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

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Under review at the Journal of Transportation Research Forum

ABSTRACT

This research examines fleet profits throughout the year, considering variations in regional travel demand in the Dallas-Fort Worth region. Using data from INRIX's RITIS platform and the 2017 National Household Travel Survey (NHTS), dynamic network-wide simulations were executed in POLARIS, an agent-based model, to mimic a hypothetical shared autonomous vehicle (SAV) demand year. The study assumed a 20% SAV mode split and a fleet size of 1 SAV per 40 persons in the region, incorporating external vehicle trip tables to generate realistic network congestion. Operating costs of SAVs were presumed to be $25 per day for ownership with an additional 50 cents per VMT, with user fares of $1 per pick-up, $0.50 per (user-occupied) mile, and $0.25 per (user-occupied) minute. Profits varied from $74 to $124 per SAV per day, highest on busy workdays and decreasing by 30-40% on holidays or summer weekends. Fleet-wide profits per SAV varied between 24¢ on typical workdays while school was in session to 18¢ on typical holidays, suggesting notable variation in travel across different seasons. A 6% decrease in % eVMT on holidays compared to workdays/school days correlated with fewer person-trips per SAV and longer average trip lengths of 9.6 miles. Seasonal variations also emerged, with lower idle times of 46-54% and increased idle times on holidays or summer weekends (up to 64%). Demand per SAV was 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.

MOTIVATION

Seasonal variation in demand significantly affects the revenue and profitability of shared autonomous vehicle (SAV) operations and fleet performance metrics such as wait time, empty vehicle miles traveled (eVMT), idle time, and response time. To address these issues, fleet operators may need to implement price adjustments or dynamic pricing based on seasonality. SAV operators must be aware of changes in demand during different seasons and must address these changes to ensure efficient and profitable operations. Seasonal variations often overshadow the effect of calendar seasons on commuting trends and patterns. Many studies have analyzed ridership changes across weather seasons. However, dividing the year into four standard calendar seasons may not reveal all the ridership fluctuations caused by human activities. This study examines this issue by dividing the year into smaller, more consistent blocks and examining factors that impact the fluctuation of SAV ridership.

Many studies have demonstrated, using models to explain and predict short-term and long-term demand, how demand for modes of transportation, such as bike-sharing systems, public transit, and taxis, varies with time and factors such as congestion, holidays, weather conditions, and special events (Changnon, 1996; Schaller, 2005). Faghih et al. (2020) used combined linear regression and time series models to analyze taxi demand using yellow taxicab data from New York. Findings indicated that temperature and precipitation were significant factors, as people opted to walk with increasing temperatures and ride taxis on rainy days. Lepage and Morency (2021) used generalized additive models developed using transactional data on workdays in Montreal, Canada to study how short-term fluctuations of travel demand resulting from seasonal events affected bike sharing and taxi, subway, and transit use. Results showed that rain decreases bike sharing, subway, and bus demand while increasing taxi demand. While wind significantly affected bike sharing, temperature significantly affected bike sharing and taxi service. Subway service disruptions increased demand for the three alternative modes studied, particularly for taxi ridership. Activities influenced demand for all four modes, although subway ridership was most affected. Shokoohyar et al. (2020) conducted a study in Philadelphia during the summer of 2018 to investigate how weather conditions and intracity routes impact wait times, trip durations, and ride fares for Uber and Lyft. Using ride estimate data from Uber and Lyft developers' Application Program Interfaces (API) and weather data from Yahoo weather API, they found that extreme weather conditions significantly affect ride-sourcing platforms, particularly through average pickup times and trip durations. TNC operators consider weather conditions and special events when adjusting the dynamics of their ride-sourcing services to offer more cost-effective services, such as pool rides, during high-demand periods. This increase in supply can improve riders' experiences of pickup wait times while increasing TNC profits by generating more revenue.

TNCs can also increase the supply of drivers during high-demand periods by predicting weather conditions and providing incentives and promotions in advance. The mismatch of supply and demand can result in increased idle time for vehicles and waiting time for passengers. Increasing SAV supply can reduce wait time, but too many unoccupied vehicles contribute to urban congestion. By understanding SAV demand and using this information to better manage SAV operations, fleet owners can improve fleet performance metrics, revenue, and profits. Jiao (2018) analyzed Uber's surge pricing patterns during a special event using Uber's developer API data from the Fourth of July weekend in 2015. The study examined how surge pricing multipliers were affected during periods of high demand, and findings indicated that, on all three nights, surge prices were not associated with ride wait time but were linked to ride request time. Such uncertainty in surge pricing mechanisms could pertain to SAV operations under varying demand in the future.

Different methods have been used to collect data on seasonal variation. Moudon et al. (2020) argued that a potential limitation of data on seasonal variability of activities is the assumption that people carry out the same activities throughout the year without considering changes throughout different seasons. Failing to account for changes in daily activities during these periods 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). Fagnant and Kockelman (2018b) used data from the 2009 NHTS travel data from the state of Texas to estimate seven typical demand days by simulating day-to-day variations in travel demand. This let them anticipate profitability for operators in settings with no speed limitations on the vehicles and at adoption levels below 10 percent of all personal trip-making in the region. Simulation results suggested that a private fleet operator paying $70,000 per new SAV could earn a 19% annual (long-term) return on investment while offering SAV services at $1.00 per mile for a non-shared trip (which is less than a third of Austin's average taxicab fare.

Huang et al. (2022) 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 accepted 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. This paper uses NHTS scaled origin–destination (OD) matrices (disaggregated to trip tables) of light-duty vehicle trips generated from the RITIS platform for various days. The trip tables are used in POLARIS, an agent-based simulation software to mimic vehicle operations serving 7% demand using 20% SAV mode splits. This section aims to understand travel behaviors and fleet operator profitability regarding supplying SAVs to meet fluctuating travel demand. Such an approach is comparable to the one used by ride-hailing services such as Lyft, Uber, and Cabify, which adjust fares in real time using dynamic algorithms to balance the needs of drivers and riders, leading to a better balance between revenue generated and costs incurred.

POLARIS SIMULATION

The agent-based activity-based travel demand simulator POLARIS simulates SAV fleet operations in the Dallas-Fort Worth region. (Auld et al. (2016) and Gurumurthy et al. (2020) explain many POLARIS details.) The framework employs agents to model individual passengers and vehicles, allowing for complex interactions and an approximation of travel behavior in transportation systems (Zhao and Malikopoulos, 2022). The framework utilizes travel demand models to simulate the daily weekday activities of agents, generating synthetic populations generated during model initialization, then calibrating and validated them (Beckman et al., 1996). Auld et al. (2011) used a non-compete hazard formulation to run itineraries, while a competing hazard formulation produced traveler trip purposes. Auld and Mohammadian's (2012) ADAPTS model informs core models, including a nested logit mode choice model, a multinomial logit destination choice model, and a hybrid random-utility random-regret minimization model for departure time. A time-dependent dynamic traffic assignment method routes individual vehicles, while a mesoscopic traffic flow model based on the link transmission model captures link-level congestion (Auld et al., 2019; Verbas et al., 2018). Finally, a conflict analyzer is used to avoid conflicts and competition in activities that could lead to inconsistent travel plans. Gurumurthy et al.'s (2020) SAV module underwent tweaks 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 DRS 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 (Yantao et al., 2023).

RITIS Trips

The RITIS platform generates OD matrices using the INRIX trip path dataset, which includes passenger trip data collected from connected light-duty vehicle fleets. It is worth noting that trips provided by the RITIS platform represent an estimated 7% of light-duty vehicle trips made daily within the DFW region during 2019 and 2020, as seen in Figure 1. The sampled dates used here are Sunday, April 28, 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.

The RITIS data rely on connected vehicles from manufacturers like GM and VW, between engine on/off periods. Spatial filters in the form of traffic analysis zone (TAZ) polygons were used to identify all available trips with pathways that included the 12-county DFW TAZs. Trips that met the designated pass-through and filter settings were retained for inclusion in the output OD matrices. Filter settings also enabled the extraction of trips with similar characteristics, such as trips arriving downtown on spring weekdays between 7 and 9 am.

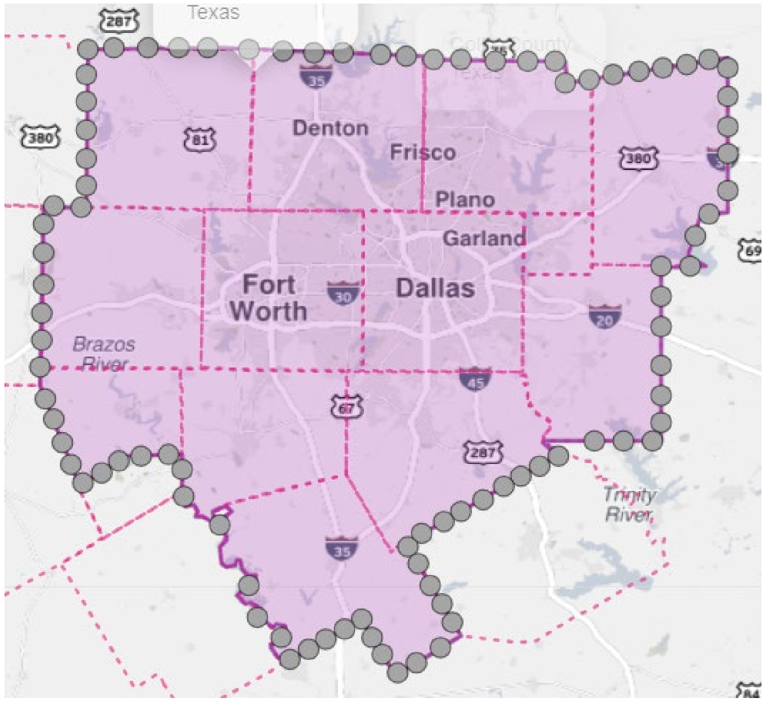

Figure 1: Study Area Spatial Filter of the NCTCOG Jurisdiction from the RITIS Platform.

The time stamps of each trip will be used to determine whether the trip occurred within the footprint of the spatial filter(s) during the specified period in the query. Regardless of the chosen spatial filters, the origins and destinations were reported based on the definitions in the setup. Table 2 shows the share of light-duty vehicle trips sampled from RITIS by distance. November 6 showed the highest VMT for shorter trips (less than 1 mile to 5 miles), which could be attributed to several factors, such as weather conditions that encourage short-distance vehicle usage, a particular event happening in the area prompting short commutes, 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 is seen in late winter and early spring (February and March), which could coincide with relatively mild weather conditions, possibly encouraging longer commutes, such as out-of-town visits or recreational trips.

Table 1: Share of Light-Duty Vehicle Trips Sampled by Distance

Date Sampled	11/26/2019	11/22/2019	10/3/2019	11/28/2019	11/6/2019	4/28/2019	3/1/2020	2/8/2020	2/17/2020
Less than 1 mile	2.6%	2.8%	3.0%	2.9	3.2	2.9	2.7	2.7	2.8
1–3 miles	25.7	27.4	28.2	26.9	29	26.9	26.1	26.1	26.4
3–5 miles	17.7	18.5	18.6	18.6	18.7	18.6	18.7	18.1	17.8
5–10 miles	22.5	22	22	22.9	21.6	22.9	23.2	23	22.4

10–25 miles	22.4	20.8	20.5	20.4	20.1	20.4	21	21.3	22
25–50 miles	7.9	7.4	6.9	7	6.6	7	7.1	7.4	7.5
Greater than 50 miles	1.1	1.2	0.9	1.4	0.7	1.4	1.2	1.3	1.0

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 2. The periods include: Evening Off-Peak from 12 am to 6 am; AM Peak from 6 am to 9:30 am; Midday Off-Peak from 9:31 am to 2:59 pm; PM Peak from 3 pm to 6:30 pm; and Late Night Off-Peak from 6:31 pm to 11:59 pm. AM and PM Peak periods comprised 3.5 hours, while Off-Peak Periods comprised 6 hours. Midday off-peaks and PM-peaks are busy on half the days sampled, and off-peaks comprise 5.5 hours while the AM and PM peaks comprise 3.5 hours.

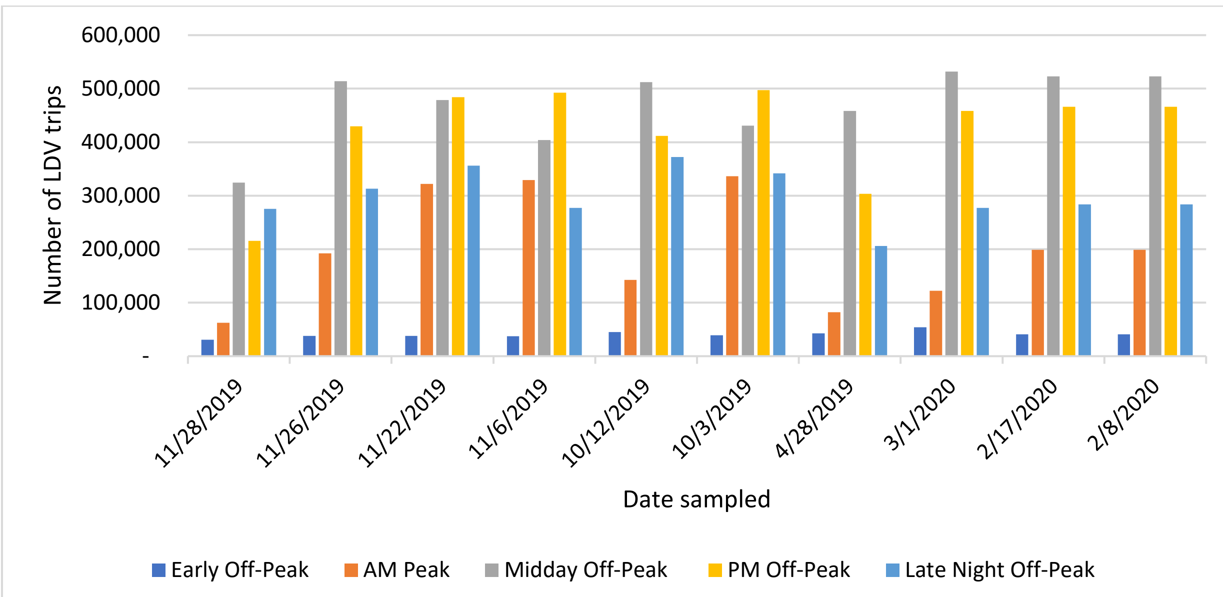

Figure 2: Vehicle Trips Generated Across Ten Different Days of the Year.

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

NHTS 2017 data 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 2 presents the results of an OLS regression analysis of 2017 NHTS data filtered for DFW light-duty vehicle trips and examines the relationship between VMT, PMT, and person-trips per capita per day, as well as several other factors, including weekdays, months, holidays, whether a day is within two days of a holiday, and the number of sampled households and persons. 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 weekdays and months depending on work schedules, school calendars, and seasonal weather and daylight hour fluctuations. 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. Additionally, the analysis uncovers statistically significant associations between the number of households and persons sampled and per capita VMT, PMT, and person-trips per capita per day. Although these relationships are significant, their practical significance may be limited due to their small effect sizes.

Table 2: 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	

Sundays in February, March, and July through January are the least busy days for person-trips per day. 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. The study does not find a statistically significant association between the number of households sampled and VMT per person, indicating that the number of households included in the dataset cannot account for the variation in VMT per person.

Origin-Destination (OD) Matrix Disintegration and Simulated Travel Days Across the Year

Output trip OD matrices were disintegrated via a parallelized procedure for selecting random locations within a specified zone while considering the land use type of each location. The method checks for nonresidential locations within the given zone, and if any such locations are available, the method randomly selects one. If no nonresidential locations are available, the method checks for available locations within the zone, regardless of land use type, and randomly selects one. If no locations are available in the specified zone, the method returns a unique value indicating no valid location exists. This disintegration method ensures realistic trips are generated by accounting for land use restrictions while ensuring that trips have uniformly allocated start-time distributions among the multitude of land uses.

RITIS data also comprises a much larger sample size of trips, with about 1.3 million vehicle-trips per day starting and ending in the DFW region across the randomly sampled 10 dates. However, the trip data sample had clustered values around the mean VMT, as shown in Table 5, which necessitated using the NHTS dataset to scale the clustered RITIS values to get relatively evenly spaced values. 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 LDV trips per resident. 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.

Table 3: 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
11/28/2019	1,092,988	11,013,024	12.12	25.38	2.52
11/06/2019	1,512,502	13,381,590	8.69	30.83	3.49
03/01/2020	1,539,812	13,439,015	9.31	30.97	3.55
2/17/2020	1,679,208	14,277,163	9.44	32.9	3.87
11/26/2019	1,443,444	14,451,363	9.72	33.3	3.33
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
02/08/2020	1,607,490	15,315,363	9.39	35.29	3.7
11/22/2019	1,484,170	15,728,693	9.37	36.24	3.42
Average and St Dev of VMT/Day/Person				**31.64**	**4.16**

The NHTS dataset had 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.

Scaling of RITIS Trips Using NHTS Data

The 2017 DFW NHTS dataset for person-trips for specific origins and destinations over the whole year (under uncapped travel distance) was filtered to retain days on which at least 30 respondents were surveyed, yielding 190 days. In the filtered dataset sorted by the VMT per capita column in ascending order, 10 clustered deciles, each containing 19 days, guided the selection of 10 middle days and VMT values. The 10 decile dates and VMT values shown in Table 3 were selected as the median value in each decile set, although some flexibility was maintained in this selection process to get a good mix of days of the year and week. These dates were mapped to similar days and months of the year among the 10 RITIS days chosen. In mapping the two sets of VMT values by date, 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.

The Z-score was used to determine the scaling factor, which scales the corresponding RITIS day's average VMT value up or down. The standard deviation above the average VMT of the ten decile days' VMT was calculated as the Z-score with the following equation:

$$Z - score = \frac{VMT_{decile} - \mu_{NHTS}}{\sigma_{NHTS}}$$

Table 4: 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

In cases where RITIS trip tables contained cells with low (1 to 20) trip counts between OD pairs, simply rounding up or down the scaled trip-count integers resulted in significant errors. A random number generator for a standard uniform distribution was used to scale the low trip counts appropriately. For shorter trips, each trip represents a more significant proportion of the total. Therefore, the decision to round up or down can significantly impact the final count, such that rounding a trip count of 2 up to 3 represents a 50% increase, whereas rounding 200 up to 201 only represents a 0.5% increase. Rounding by the fractional part of the scaled RITIS VMT value as a probability impacts trip counts that are less than 20, especially single-digit figures. For instance, if the scaling factor required multiplying all trip counts by 1.2, one would round down to the closest integer 80% of the time and up 20% of the time. 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 5: 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

Understanding these day-to-day variations is crucial to maintaining fleet efficiency with fewer service disruptions, especially on peak demand days. In Figure 3, the ten days (green lines) reflect the average daily VMT per person within the inner five quintiles for the year (between the 50th and 95th percentiles). The selection of these representative days provides a snapshot of the variations in travel patterns throughout the year, ranging from the most demanding days to days with average demand.

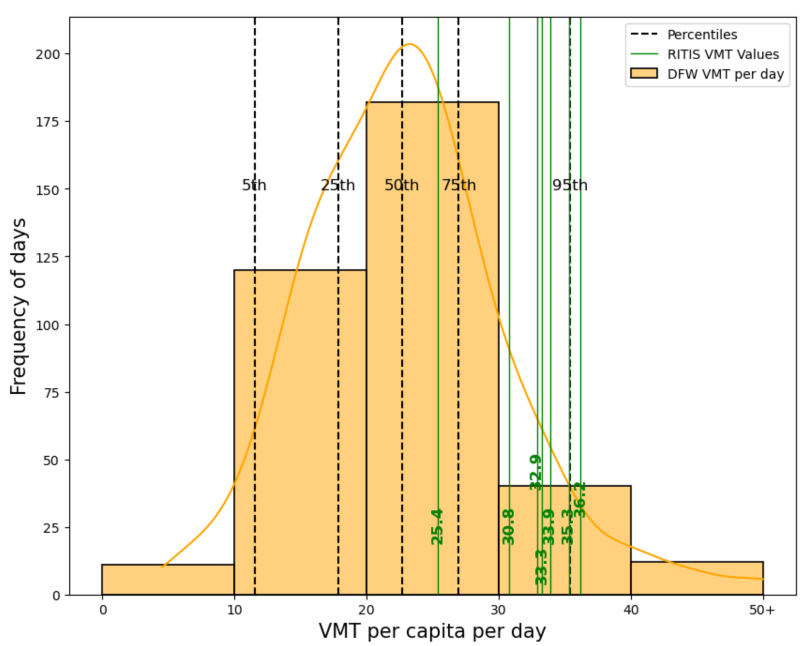

Figure 3: Ten RITIS Days Selected for Simulation in POLARIS

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 in Table 5 were analyzed, including total VMT, empty VMT (SAVs without occupants), revenue, and profit margins of the SAV fleet. This study implements a fixed fare of $1, $0.25 per minute, and $0.5 per mile, while operational costs consist of $0.50 per mile and $25 per day ownership costs. Daily profits range from a low of $1,027,905 to a high of $1,664,153, while profits per SAV per day span from $165 to $267. 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. Autonomous vehicles are also susceptible to encountering difficulties in winter, like snow-covered lane markers and subpar perception performance during active snow or rain. These challenges could compromise the efficiency of SAV operations and inflate operational costs during these months, mirrored in a 30 to 40% drop in profit per SAV compared to a typical workday in spring (with the school semester in progress).

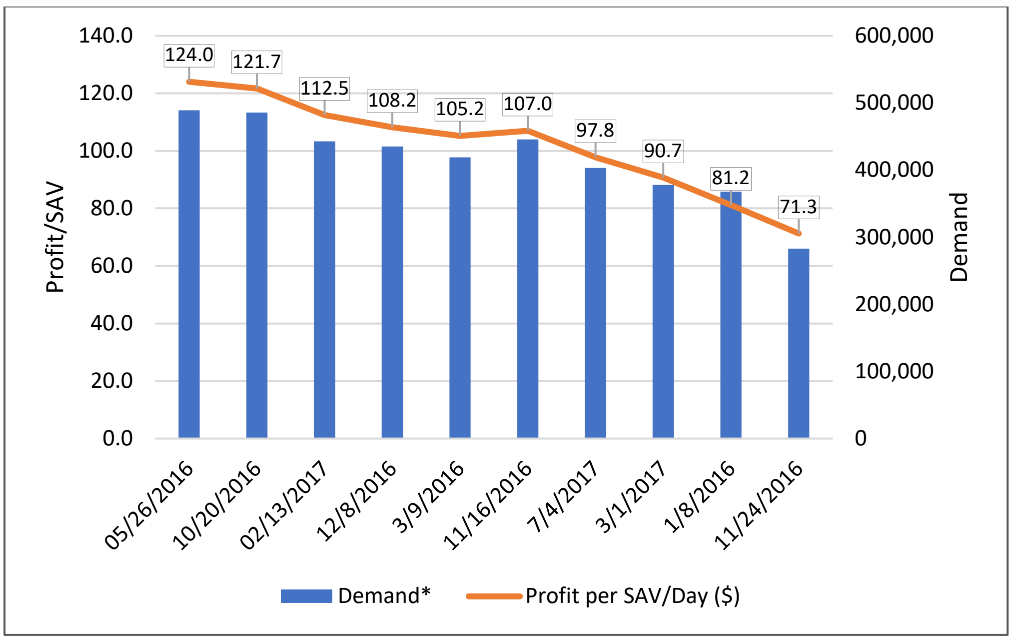

Figure 4: Profit per SAV per day

Daily revenue generated and costs incurred demonstrate considerable variations, directly impacting daily profit and profit per SAV. 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 eVMT and person-trips per SAV daily, where eVMT denotes the extent of deadheading trips within a TNC. It warrants mentioning that this analysis did not incorporate a time-dependent fleet, which is essential to simulate a realistic ride-sourcing scenario. The presumption of a consistent 20% SAV mode split derived from the regional population merely represents the actual ratio of person-trips to SAVs. The observed decrease by 6% 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. Further, lower % idle times on typical workdays in the spring and fall seasons indicate the potential exhaustive utilization of the fleet, while a 2 to 5% increment 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.

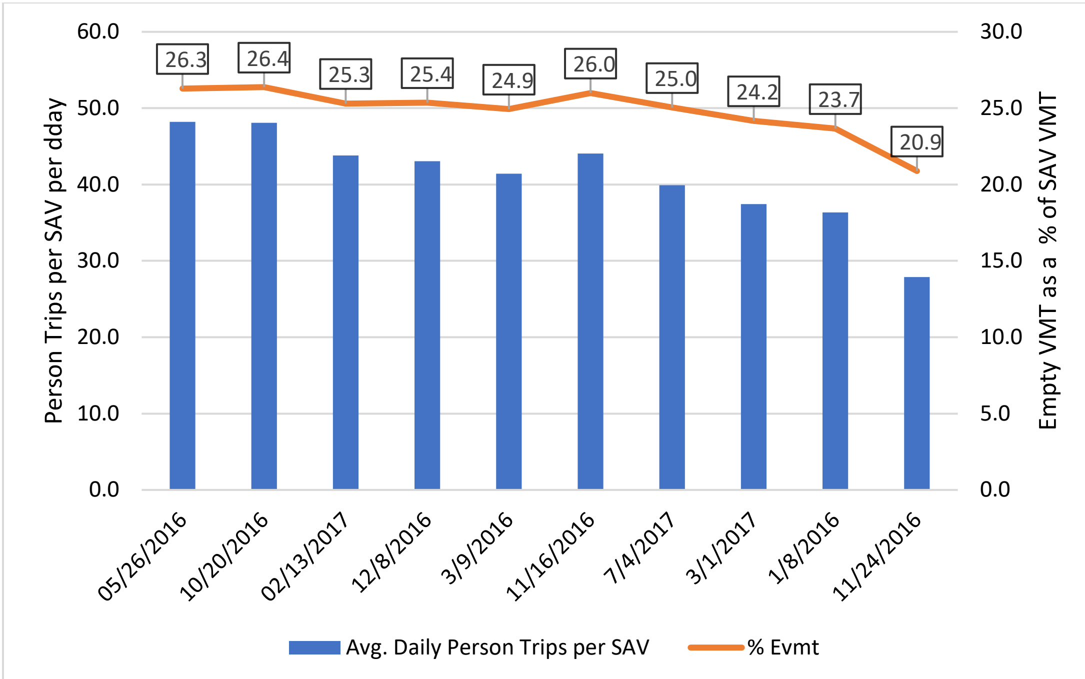

Figure 5: Person-trips per SAV and Empty VMT

Table 6: 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, profitability ranges 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 specific origins and destinations. This study reveals that the assumed 20% SAV mode split corresponds to the ratio of person-trips to SAVs. A 6% 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.

ACKNOWLEDGEMENTS

The work done in this paper was sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

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