Feast or Famine: Fleet Profitability and Other Performance Metrics Across Days of the Year

Phillip A. Ayebare
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
payebare@utexas.edu

Krishna Murthy Gurumurthy, Ph.D.
Argonne National Laboratory, Transportation and Power Systems Division
9700 S. Cass Avenue
Argonne, IL 60439
kgurumurthy@anl.gov

Kentaro Mori
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
mori@utexas.edu

Kara M. Kockelman, Ph.D., P.E. (corresponding author)
Dewitt Greer Centennial Professor in Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Tel: 512-471-0210

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ABSTRACT

This study examines fleet profits throughout the year, considering variations in travel demand in the Dallas-Fort Worth region. Using INRIX's probe-vehicle data and the 2017 National Household Travel Survey, dynamic network-wide simulations were executed in POLARIS, an agent-based transportation simulation model, to mimic a hypothetical shared autonomous vehicle (SAV) demand year. Profits varied from \$74 to \$124 per SAV per day, highest on busy workdays and decreasing by 30-40% on holidays and summer weekends. Profits per mile driven varied between \$0.24 on typical workdays while school was in session to \$0.18 on typical holidays, suggesting notable seasonal variations in travel. A 6 percentage-point decrease in empty VMT on holidays compared to workdays/school days correlated with fewer person-trips per SAV and longer average

trip lengths of 9.6 miles. Demand per SAV was particularly high on fall and winter workdays, suggesting that fleet size optimization could cater to suburban trips.

MOTIVATION

Addressing seasonal variations in travel demand has long been a challenge in transportation system design (Tyrinopoulos et al., 2010). These variations are also expected to significantly affect the revenue and profitability of shared autonomous vehicle (SAV) operations and fleet performance metrics, such as wait time, empty vehicle miles traveled (eVMT), and idle time (Huang et al., 2024). To ensure efficient and profitable operations, SAV operators must factor this in when procuring vehicles and pricing their services. However, travel demand forecasts and SAV simulations are usually only conducted for a single typical weekday, neglecting any variations in demand throughout the year. To our knowledge, only two studies have discussed the importance of considering day-to-day and seasonal demand variations in the evaluation of SAV fleet performance. Fagnant and Kockelman (2018) used the 2009 National Household Travel Survey (NHTS) records for the state of Texas to estimate seven different typical demand days. Travel demand varied by as much as ±40% from the annual average over the course of a year. However, they faced challenges in estimating metro-specific demand variations due to the small sample size in NHTS. They note that properly assessing demand variability is crucial for fleet sizing and maintaining quality service on high-demand days. Huang et al. (2024) investigated demand variation impacts during different days and seasons on SAV services in Austin, Texas, emphasizing shared rides and realistic travel party sizes. Using the POLARIS agent-based model and National Household Travel Survey data, the study incorporated daily and seasonal variations, which significantly influenced SAV fleet performance. This resulted in 10% higher service rates (number of requests satisfied within 15 minutes), 5-minute lower journey times, 28% higher vehicle occupancy, 4-percentage points lower empty fleet VMT, and 6.4% fewer person-trips served per SAV on weekends than weekdays. This study underlines the importance of including realistic travel demand variations and travel party sizes in SAV modeling to improve vehicle occupancy and address potential operational challenges.

Local demand patterns differ from national and state averages and cannot be reliably extracted from travel surveys like NHTS due to small sample size, necessitating another data source. Furthermore, dividing the year into four standard calendar seasons may not reveal all the ridership fluctuations caused by human activities (Kashfi et al., 2015). While various methods have been used to collect data on seasonal variations in travel demand, a potential limitation is the assumption that people carry out the same activities throughout the year. Failing to account for changes in daily activities across seasons could lead to overestimating the importance of primary activities in shaping travel decisions, resulting in inaccurate conclusions. Panel or longitudinal data describing variability over months of travel and activity behaviors are required to capture heterogeneous land use and travel patterns, seasonality, and weekends (Manout and Ciari, 2021). In some studies, data are collected twice a year to account for seasonal demand variation due to tourism (Zhang et al., 2012). Other methods of data collection are enabled by emerging technology (e.g. web-based, GPS, License Plate, cell/Smartphone, Bluetooth, social media) which can overcome several limitations of the traditional household-based survey method but may not provide all required information (e.g. trip purpose and traveler characteristics). Using mobile positioning data of foreign tourists, Raun et al. (2016) analyzed the distribution of call activities, temporal variation of visits, and the composition of tourists in Estonia. However, most existing research only focuses on mining macro-level aggregated movement patterns and cannot achieve the identification of fine-grained travel on a large scale. Elango et al., (2007) conducted a study of intra-household travel variability in Atlanta, Georgia using a GPS-based monitoring system installed in approximately 500 vehicles from 260 representative households. In this study, this approach is expanded to a larger scale using hundreds of thousands of INRIX probe vehicles (INRIX 2024).

Many studies have demonstrated how demand for different modes of transportation react to weather conditions. Faghih et al. (2020) used linear regression and time series models to analyze taxi demand in Manhattan. They found that that low temperatures and precipitation were significant factors contributing to increases in taxi trips. Lepage and Morency (2021) used generalized additive models to study short-term fluctuations in demand for bike-sharing, taxi, subway, and transit in Montreal, Canada. Results showed that rain increases taxi demand while decreasing demand for the other three modes studied. Shokoohyar et al. (2020) investigated how weather conditions impacted wait times, trip durations, and ride fares for Uber and Lyft in Philadelphia during the summer of 2018. They found that extreme weather conditions significantly affected ride-sourcing platforms, particularly through average pickup times and trip durations. However, it had contrasting effects between weekdays and weekends, with both metrics increasing on weekdays but decreasing on weekends. By extension, it can be expected that seasonal climate patterns will impact travel behavior and demand for SAVs.

This study examines these issues by dividing the year into smaller, more consistent blocks and examining factors that impact the fluctuation of SAV ridership. INRIX probe vehicle trip records are obtained from the Regional Integrated Transportation Information System (RITIS) Nextgen Trip Analytics interface (CATT Lab, 2024) and scaled using NHTS data to generate trip tables for 10 different days of the year, reflecting spatiotemporal differences in regional travel across seasons. The trip tables are then used in POLARIS, an agent-based simulation software, to study fleet operator performance and profitability.

POLARIS SIMULATION

The POLARIS agent-based activity-based travel demand simulator (Auld et al., 2016) was used to simulate SAV fleet operations in the Dallas-Fort Worth (DFW) region. The framework employs agents to model individual passengers and vehicles, allowing for the modeling of complex interactions of travel behavior in transportation systems (Zhao and Malikopoulos, 2022). While POLARIS typically uses activity-based travel demand models to simulate the typical daily weekday activities of synthetic populations generated during model initialization, this study uses exogenous demand, namely LDV trips from RITIS and external commercial trips from the North Central Texas Council of Governments (NCTCOG), in order to simulate travel demand on specific days rather than a typical weekday. POLARIS features a central fleet operator module to manage SAVs (Gurumurthy et al., 2020). Dynamic ridesharing allows multiple requests to concurrently be served by a single vehicle within a detour threshold (Gurumurthy and Kockelman, 2022). This module was modified to incorporate and implement party-size constraints for shared trips. Given the concentration on party-size constraints and the influence of seasonal shifts, the default dynamic ridesharing algorithm was utilized and adapted to ensure that the aggregation of number of parties on a shared trip does not exceed the vehicle's seating capacity (Huang et al., 2024). Vehicles are routed through the network by the time-dependent A* algorithm, while a mesoscopic traffic flow model based on the link transmission model captures link-level congestion (Auld et al., 2019; Verbas et al., 2018).

RITIS Trips

The RITIS platform generates origin-destination (OD) matrices using the INRIX trip path dataset, which include vehicle trajectories collected from connected vehicles and location-based services (INRIX, 2024; Mori and Kockelman, 2024). The trips provided by the RITIS platform represent approximately 7% of light-duty vehicle (LDV) trips made daily within the Dallas-Fort Worth (DFW) region (Figure 1) during 2019 and 2020. Trip tables were downloaded for Sunday, April 28, 2019; Thursday, October 12, 2019; Saturday, October 12, 2019; Friday, November 22, 2019; Tuesday, November 26, 2019; Thursday, November 28, 2019; Wednesday, November 6, 2019; Saturday, February 8, 2020; Monday, February 17, 2020; and Sunday, March 1, 2020. These dates were selected to create a variety of days of weeks and months in the 6 months of TxDOT-purchased INRIX data (which were solely fall and spring months, with no summer or winter months): March to May and September to November in 2019, February to April and September to November in 2020, and February to April and September to November in 2021.

Figure 2 shows the share of light-duty vehicle trips sampled from RITIS by distance. November 6 showed the highest share of shorter trips (less than 5 miles), which could be attributed to several factors, such as weather conditions that encourage short-distance vehicle usage or a typical workday with usual commuting patterns. November 26 (two days before Thanksgiving Day) had the highest share of long-distance trips (greater than 25 miles) and the lowest share of short-distance trips, showing that people often travel long distances for holidays. A higher share of mid-range distance trips (10 to 25 miles) is seen in late winter and early spring (February and March), which could coincide with relatively mild weather conditions, possibly encouraging longer trips, such as out-of-town visits or recreational trips. The distribution of light-duty vehicle trips generated from the RITIS platform across different time periods on sampled days of the year in 2019 and 2020 is shown in Figure 3. It can be seen that the temporal distribution of trips varies greatly from day to day. For example, weekends and holidays are characterized by a high share of midday and afternoon trips, while high shares of AM peak trips are only observed on weekdays.

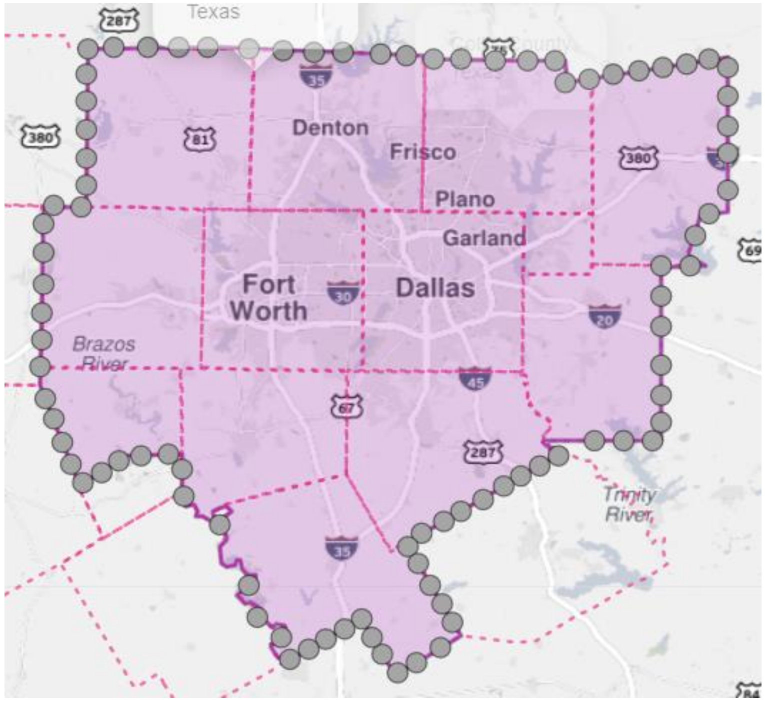

Figure 1: Study Area Spatial Filter of NCTCOG Jurisdiction from the RITIS Platform.

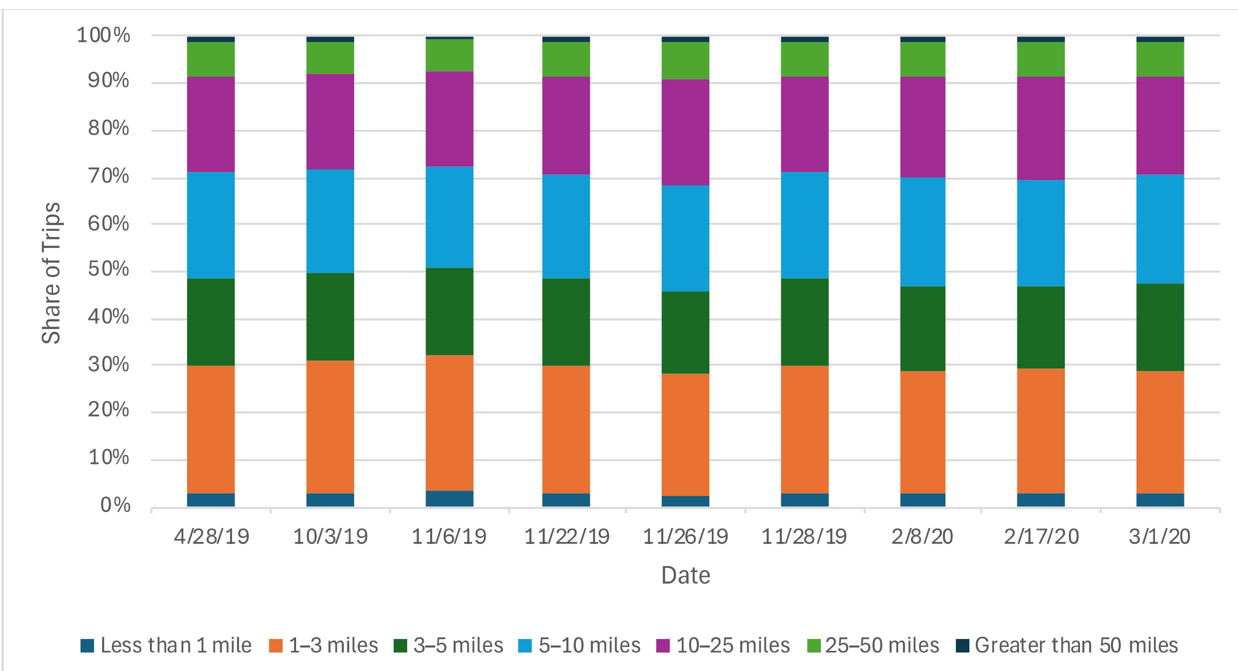

Figure 2. Share of Light-Duty Vehicle Trips by Distance

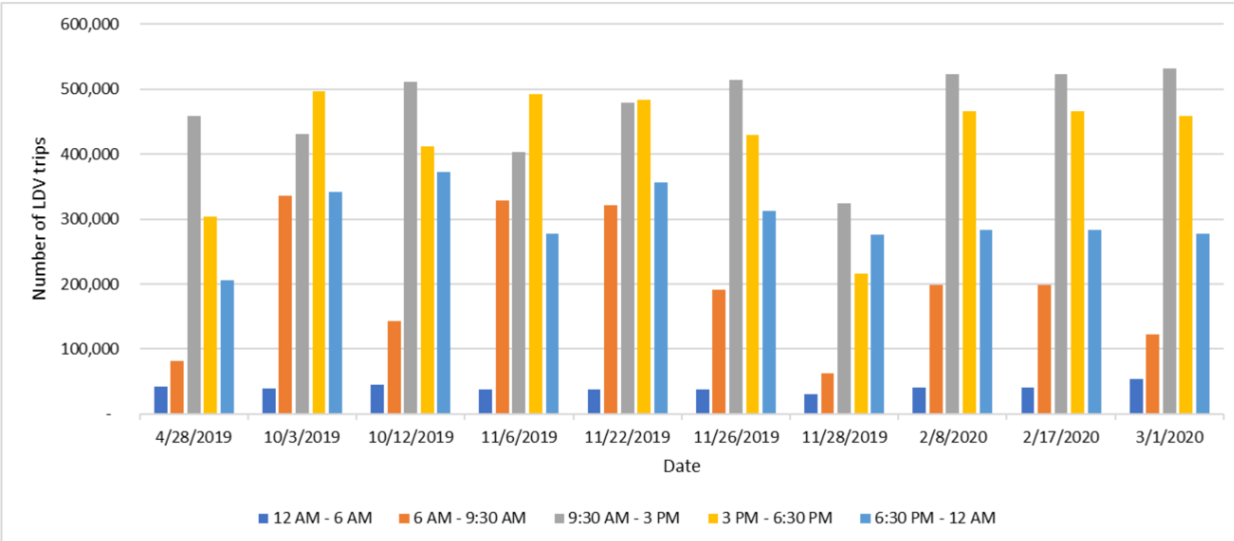

Figure 3: Vehicle Trips Generated Across Ten Different Days of the Year.

Ordinary Least Squares Analysis to Study Travel Demand Variation Across the Year

The Federal Highway Administration (FHWA) of the U.S. Department of Transportation conducts the National Household Travel Survey (NHTS) to collect information on Americans' travels. The resulting database provides a sample of actual trips taken by Americans during the year. NHTS 2017 (FHWA, 2017) data, filtered for light-duty vehicle trips in the DFW region, were analyzed using ordinary least squares (OLS) regression to determine the impact of several factors on the passenger miles traveled (PMT), vehicle miles traveled (VMT), and person-trips per capita, clarifying dates from which to sample light-duty vehicle trips on the RITIS platform. Table 1 presents the results of OLS regression analyses, examining day-of-week, month, and holiday effects on VMT, PMT, and person-trips per capita. The analysis shows that VMT and PMT per capita are highest on Saturdays, while person-trips per capita per day are highest on Fridays. Regarding monthly variations, VMT and PMT per capita per day are highest in June, whereas person-trips per capita per day reach their maximum in May.

Travel patterns vary across days of the week and months, which have different work schedules, school calendars, seasonal weather, and daylight hours. Notably, findings reveal a significant reduction in VMT, PMT, and person-trips per capita per day on holidays and the two days preceding a holiday. This finding underscores the impact of holiday schedules on travel behavior, potentially indicating a decrease in work- and school-related travel and overall person-trips during these periods. It suggests that people may be inclined to stay home, engage in leisure activities, or travel shorter distances during holidays and surrounding days. However, the effect can vary for specific holidays and the day of the week, as most federal holidays in the U.S. fall on Mondays. A more detailed analysis of travel demand variations, including specific holidays, for the state of Texas using loop detector counts and RITIS trips are presented in Mori and Kockelman (2024). Sundays in February, March, and July through January are the least busy days for person-trips per day, and Mondays and Sundays have the lowest VMT and PMT per day. Saturdays in June are the busiest days for PMT and VMT, while Fridays in May have the highest number of trips per person. This regression gives insight into the types of days that should be sampled to capture demand variations throughout the year.

Table 1: OLS Model Results (N=365)

	PMT/Capita/Day		**VMT/Capita/Day**		**Person Trips/Capita/Day**	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	55.33	15.35	11.73	8.52	3.76	10.75
# Households sampled	0.01	4.62	0.00	4.40	0.00	2.57
# Persons sampled (log)	-6.97	-10.47	-1.25	-4.90	-0.23	-3.56
Federal holiday	-2.87	-2.47	-1.23	-2.77	-0.55	-4.95
Within 2 days of fed. holiday	-1.50	-2.43			-0.21	-3.65
Monday					0.29	4.15
Tuesday					0.37	5.22
Wednesday					0.44	6.36
Thursday	2.18	3.51			0.40	5.65
Friday	2.03	3.29			0.47	6.63
Saturday	3.14	5.12	0.70	3.19	0.27	4.20
April	2.27	2.99	0.89	3.03	0.15	2.16
May	3.75	4.82	2.20	7.30	0.39	5.31
June	3.97	4.96	2.28	7.42	0.31	4.10
July			0.46	1.67	0.00	0.00
August	1.39	2.00	0.57	2.06	0.00	0.00
September			0.65	2.34	0.00	0.00
October	1.14	1.62	0.95	3.41	0.00	0.00
Adj R-sq	0.4321		0.2614		0.3785	

Scaling of RITIS Trips Using NHTS Data

The demand inputs for the simulation were LDV trips from RITIS and external trips (medium and heavy-duty trips) from North Central Texas Council of Governments (NCTCOG). POLARIS uses discrete location points as ODs instead of zone centroids. Trip OD matrices from these two sources were disaggregated via a parallelized procedure for selecting random locations within the specified zone. For commercial trips from NCTCOG, nonresidential locations were prioritized for matching.

Compared to NHTS, RITIS data comprises a much larger sample size of trips, with more than 14 million vehicle-trips per day starting and ending in the DFW region across the 10-day sample. To further investigate the variations in travel demand between the 10 selected days, a distance skim for the DFW region was generated in TransCAD and used to determine VMT between OD pairs in the sampled RITIS trip tables. An assumed population of 434,000 in 2019 was determined based on the 6-8% vehicle penetration rates and used to calculate values depicting average VMT and light-duty vehicle (LDV) trips per resident, as shown in Table 2. Despite our best efforts to select different types of days from the available days in the dataset, this analysis showed that the VMT values of the 10 selected days were too clustered around the mean. In order to address this issue, the NHTS dataset was used to scale the clustered RITIS values to obtain relatively evenly spaced values, creating more meaningful variations for analysis.

Table 2: RITIS Sample VMT Values

RITIS Dates Sampled	Total trips sampled from RITIS after (6-8% of trips sampled)	Total VMT by LDVs /day	Average VMT by LDVs/day/ Trip	Estimated VMT per day/Resident	RITIS LDV Trips/Day /Resident
4/28/2019	1,645,800	10,206,851	9.34	23.52	3.79
10/03/2019	908,775	14,708,369	8.94	33.89	2.09
10/12/2019	1,486,986	14,779,127	9.96	34.05	3.43
11/06/2019	1,512,502	13,381,590	8.69	30.83	3.49
11/22/2019	1,484,170	15,728,693	9.37	36.24	3.42
11/26/2019	1,443,444	14,451,363	9.72	33.3	3.33
11/28/2019	1,092,988	11,013,024	12.12	25.38	2.52
2/17/2020	1,679,208	14,277,163	9.44	32.9	3.87
02/08/2020	1,607,490	15,315,363	9.39	35.29	3.7
03/01/2020	1,539,812	13,439,015	9.31	30.97	3.55
Average and St Dev of VMT/Day/Person				**31.64**	**4.16**

The NHTS dataset has more detailed variation in VMT across the year at the expense of a relatively small sample size of over 200 vehicle trips occurring on any given day. The 2017 NHTS dataset for DFW person-trips was filtered to retain days on which at least 30 respondents were surveyed, yielding 190 days. The filtered dataset was sorted by VMT per capita, forming 10 clustered deciles, each containing 19 days, guided the selection of 10 middle days and VMT values. Table 3 shows the 10 days with the median value in each decile set (with some flexibility in the selection to obtain a good mix of days of the year and week) and the corresponding VMT values. These dates were mapped to the most similar day sampled from RITIS. Caution was taken to separate weekdays, weekends/holidays, school days, and summer days to accurately compare days with similar travel patterns from both datasets. For instance, due to the absence of summer trips sampled from RITIS, high VMT NHTS days (like 8/12/2016) were used to scale RITIS VMT values sampled on workdays during the school season (11/22/2019). Conversely, a low VMT NHTS day, like the Thanksgiving holiday from NHTS, was used to scale the VMT from RITIS' Thanksgiving Day.

For each of the 10 days in NHTS, the Z-score of the VMT per capita was calculated and used to derive the scaling factor of the VMT values in RITIS. The factors were applied to trip counts between OD pairs, and stochastic rounding was used to prevent errors for low count entries in the OD matrix. The 10 decile days from this process were used to create 10 POLARIS scenarios representing variations in demand and profit for a "typical year" of SAV fleet operations. The total scaled RITIS trips simulated in POLARIS with SAVs are shown in Table 4. The average scaled VMT per Resident across the 10 days of the year was 31.8 miles, while the standard deviation was 2.91.

Table 3: NHTS Average VMT per Person/Day and Corresponding Z-score

NHTS date	Number of Persons Sampled	VMT per person /day	Deciles	Number of SD from mean (Z-score)
Thursday, November 24, 2016	36	15.17	1st	-1.00
Monday, August 1, 2016	63	17.68	2nd	-0.68
Tuesday, January 3, 2017	48	19.07	3rd	-0.50
Friday, April 7, 2017	49	20.93	4th	-0.27
Wednesday, November 16, 2016	49	22.54	5th	-0.06
Saturday, September 3, 2016	33	23.84	6th	0.10
Friday, August 12, 2016	67	25.31	7th	0.29
Monday, February 13, 2017	40	26.93	8th	0.49
Thursday, October 20, 2016	43	29.67	9th	0.84
Thursday, May 26, 2016	32	32.98	10th	1.26

Table 4: Scaled RITIS VMT Values

NHTS Decile Date	RITIS Date	Total Trips Sampled from RITIS	Total Trips After Scaling	RITIS VMT/day /Person	Scaled VMT /Day /Resident	Scaling Factor
11/24/2016	**11/28/2019**	908,775	983,942	25.4	27.5	1.083
08/01/2016	**11/26/2019**	1,486,986	1,286,171	33.3	28.8	0.865
01/03/2017	**11/26/2019**	1,486,986	1,319,097	33.3	29.5	0.887
04/07/2017	**11/22/2019**	1,679,208	1,414,079	36.2	30.5	0.842
11/16/2016	**11/06/2023**	1,092,988	1,111,724	30.8	31.4	1.017
09/03/2016	**02/08/2023**	1,607,490	1,460,871	35.3	32.1	0.909
08/12/2016	**11/22/2019**	1,679,208	1,521,765	36.2	32.8	0.906

2/13/2017	**2/17/2023**	1,512,502	1,549,767	32.9	33.7	1.025
10/20/2016	**10/03/2023**	1,645,800	1,706,713	33.9	35.1	1.037
5/26/2016	**11/22/2019**	1,679,208	1,708,793	36.2	36.9	1.018

RESULTS AND DISCUSSION

A fleet size of 1 SAV for every 40 persons and 20% SAV mode splits was used to serve a 7% fixed demand, while external trips (medium and heavy-duty trips) from NCTCOG added congestion to the network. Various fleet performance metrics were analyzed, as shown in Table 5, including total VMT, empty VMT (eVMT), revenue, and profit margins of the SAV fleet. For calculating revenue and profit, a fixed fare of $1, $0.25 per minute, and $0.5 per mile were assumed, while operational costs consist of $0.50 per mile and $25 per day ownership costs. These values are in line with the range of values proposed in literature (Becker et al., 2020; Bösch et al., 2018; Litman, 2023). Daily profits range from a low of $1.03 M to a high of $1.66 M, while profits per SAV per day span from $74 to $124 (Figure 4). Revenue person-miles and daily revenue generated reveal a peak on May 26, a standard work and school day. Fleet utilization rates remain relatively consistent across all days, irrespective of demand. During the holiday season or the days leading up to it (like November 24, 2016), demand dips by 42% compared to regular business working days due to reduced movement as people take time off (Figure 4).

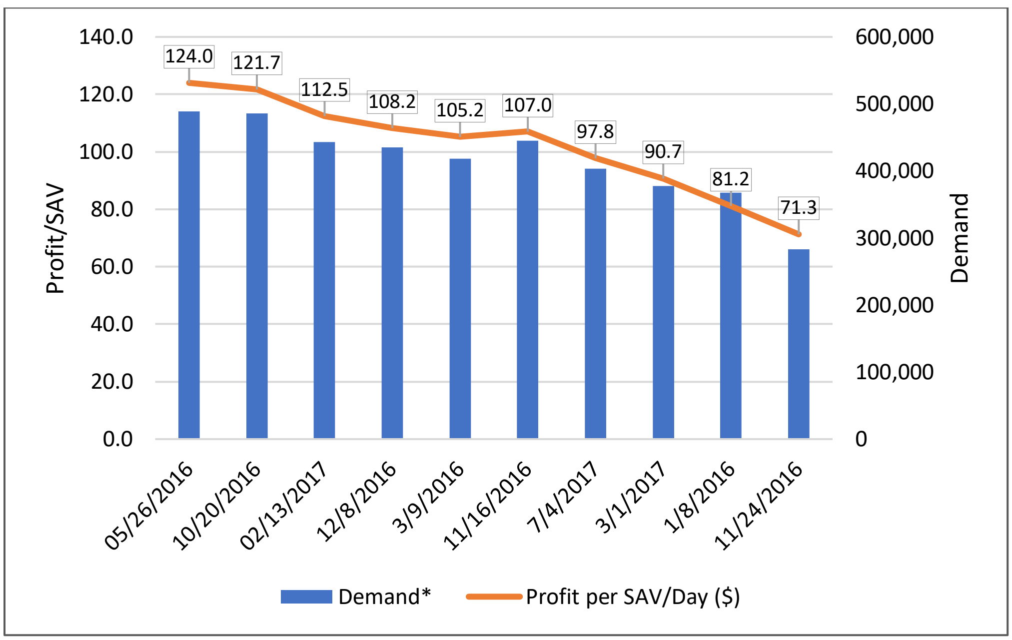

Figure 4: Profit per SAV per day

Daily revenue generated and costs incurred demonstrate considerable variations, directly impacting profits. Profit per mile, the financial efficiency of each mile driven, ranges from $0.18 on a typical holiday to $0.24 on a workday in the winter and fall. Average peak hour wait time demonstrates considerable stability, between 4.1 to 4.5 minutes across all scenarios. This consistency points towards an effective operation that maintains a high service quality concerning wait times, irrespective of changes in fleet utilized and corresponding variations in demand. Figure 5 presents a bar chart showcasing the relationship between person-trips/SAV/day and eVMT, which denotes the extent of deadheading. The observed decrease by 6 percentage-points in %eVMT from 26.2 to 20.9% on typical holidays relative to the busier workdays/weekdays (or school semester days) correlates with the reduced person-trips per SAV, as well as with the longest average trip length of 9.6 miles/trip, typically within the holiday or two-day interval. Furthermore, a lower percentage of idle times on typical workdays in the spring and fall seasons indicates the potential exhaustive utilization of the fleet, while a 2 to 5% increase in idle times on typical holidays or summer weekends suggests otherwise. The study also noted a higher-than-usual average SAV VMT per day, potentially owing to a significant increase in demand per SAV, during regular workdays in fall and winter. Therefore, appropriately sizing the fleet to accommodate trips within the suburban region seems promising, given the volume of trips served within a relatively confined area. The SAV fleet served up to 48.2 person-trips per SAV per day on average for the busier weekdays/workdays, while person-trips dwindled by 40% on holidays or summer weekends to 27.9 person-trips per SAV. Shares in demand served remained comparable at 97-99% from the assumption of a fixed fleet across all days. Higher demand densities should allow smaller fleets to serve trips, albeit with some loss in percent demand served. Increased fleet utilization does not automatically translate to augmented profits. A delicate equilibrium emerges where a larger fleet may escalate operation costs yet simultaneously present the opportunity to serve a higher demand, thus potentially generating more revenue. Conversely, a smaller fleet may curtail capital costs but limit revenues if it falls short of meeting all demand. These results indicate that a fleet of 1 SAV for 40 people – assuming market shares, fleet sizing, and cost decisions used – may be very realistic long-term but are too optimistic for near-term applications since AV technologies are currently expensive and only in pilot operation.

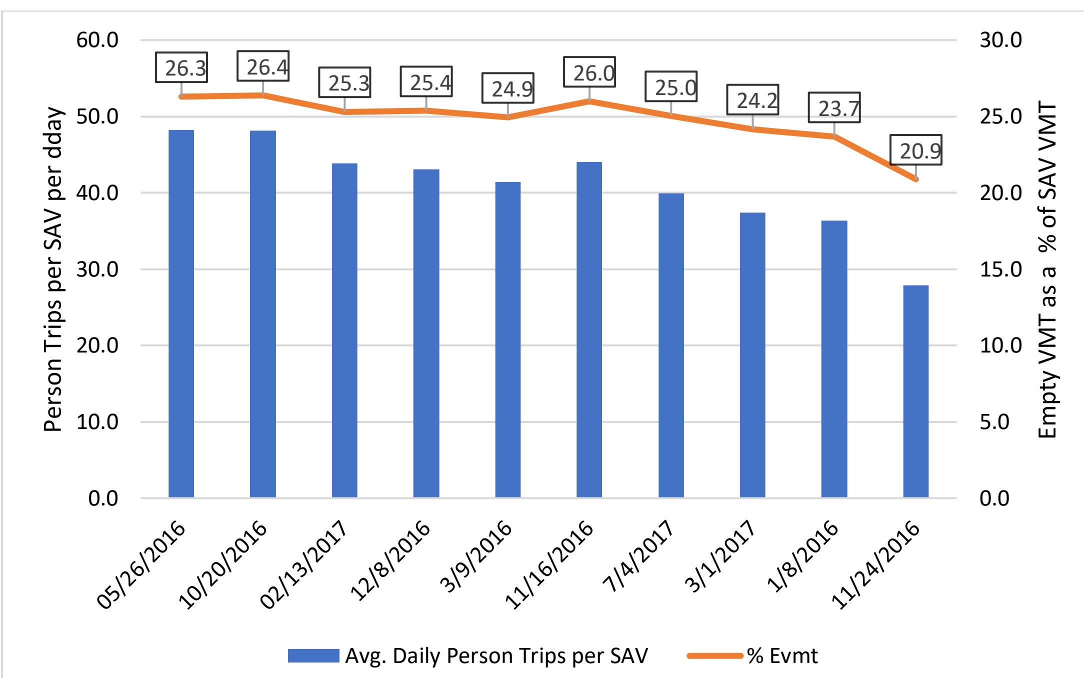

Figure 5: Person-trips per SAV and Empty VMT

Table 5: Operator Profit and Fleet Performance Metrics

NHTS DATE	05/26/2016	10/20/2016	02/13/2017	08/12/2016	09/03/2016	11/16/2016	04/07/2017	01/03/2017	08/01/2016	11/24/2016
RITIS DATE	11/22/2019	10/3/2019	02/17/2020	11/22/2019	02/8/2020	11/6/2019	11/22/2019	11/26/2019	11/26/2019	11/28/2019
Average Peak Hour Wait Time (min)	4.4 min	4.2 min	4.1 min	4.2 min	4.1 min	4.0 min	4.2 min	4.0 min	3.9 min	3.9 min
Revenue Person Miles (in millions)	7213 M mi	6881 M mi	6568 M mi	6428 M mi	6280 M mi	6115 M mi	5997 M mi	5794 M mi	5625 M mi	5371 M mi
Avg. Daily Trip Length (miles/trip/day)	6.9 mi/trip/d	6.5 mi/trip/d	6.9 mi/trip/d	6.8 mi/trip/d	7.0 mi/trip/d	6.2 mi/trip/d	6.9 mi/trip/d	7.2 mi/trip/d	7.2 mi/trip/d	9.6 mi/trip/d
Avg. Daily VMT/SAV (miles/SAV/day)	528.8 mi/SAV/d	502.8 mi/SAV/d	479.4 mi/SAV/d	469.2 mi/SAV/d	458.4 mi/SAV/d	445.0 mi/SAV/d	440.6 mi/SAV/d	427.9 mi/SAV/d	410.2 mi/SAV/d	398.3 mi/SAV/d
Avg. Daily Person Trips per SAV	48.2 person trips/SAV/day	48.1 person trips/SAV/day	43.8 person trips/SAV/day	43.0 person trips/SAV/day	41.4 person trips/SAV/day	44.1 person trips/SAV/day	39.9 person trips/SAV/day	37.4 person trips/SAV/day	36.4 person trips/SAV/day	27.9 person trips/SAV/day
Avg. % Daily Idle Time per SAV	46.6% idle	48.4% idle	51.8% idle	53.0% idle	54.2% idle	54.4% idle	56.3% idle	58.4% idle	59.8% idle	64.0% idle
%eVMT	26.3% eVMT	26.4% eVMT	25.3% eVMT	25.4% eVMT	24.9% eVMT	26.0% eVMT	25.0% eVMT	24.2% eVMT	23.7% eVMT	20.9% eVMT
Demand*	489K trips served/day	486K trips served/day	443K trips served/day	435K trips served/day	419K trips served/day	445K trips served/day	403K trips served/day	378K trips served/day	368K trips served/day	283K trips served/day
Daily Revenue	$2,58M/day	$2.49M/day	$2.36M/day	$2.30M/day	$2.25M/day	$2,22M/day	$2.14M/day	$2.06M/day	$1.95M/day	$1.85/day

Generated ($)										
Profit/Day ($)	$775K/day	$761K/day	$703K/day	$676K/day	$658K/day	$669K/day	$611K/day	$567K/day	$508K/day	$445K/day
Profit per SAV/Day ($)	$124.0 per SAV/d	$121.7 per SAV/d	$112.5 per SAV/d	$108.2 per SAV/d	$105.2 per SAV/d	$107.0 per SAV/d	$97.8 per SAV/d	$90.7 per SAV/d	$81.2 per SAV/d	$71.3 per SAV/d
Profit per SAV/mile ($)	$0.23/mile	$0.24/mile	$0.23/mile	$0.23/mile	$0.23/mile	$0.24/mile	$0.22/mile	$0.21/mile	$0.20/mile	$0.18/mile

7% demand*

Note: 98.2% to 99.5% of SAVs were used each day (6136 to 6219 SAVs).

CONCLUSIONS

By effectively pooling multiple-person trips within the same vehicle to increase party sizing, % eVMT can potentially be maintained within 20.9% to 26.4% across different fleet sizes and operational scenarios. Based on the results, assuming the average revenue per SAV at $1 per trip-mile (considerably lower than traditional taxi fares) and no competition, profits range from $74 to $124 per SAV per day. These estimates suggest the potential for operators to achieve significant returns on their investments, assuming low fixed and variable costs. There could be potential for losses by the operator if the fleet operated within small geofences or had limited origins and destinations. A 6 percentage-point decrease in % eVMT on holidays compared to workdays/school days correlates with fewer person-trips per SAV and longer average trip lengths. Seasonal variations also emerge, with lower idle times indicating fleet saturation on typical workdays and increased idle times on holidays or summer weekends. Demand per SAV is particularly high on workdays during fall and winter, suggesting that fleet size optimization to cater to suburban trips could be advantageous. On average, each SAV served up to 48.2 person-trips on busy workdays, which decreased by 40% on holidays or weekends. Demand served remained relatively stable, regardless of fleet size. However, increased utilization does not necessarily boost profits. An optimal balance must be found between larger fleets, which may raise operational costs but can also meet higher demands, and smaller fleets, which might reduce capital costs but limit potential revenues.

Nonetheless, it is essential to remember that outcomes like VMT impacts and profits heavily depend on specific implementation details. Factors such as market penetration, fleet relocation strategies, trip pricing decisions, geofenced service areas, and maximum SAV occupancies will substantially impact these outcomes. Larger fleets, while capable of reducing unoccupied vehicle relocations and trimming operation costs, require higher capital investment. Smaller fleets might mitigate capital expenditure but could result in higher wait times and costs (Fagnant and Kockelman, 2018). Consequently, balancing fleet size, operational costs, and wait times becomes crucial to ensure efficient operations and service delivery. The assumptions in this study might accurately reflect long-term scenarios but could be too optimistic for near-term applications, given the high cost and current pilot status of autonomous vehicle technologies.

In the SAV scale system envisioned here, one could anticipate reduced household vehicle ownership rates, decreased parking requirements, traveler cost savings, and substantial opportunities for operator profits. However, to avoid excess VMT scenarios inherent to SAV operations, it is vital to incentivize demand-responsive service opportunities appropriately. This study contributes case study applications, simulation techniques, and evaluation methods that can be used to understand and anticipate the potential impacts of SAV operations under varying demand on profitability. SAV operations provide an intricate interplay between various elements, each significantly influencing the overall profitability and efficiency of the fleet. Balancing these factors to maintain service quality while maximizing profit is complex and relies on strategic planning and adaptive management. Further research in this field will continue to unravel these complexities, helping operators refine their strategies and better meet the challenges of this burgeoning field.

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