answers to two questions: (1) How does fleet performance vary in agent-based simulations of AVs' ridesharing service considering seasonal travel trend? (2) What are the impacts of varying 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 travel demand tables for use in POLARIS (Auld et al., 2016).

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 on these two quantities, before introducing the methodology of generating realistic travel party size and seasonal travel shifts as inputs for POLARIS. Scenario design and model results are then presented, before concluding the paper with recommendations for future research.

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. Long-distance travel data (rJourney) for the year 2010 from FHWA shows an average party size of 2.18 travelers (Federal Highway Administration, 2015), while a recent long-distance travel survey conducted by Huang et al. (2022) shows an average party size of 2.8 travelers 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).

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 entire 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 (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 choice models stated previously, Stefan et al. (2016) designed a logit model with three alternatives: all household members travel together, a subset of members travel together, or one household member travels solo. The solo traveler is selected through another logit choice model, while the "primary" traveler (e.g., a parent taking children along) is selected for the subset case (followed by another model to decide travel party size). However, this model considers travel only among household members, neglecting travel with colleagues and friends. Many studies have also demonstrated the interaction between other travel decisions like mode choice and destination choice (Hsieh et al., 1993; Rashidi and Koo, 2016).

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. Seating capacity is often specified in ride-sharing simulations, but travel party size is generally ignored since that information does not appear in the publications (see e.g., Fagnant and Kockelman, 2018; Hörl, 2017; Loeb et al., 2018; Milakis et al., 2017). For example, Fagnant and Kockelman (2018) designed an agent-based model for SAV operation to explore the environmental benefits versus conventional vehicles with assumed party size of one, and noted such kind of limitation as future work. Loeb et al. (2018) simulated shared automated electric vehicle (SAEV) operations in Austin, Texas, to investigate the charging station placement and fleet performance based on battery range, charging times, and fleet size. The average party size is assumed unform for all travel parties and further used as an input for sensitivity analysis. Therefore, although there are specific modeling efforts to capture party size, travel party size is often ignored in agent-based simulations, especially in the context of ride-sharing service that requires detailed modeling of persons occupying seats in a vehicle.

Seasonal Variation

Seasonality in travel varies by definition, such as across the four seasons of a year, months of a year, days of a week, or weeks of the year. They are sometimes incorporated as variables in models to differentiate the seasonal impact on travel demand (see examples: Chakrabarti, 2018; Müller et al., 2020). Similar to the use case of party size, 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

1 that the variation in the number of trips per day by demographic factors for spring and fall was similar to
2 that for the full year. However, households exhibit significant differences between annual and summer,
3 except for those low-income households, single-person households, and households with no children..
4 Hasnine et al. (2021) leveraged historical Uber data from 2016 to 2018 and revealed that TNC demand
5 from earlier months than September (as the base) has a positive correlation with the TNC trip generation
6 in September.

7 A 24-hour agent-based simulation (if not an analysis for just morning or afternoon peak times) often uses
8 a synthetic population with corresponding travel behaviors (e.g., trip-making rates, destination choice,
9 and mode choice) for a typical travel day (with schools in session), often defined loosely and based on
10 "engineering judgement". As seen from a review paper for agent-based simulations of automated vehicles
11 back in 2020 (Jing et al., 2020), no paper considered demand variations over week or year in the
12 scenarios, although demand variation over the 24-hour day is commonly considered (e.g., Bischoff and
13 Maciejewski, 2016).

14 Recognizing gaps in the existing literature, this paper's contributions are significant: by incorporating
15 both travel-party size and seasonal demand variations in agent-based simulations for SAV ride-sharing
16 operations, this work delivers more realistic system-level findings for transportation policy and practice."

17 **NHTS DATA SET**

18 Various data sources and surveys (California Department of Transportation, 2013; Federal Highway
19 Administration, 2017) reveal the party size of the travelers. In this paper, the NHTS 2016/2017 data was
20 leveraged to explore and generate party size as well as seasonality in travel demand. The NHTS
21 2016/2017 was deployed in 2016, which collected the daily travel of Americans over the whole year from
22 April 2016 to April 2017. The survey provides detailed demographic information of surveyed households,
23 along with their travel history on a particular day during the survey time horizon. The trip, person,
24 vehicle, and household records are weighted to represent the annual travel pattern of Americans. There
25 are 923,572 person-trip samples collected from 263,991 persons in 129,696 households. Many trip details
26 are revealed through the survey, including trip distance, departure and arrival times, travel mode, and trip
27 purpose. Party size is revealed through a question that asks each respondent for the "number of people on
28 trip including respondent" - with follow-up questions regarding the number of household members in the
29 travel party. Knowing the exact travel day (in 2016 or 2017) allows us to explore season, day of week,
30 and other effects. Therefore, the NHTS 2016/2017 data is a good source that can reveal the year-round
31 travel variations, with sufficient data records suitable for statistical analysis.

32 Figure 1 shows the number of total person-trips made each week from April 2016 to April 2017. The
33 travel pattern fluctuates due to the occurrence of holidays and possible weather conditions, but the overall
34 pattern shows that people travel more (sum of weekdays and weekends) during spring and summer than in
35 cold-weather months. Low trip rates are observed at both ends of the survey-year (the first week and the
36 last week of the NHTS survey periods), since sample size was halved in those overlapping periods.
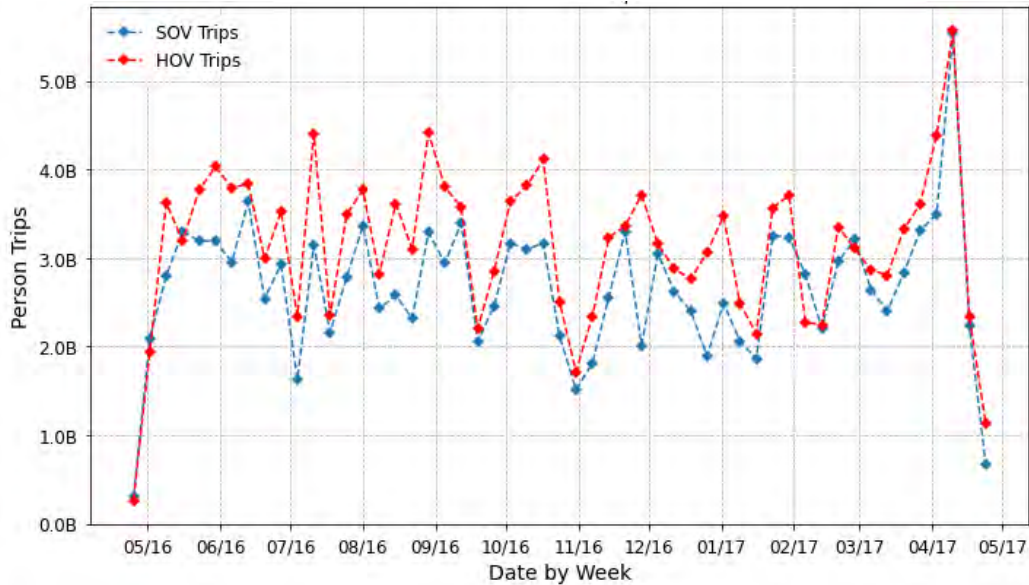
Fig. 1 Number of person-trips (in billions) by the week of year

In terms of party size, NHTS 2016/2017 data shows an average value of 1.43 travelers per trip across all automobile modes for party sizes smaller than four. Figures 2 and 3 show the share of person-trips by party size for seasonal shifts and different times of day, respectively, on weekdays and weekends. Figure 2 indicates that the share of person-trips by party size does not vary much across seasons, especially on weekdays, with solo travelers and 2-person travel parties making up more than 50% and 30% of all trips made, respectively. Compared to weekday trips, weekend trips favor multiple-traveler parties, shifted from solo travelers. Figure 2 also shows that 4-person travel parties occur more often in spring, and typically on the weekends, than in other seasons. Figure 3 demonstrates the shares of person-trips by party size across six times of day, on weekdays and weekends. Time of day bins are chosen so that they align with the timing choice model using in POLARIS. This allows shifting demand according to the variation observed in the NHTS data. 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", and "7 pm to 12 am". Solo travelers are most observed in nighttime hours, accounting for 76% of person-trips on weekdays and 59% on weekends. Similarly, people tend to travel solo more on weekdays than weekends across the six times of day.
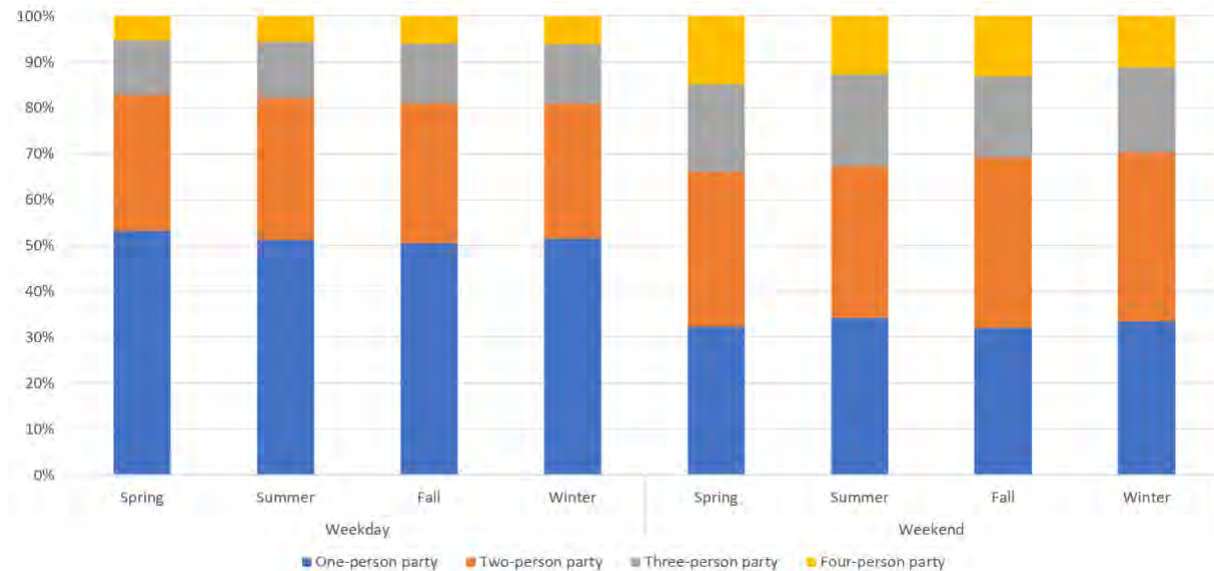
Fig. 2 Share of person-trips by party size across four seasons
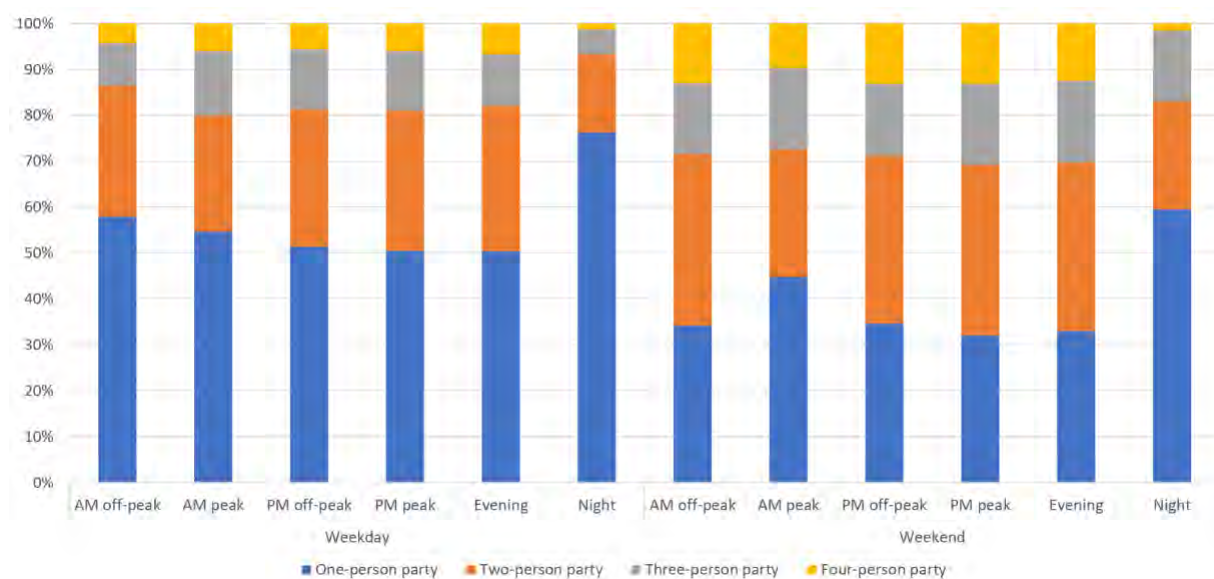
Fig 3 Share of person-trips by party size across six times of day

METHODOLOGY

Austin's POLARIS model

Agent-based micro-simulations have been a key method to explore SAV services (Jing et al., 2020). They track individual travelers and vehicles across detailed networks to infer key operational metrics (like person- and vehicle-miles traveled, average response times, and vehicle idle times) to anticipate environmental, safety, economic, and land use impacts (see e.g., Chen and Kockelman, 2016; Clements and Kockelman, 2017; Gurumurthy and Kockelman, 2022; Horl et al., 2019; Huang et al., 2021; Kondor et al., 2019; Simoni et al., 2019). SAV modeling efforts have focused on off-street parking, emissions, vehicle assignment strategies, road pricing and fare strategies, vehicle charging, and many other areas (Dean et al., 2022; Gurumurthy and Kockelman, 2022; Hyland and Mahmassani, 2018; Levin et al., 2017; Simoni et al., 2019). The agent-based travel demand and traffic simulator called POLARIS (Auld et al.,

7

1 2016) was enhanced in this work, to explore the effects of variations in party-size and seasonal travel
2 shifts on shared fleet operations across the Austin, Texas region.

3 POLARIS is an end-to-end travel demand simulator in that it provides a population synthesizer that fits
4 the agent population characteristics across several categories to the regional cross-tables iteratively (Auld
5 and Mohammadian, 2010). A series of activity models are executed on the synthetic population to
6 generate, schedule, and plan each agent's travel day (Auld et al., 2011). Destination, mode, and route
7 choice is then conducted to have a cogent 24-hr day plan for each person agent in the simulation (Auld
8 and Mohammadian, 2011, 2012; Gurumurthy et al., 2020). The synthesizer allows scaling of person
9 agents simulated allowing flexibility to model different proportions of the population. POLARIS is a
10 powerful C++ framework that is able to simulate 100% of most regional populations in relatively low
11 runtimes, so a scaling factor of 1.0 is used throughout this study. Austin's 1.9 million population making
12 530,500 TNC person-trips is simulated in under 2 hours on a supercomputer utilizing about 40 GB of
13 memory.

14
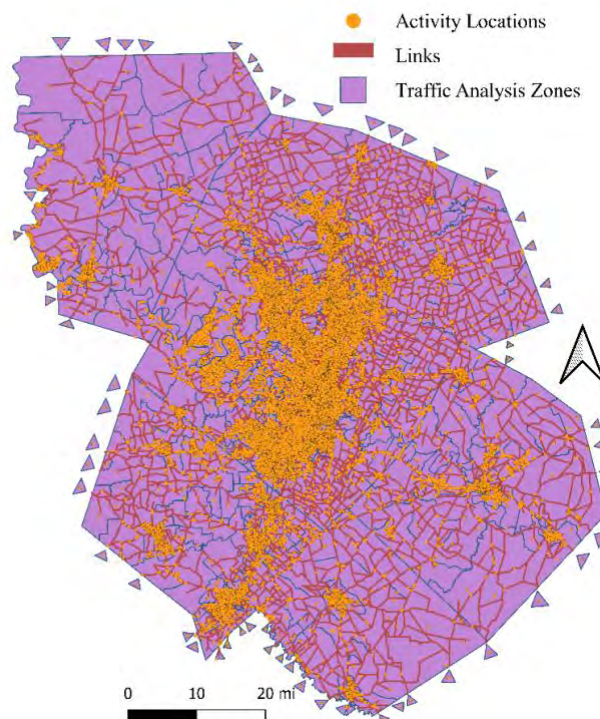
15   **Fig 4** Austin 6-county POLARIS model

16 The Austin network shown in Figure 4 is comprised of over 22,863 bi-directional links and 17,231 nodes
17 with different controls (two-way or four-way stop, or signal control). The 6-county region is spread over
18 5,480 sq. mi and the local MPO consolidates this region into 2,161 traffic analysis zones (TAZs). About
19 94% of all travel is made with an automobile (personal or TNC).

20 In order to isolate the effect of seasonality and party-size impacts on fleet operations, a fixed travel
21 demand was used. Figure 5 illustrates the network loading from an Austin simulation, defining the clear
22 bimodal peaks that are wider in the PM. The trip data from this simulation was converted as a fixed travel
23 demand input for POLARIS. By using all travel demand, the speed profile for the region will remain
24 consistent and reflect routes chosen by SAVs that react on-demand in the simulation. The oscillations
25 from a certain point from the profile indicate an increase in the replanning process of the agents as the
26 network congestion changes. At the beginning of the day, trips made are predominantly work-related
27 trips. Routine activities are considered fixed in start time and duration as planned at the beginning of the

1 simulation day. There is little flexibility, typically, in when work starts and it's a more frequent activity
2 made, so travelers are assumed to be capable of assessing the variability in morning traffic. Trips made
3 after the AM peak arise as subtours related to work, and other activities that are flexibly scheduled.

4 The SAV module (Gurumurthy et al., 2020) was extended to read in and execute party-size restrictions
5 for shared trips. Since the focus was on party-size restrictions and seasonal variations, an existing
6 algorithm for dynamic ride-sharing (DRS) was used (Gurumurthy and Kockelman, 2022), with
7 modifications to ensure the total parties involved in a shared trip are less than or equal to the vehicle's
8 seated capacity. The algorithm considers vehicle location and the directionality of a trip request, while
9 trying to control for detours imposed on all traveling parties. When the trip request aligns with the
10 direction of travel (if any) for the SAV, and the maximum detour for any parties already in the vehicle is
11 not violated, a match is confirmed, and the SAV finds the shortest path to execute the series of pickup and
12 drop-offs. For more details on the DRS ride-matching algorithm, refer to (Dean et al., 2022).
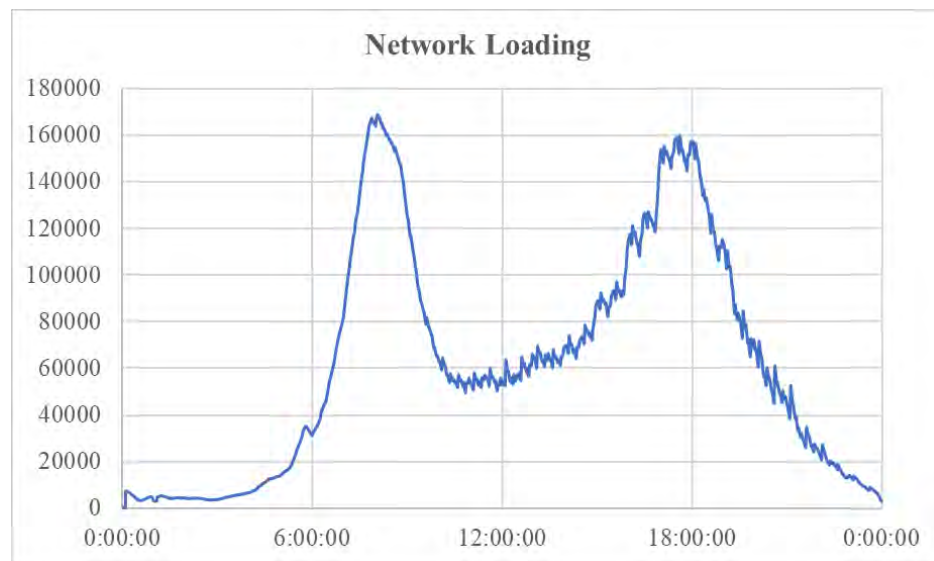
13

14 **Fig 5** Network loading in Austin's 6-county region

15 **Seasonal travel adjustments**

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

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

25   2. The seasonal travel shifts are mainly revealed through four seasons of year (spring, summer, fall,
26   and winter) and two types of days (weekday vs. weekend). This gives a lower resolution of the
27   temporal picture compared to 12 months of a year and seven days of a week, but it provides relatively
28   clear distinctions among the demand patterns. Four seasons of a year can better represent the
29   temperature and activity changes across a whole year, while a weekday-weekend setup can often tell
30   the commuting trips of a weekday pattern apart 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 Texas or a Southern city like Austin would likely see more trips in winter compared to the Northern states and cities. 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. Weekdays are usually the assumption for most agent-based simulations, as they incorporate commuting trips. Therefore, 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 (similar to the party size) are calculated based on the "auto" mode in NHTS 2016/2017, which consists of 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 obtained after processing the NHTS data that capture the change in travel demand across four seasons of year (f_s) and two types of days (f_w) relative an annual average. People make more daily trips on weekends as compared to workdays except in summer. Daily automobile use is even higher on weekends in the winter since they are less likely to drive personal cars or use public transit due to weather conditions. An overall reduction in trips, however, occurs generally in fall and winter in contrast to spring and summer, which have about 5% more trips. After applying the adjustment factors, there are eight sets of travel demand (four seasons by two types of day) for the process of party size generation.

Table 1. Adjustment factors for seasonal daily 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 from the NHTS data to reflect a realistic party-trip instead of a single 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. However, travel party sizes are assumed unaffected by trip distance, purpose, and destinations, although the trip purpose and destination choice may 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.

1 A few papers have discussed the potential of different SAV seat configurations for different services
2 (Alonso-Mora et al., 2017; Huang et al., 2022a, 2021; Inturri et al., 2021), but many agent-based
3 simulations still introduce SAVs as a vehicle with four available seats (Farhan and Chen, 2018;
4 Lokhandwala and Cai, 2018). The NHTS 2016/2017 data have trips made by a travel party of more than
5 four people, but the situation is rarely observed, and those trips often occurred with other modes, like bus
6 or school bus. In addition, more than 4 people using a dynamic ride-sharing service could lead to more
7 detours unless their routes align very well. Therefore, this paper follows the commonly used vehicle size
8 of four seats, while party sizes over four (the request of which can never be served) are considered outside
9 the scope of this paper.

10 In addition, the party size of TNC users is considered to have the same distribution as other automobile
11 modes, like SUVs, vans, pickup trucks, and rental cars, as mentioned in the seasonal shift section.
12 Although these vehicles are distinct in the number of seats designed, variations in traveling party size
13 using different vehicles remain an unclear picture. Due to insufficient data on the party size distribution of
14 TNC users, the automobile mode in NHTS 2016/2017 is used as a proxy to generate party size
15 distributions. An inherent assumption here is that different party sizes would have the same rate of
16 requests as shown in the NHTS data. This could vary in different networks, but a larger travel group size
17 may tend to use personal vehicles to travel so they often have lower request rates.

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

27 In POLARIS' baseline demand data, Austin's TNC serves just 1.5% of the region's 5.3 million person-
28 trips (per day). Considering a future of SAV fleet services, the original mode share of TNC (in person-
29 trips) was adjusted to be 10%, based on predictions and discussions mentioned in previous studies
30 (Milakis et al., 2017; Narayanan et al., 2020). This mode share was further tuned by applying two factors
31 shown in Table 1 to pivot off the original number of person-trip records (N_0), and shift from an annual
32 average to a seasonal average (f_w), and from a weekday to a weekend (f_s). This provides the number of
33 person-trips calling on SAV fleets after considering the seasonal shifts (i.e., $N_s = N_o \times f_w \times f_s$).
34 Moreover, Figure 3 is used to scale down person-trip records to reflect actual party sizes. In this way, the
35 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
36 time-of-day t divided by party size n:

37
$$P_n = \sum_t \frac{N_{n,t}}{n} \quad \forall n = 1, 2, 3, 4$$

38 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
39 shown in Figure 3):

40
$$N_{n,t} = N_s \times p_{n,t} \quad \forall n, \forall t$$

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

42
$$N_p = \sum_n \sum_t \frac{N_s \times p_{n,t}}{n}$$

11

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. It is recognized that removing and duplicating some existing trips may break some spatial patterns such that requests at origins and destinations may be aggregated more or less. The purpose of using random selection is to mitigate such imbalances as much as possible.

RESULTS

This section discusses Austin POLARIS simulation results by comparing the seasonal shifts and the incorporation of party size to the available travel demand. 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 (percentage of requests that are fulfilled) of 93.5% for 530,500 total TNC requests, using an SAV fleet of about 15 thousand vehicles (assuming one SAV for every 35 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.

System-wide fleet performance

Table 2 provides clear insights into how simulations would differ when travel party size comes into play. The service rate rose under seasonal shifts, from a 0.64% increase (on summer weekdays, vs. non-party-size scenario) to an 8.5% increase (on winter weekends, vs. non-party-size scenario). The leading reason for this increase is that there are not as many requests as the case when the party size is always 1 person, since a party of two people makes just one request (rather than 2). Fewer requests also lead to the improvement in passenger travel and wait times: about 5 minutes savings in total journey time and more than 1 minute wait time on weekends (for the same number of total passengers, theoretically, but with fewer requests made). 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 occupy two or more seats. Although the number of available seats in an SAV may lead to some rejections of requests (e.g., a vehicle with one seat cannot serve a party of two travelers), this situation avoids long detours for every travel party and demonstrates more efficient ride-sharing than typical results from agent-based simulations.

Table 2 also shows that people tend to use SAV services more during winter and spring weekends than during summer and fall weekends. The NHTS data suggest 44% more daily person-trips made in spring and winter weekends (versus summer and fall summed together), although total number of trips (5 * daily weekday trip counts + 2 * daily weekend trip counts) are still observed higher during summer and fall (see Figure 1). For both party-size and non-party-size scenarios, seasons that have more travel requests observe longer wait and travel times per party. More requests also increase the possibility that a large party (3 or 4 persons, for example) will not be served, so service rates are also higher in summer and fall. Weekday trips saw almost equally distributed person-trips across all four seasons, with slightly more requests in spring and summer.

Table 2. SAV fleet performance metrics

Scenarios	Party-size scenario				Non-party-size scenario			
	Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter

		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 min	25.3	25.4	26.0	30.0	28.7	29.4	30.6
	Avg wait time per party-trip	6.0 min	5.5	5.8	6.4	7.8	6.5	7.1	8.2
	empty VMT (million)	1.20M mi	0.79	0.98	1.46	1.86	1.27	1.56	2.11
	VMT (million)	3.63M mi	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 persons	2.09	2.12	2.16	1.68	1.61	1.65	1.71
	Party-trips per SAV per day	28.5 trips/d	19.4	23.4	34.0	43.1	30.5	37.0	48.4
	Person-trips per SAV per day	45.3	30.8	37.3	53.2	43.1	30.5	37.0	48.4
	Total person-trips served by SAVs per day	680k	462k	559k	797k	647k	458k	555k	726k
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 min	26.7	26.7	26.4	29.3	29.3	28.8	28.8
	Avg wait time per party-trip	6.1 min	6.1	6.0	5.9	7.0	6.9	6.6	6.6
	empty VMT (million)	1.10M mi	1.07	1.00	0.97	1.36	1.45	1.33	1.30
	VMT (million)	3.27M mi	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 persons	1.94	1.92	1.91	1.66	1.64	1.62	1.61
	Party-trips per SAV per day	26.0 trips/d	25.5	23.7	23.3	32.5	34.7	32.0	31.3
	Person-trips per SAV per day	34.7	34.8	32.1	31.5	32.5	34.7	32.0	31.3
	Total person-trips served by SAVs per day	521k	523k	482k	472k	488k	520k	481k	469k

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 per vehicle, averaged over four seasons and all times of day), and 17.8% on weekdays (from 1.63 to 1.92 persons). Again, weekday AVO increases are less notable, due to more solo travelers, leading to lower overall seat utilization.

Person-trips served per SAV per day are similar across party-size and non-party-size scenarios, across all four seasons. This is due to the approximately equal total number of person-trips simulated, with an adequate fleet size, delivering relatively high service rates (i.e., few SAV ride requests turned down due

to inadequate vehicles). As expected, larger travel parties require fewer SAV trips, since more seats are occupied at once (more people are served at once in those parties), which is about 68% of the total one-person parties in non-party-size scenarios.

Fleet performance by party sizes

A closer look at the fleet performance with various party sizes offers more insights into how the system reflects the true travel demand. Weekends generally have more people traveling together, compared to weekdays, with 5% more served requests for party sizes of three and four, on average. In contrast, solo travelers and two-person trips had a 4-5% drop in the number of overall served requests during weekends. When the overall travel party size shifts to larger group sizes, the average number of parties seated in the same vehicle drops. This indicates that SAVs make fewer detours to pick up additional parties along the way, and therefore, there is less wait time after SAVs accept the requests and the travel parties can arrive at their destinations with less detour time. This is revealed through the drops in both average wait time and average travel time from weekday to weekend, and from solo traveler to parties of larger sizes. Clearly, for four-person parties, the SAV picks them up and heads directly to their destination without considering other requests, so the wait time is minimized, and the travel time is not impacted by detours. Table 3 shows that the impact of larger party sizes (party size of 4 vs. 1) is most outstanding on weekdays during summer, with a 7.5-minute (27.7%) reduction in average travel time and a 1.3-minute (21.8%) reduction in average wait time.

VMT and PMT also vary among party sizes. Here, eVMT for a party size category is the empty VMT associated with picking up parties of that size. VMT is vehicle-miles traveled when the party of that size is on board the SAV. During weekdays, solo travelers contribute half of the PMT, but just 35% of regional PMT during weekends. It is worth noting that PMT share from 4-person parties almost doubles on weekends, and actual PMT more than doubles for spring (factor of 2.4) and winter (factor of 2.7). Interestingly, two-person parties traveled more person-miles than solo travelers on weekends, although their PMT share is slightly larger than that on the weekdays. This shows that, from weekdays to weekends, people mostly shift from traveling solo to party sizes of three or more, with a small shift to two-person parties. In either case, the importance of incorporating party size is noteworthy, since 1-person PMT is simulated in most SAV use models, though their PMT is less than half of the total taking place. VMT and eVMT from parties of larger sizes take a smaller share (due to people traveling in a group), but weekends still observe a higher rate than weekday. And larger travel parties result in more efficient SAV seat (and thus fleet) use, they have fewer emissions, empty VMT distances, and congestion impacts per person-mile served (For example, 200 people make 100 trip requests, rather than 200 different trip requests, if those 200 persons always travel in parties of 2.).

Table 3. SAV fleet performance metrics across 1- to 4-person travel-party sizes

	Party size	Weekday				Weekend			
		Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter
Requests served	1	37%	36%	36%	36%	32%	32%	31%	32%
	2	40%	39%	39%	40%	34%	34%	34%	34%
	3	11%	12%	12%	11%	16%	17%	17%	16%
	4	12%	13%	13%	13%	18%	18%	18%	18%
Avg. wait time per party (minutes)	1	6.2 min	6.2	6.0	5.9	6.1	5.7	5.9	6.5
	2	6.1	6.0	6.0	5.8	5.9	5.4	5.6	6.3
	3	6.2	5.9	6.3	5.9	5.9	5.2	5.8	6.1
	4	5.3	4.9	5.4	5.3	5.1	4.5	5.0	5.5

Avg. travel time per party (minutes)	1	27.3 min	27.3	27.1	26.9	26.5	26.5	26.5	27.0
	2	26.0	25.5	25.9	25.4	24.9	24.5	24.6	25.4
	3	24.5	24.0	24.9	24.5	23.6	22.9	23.8	23.7
	4	20.8	19.8	20.6	21.1	20.0	19.9	20.1	20.2
PMT shares	1	50%	48%	49%	49%	35%	35%	34%	35%
	2	33%	33%	32%	33%	35%	35%	37%	38%
	3	13%	14%	13%	13%	19%	18%	18%	17%
	4	4%	5%	5%	5%	11%	12%	11%	10%
VMT shares	1	70%	69%	69%	69%	56%	57%	56%	56%
	2	23%	23%	23%	23%	29%	29%	30%	31%
	3	6%	7%	6%	6%	10%	10%	10%	9%
	4	2%	2%	2%	2%	5%	5%	4%	4%
eVMT shares	1	74%	73%	73%	74%	60%	61%	60%	60%
	2	19%	20%	20%	19%	27%	27%	28%	28%
	3	5%	6%	6%	5%	9%	9%	9%	8%
	4	1%	2%	2%	1%	4%	4%	4%	4%

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Average vehicle occupancy variations

The incorporation of realistic party sizes also brings AVO shifts, as illustrated in Figure 6, which shows the pattern in winter. 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 on weekdays (thanks to less 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 one), 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), although the morning peak and afternoon peak are similar in AVOs, respectively.
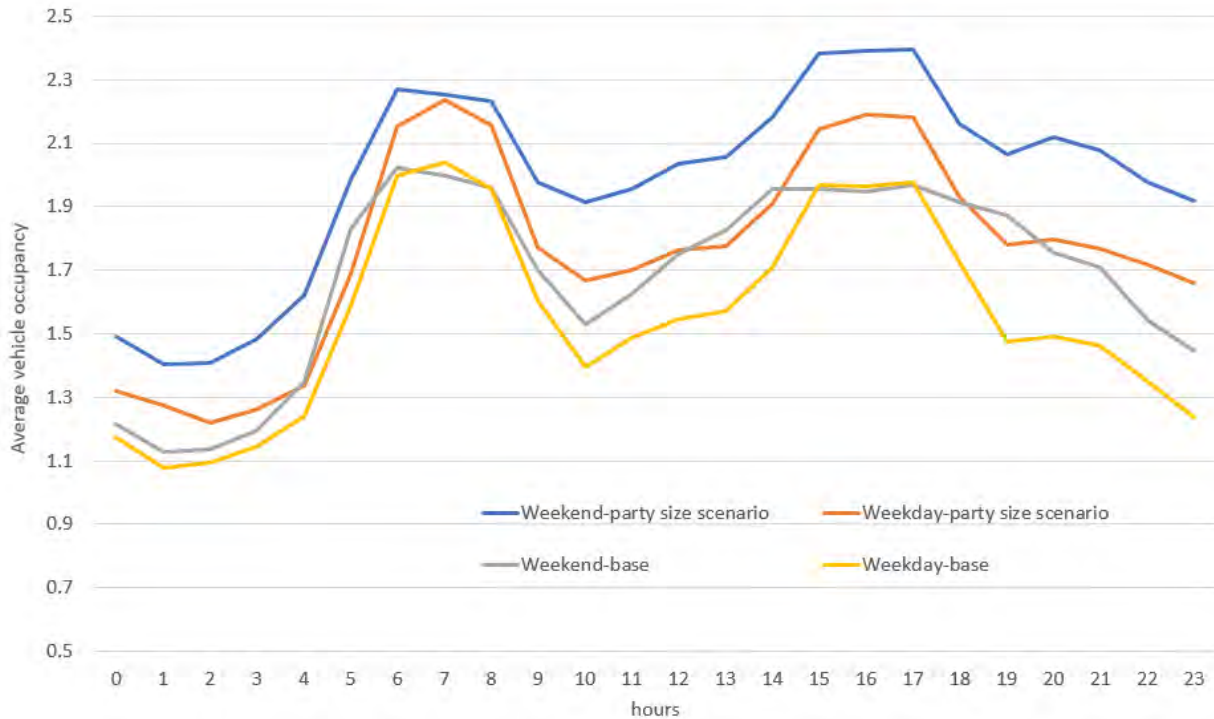
Fig 6 Average vehicle occupancies across a day in winter

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

Seasonal variations in fleet performance

Table 2 presents the shifts between the seasons and between weekdays and weekends. During summer weekends, people are less likely to use SAVs, as seen from fewer person-trips and higher service rates, which aligns with Table 1 assumptions. The performance across the four seasons is mainly impacted by the total number of requests or person-trips, 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 than on weekdays, because weekday travel demand is stable, and travel patterns are uniform.

One particular insight from the seasonal shifts is how the system performance would change compared to the agent-based simulation results that have been demonstrated so far. Table 4 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.

Table 4. Comparisons between the base case and the boundary values in seasonal shift scenarios

	Base	Party-size scenario	

		Max	Source	% diff	Min	Source	% diff
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%

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2 Figure 7 is an illustration of the seasonal shifts regarding the service rate across different party sizes. It is
3 straightforward that small party sizes (i.e., one or two) can be served more easily, because they can fill in
4 the vacant seats quickly, in contrast to large party sizes. For a similar reason, there is not much of a
5 difference in the service rate between party sizes of one and two. In summer the service rates are robust to
6 party sizes for various days, as they are all above 92%. Despite the seasonal discrepancy, the overall
7 service rate is acceptable, because the lowest rate is still near 90% for 4-person parties on weekdays in the
8 fall.
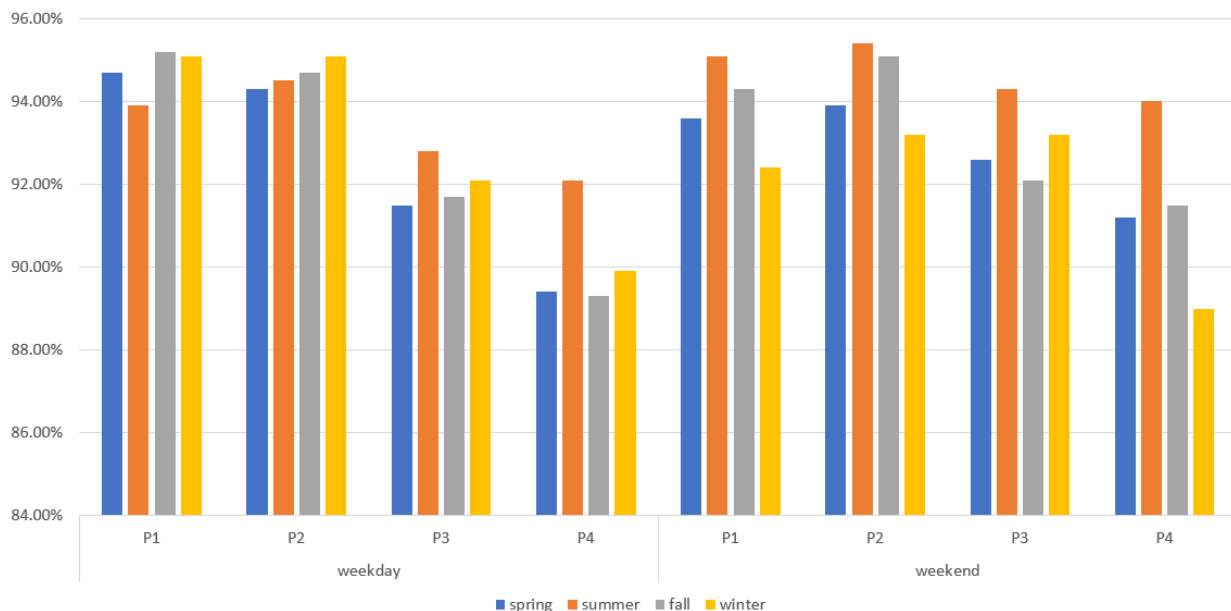

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10 **Fig 7** Service rates by party size

11 **CONCLUSION**

This paper explores the inclusion of realistic day of year demand variations and travel party sizes in agent-based simulations of SAV fleets and its impact on 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 on weekdays and weekends.

If SAVs are assumed to capture 10% of person-trips in the region, on any given day, a fleet size of 15,000 SAVs can serve 93.5% of single-person calls within 15 minutes for 530,500 total TNC ride requests on a typical day (an average annualized 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 sizeswhile keeping fleet size constant increased service rates by up to 8.5% (in the 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). A larger party can arrive at their destination with less detour time, as no other parties need to be accommodated, revealed through the drops in both average wait time and average travel time from weekday to weekend, and from solo traveler to larger party sizes. 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 (with 15-minute wait times) overall, once demand variability is explicitly recognized. NHTS data, which was fed into the party size generations of SAV use in this paper, suggest that Americans have 44% more daily trips during weekends in winter and springtime than during fall and summer weekends. More requests for the same fleet make it harder to serve all trips, so trips-served rates are higher/better during summer and fall weekends (when demand for SAVs is lower). Interestingly, weekday travel demands are almost equally distributed across all four seasons.

Fleet performance of various party sizes offers more insights into how the system reflects the true travel demand. Weekends witness more people traveling together (i.e., more 3- and 4-person parties than 1- and 2-person parties). As expected, when party sizes rise, ride-pooling or dynamic ride-sharing among strangers is less common, and SAVs take fewer detours en route (to pick up strangers). This comes with lower average wait times and travel times (with weekdays having longer times, on average. From weekdays to weekends, travelers shift from moving solo to party sizes of three or more, with a small shift to 2-person parties. Solo travelers' total PMT ends up being less than half of weekday PMT and just 35% of weekend PMT. Such results underscore the importance of reflecting party size in agent-based simulations, to better appreciate fleet performance.

Future work in this general topic area may explore more local demand variations (in time and space), rather than relying on a national sample (and broad seasons). For example, Texans may travel more in winter months than those living in snowy states, and those in hot southern latitudes may head to cooler zones for summertime vacations. Special events like Austin's 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 (Austin/local) fleet can serve demand while avoiding being idle on other days of the year. Fleets can also be shared across regions, much like rental cars move with travelers, to meet demand at a wider scale: over time and space. Regional specific party-size and seasonality distributions can help improve results instead of using the US trend from NHTS data. Some randomness in party-size generation and the multi-threaded nature of POLARIS will exist, but may not be observable enough when reporting metrics for an average day. More experiments can be conducted to explore the randomness of party sizes that form different ride-sharing patterns. 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.

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