A TOOL FOR COMPLEX SYSTEM DYNAMICS USING SHARED-FLEET-SIZE FEEDBACKS

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ABSTRACT

This study introduces system dynamics (SD) modeling as a tool for transportation system design. It is used here to size a fleet of shared autonomous vehicles (SAVs) in concert with an agent-based model (ABM) of travel demand, recognizing wait times and within-day demand dynamics across the Austin, Texas region. This approach balances profitability for a business alongside customer service levels. Here, SD's inclusion improves fleet operations and vehicle use while moderating user delays, suggesting that SD-based fleet sizing is one way to design for realistically complex conditions with current and future mobility systems.

KEYWORDS: Agent-based simulation, system dynamics model, autonomous vehicles, ride-sharing

1. QUESTIONS

Agent-based modeling (ABM) of travel demand across metro regions with dynamic traffic assignment (DTA), as in POLARIS (Auld and Mohammadian, 2009; Auld et al. 2016), MATSim (Balmer et al., 2009; Zhuge et al., 2021) and TRANSIMS (Jeihani et al. 2006), requires a highly complex and variable system of equations. Any market with a large number of customers, like transit buses or airport operations (Peng et al., 2021), international trade and supply chains (Rathore, Thakkar, and Jha, 2021), vehicle manufacture and factory staffing (Song et al., 2020), energy sourcing and power delivery (Akbari, Mahpour, and Ahadi, 2020), or housing development, can be viewed this with agent-based modeling. SD modeling can reflect complex feedback loops that exist between supply and demand systems, affecting costs and service quality (Sun et al., 2023). In a transportation context, key system performance metrics include cost per passenger or ton-mile, delay, empty vehicle-miles traveled (eVMT), noise, and emissions, while destination, mode and departure-time (and even party-size) choices vary (Karamanis et al., 2020; Monteiro et al., 2021; Dean et al., 2023).

Given the numerous decision variables that fleet service suppliers must provide, most studies and simulations of realistic market settings assume a single fleet size (Dean et al., 2022; Kavianipour et al., 2024) or perform very limited sensitivity testing of that key design variable to improve service performance (Seppecher and Leclercq, 2024). We are not aware of any studies of realistic regions using both ABM and DTA that endogenize fleet size, leading to the following research questions:

1. Can one use an SD model for SAV fleet sizing in a realistic urban system?
2. How do different SAV fleet sizes affect traveler wait times, fleet revenue, and other key metrics?

2. METHODS

Developing an SD model to emulate complex system behaviors (including iterative feedback) requires defining a causal (multi-) loop diagram (CLD) and its many underlying equations. The CLD illustrates dynamic interactions between various factors (demand, supply, travel cost, time, and other variables). Figure 1 shows the mobility service model used here for sizing an SAV fleet, with magenta contents indicating improvements to Smith's (2023) AV-fleet model, red arrows representing balancing (negative) feedback, and blue arrows for reinforcing (positive) feedbacks. Variables inside rectangles denote stocks or accumulations, such as SAV fleet size and mode share. Other variables, like fares and area size, are exogenous (in green) or auxiliary (in black–like SAV fleet revenues and SAV density).

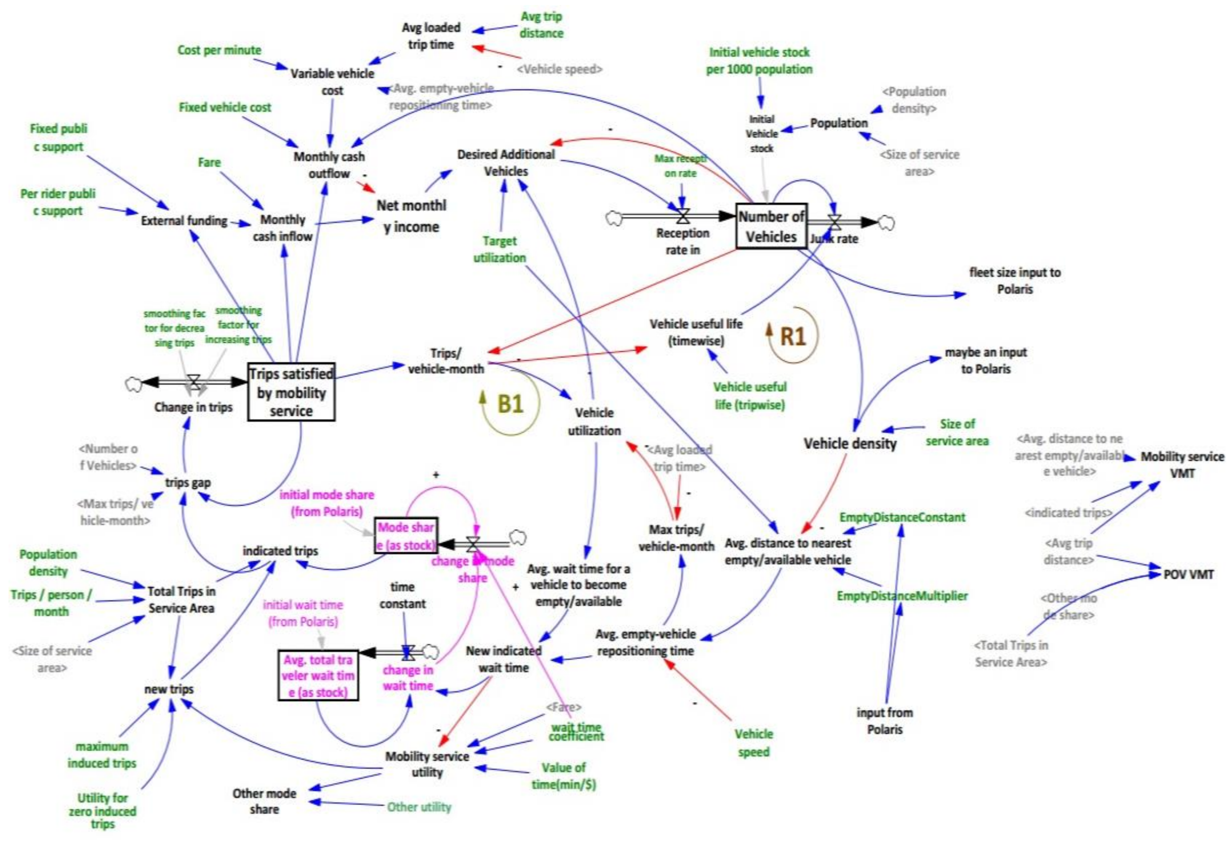

Figure 1. Causal Loop Diagram (CLD) for Shared-Fleet Sizing System (pivoting off of Smith et al.'s (2023) fleet-size model)

This model has three major subsystems: the business model, service performance, and user response. Fleet size, a key business model output, adjusts based on monthly revenue and vehicle use fraction. When revenue is positive and fleet use exceeds the target, additional vehicles needs are estimated by Eq. 1., bringing costs that influence profit through balancing loops.

$$Desired\ additional\ vehicles = Fleet\ size \times max\,(0, vehicle\ use - target\ use) \qquad Eq.1$$

Fleet size affects both vehicle density and use fraction, which are important causal inputs for estimating average traveler wait time. Based on queuing theory, wait time for an available vehicle is proportional to $\frac{1}{1-vehicle\ use\ fraction}$. Wait time, along with fare, impacts SAV utility and mode share components through balancing loops, iteratively aligning SAV trips served with fleet size and mode share.

POLARIS, an agent-based modeling tool developed for simulating large-scale transportation networks (Auld et al., 2016), is used to simulate both individuals and SAVs within the 6-county Austin region (containing 5300 square miles and 1.8 million residents in 2018) to run in sync with the SD model. By dynamically loading demand on the transportation network, enabling dynamic ridesharing, tracking individual agents and vehicle trajectories at the link level, and post-processing the simulation outputs, POLARIS reveals how ride-hailing fleet assumptions impact fleet performance and network operations. Table 1 outlines key assumptions for SAV fleet operations, allowing the SD model to focus on the fleet size variable and POLARIS focus on fleet performance examination.

Table 1. SAV Fleet Key Parameter Assumptions

Model	Parameter	Description	Assumption
POLARIS	Initial fleet size	Initial SAV fleet size	15,000 SAVs
	SAV max wait time	Maximum wait time before a new ride request	10 minutes
	SAV fixed cost	Cost for owning an SAV	$40/day
	SAV operating cost	Cost associated with running SAV fleet	$0.6/mile
	SAV base fare	Fixed pickup fee for each SAV trip	$1 pickup fee
	SAV fare per mile	SAV trip fare by cost per mile	$1.05/mile
	SAV ride-share fare per mile	SAV trip fare by cost per mile with ride-sharing	$1.5/mile
	SAV fare per minute	SAV trip fare by cost per minute	$0.25/minute
	SAV ride-share fare per minute	SAV trip fare by cost per minute with ride-sharing	$0.175/minute
SD model	SAV starting mode share	Initial SAV mode share	6.54% SAV mode
	Initial # of residents per SAV	Inverse of SAV fleet size per resident	125 persons/SAV
	Maximum induced trip factor	Multiplier applied to total trips to estimate additional trips triggered by an attractive mode in terms of price or wait time	0.2
	Empty-distance multiplier	Multiplier in eVMT equations to reflect inefficiency	0.5

Figure 2 shows how the SD model ties to POLARIS to improve SAV fleet efficiency and performance through an iterative process. In each iteration, POLARIS variables (like fleet size and person-trip records by mode) are processed as key inputs for the SD model. The SD model then runs thousands of iterations to determine a stable fleet size (within 1% fluctuation), which is input to POLARIS for the next iteration. Simulations were conducted on a 13th Gen Intel ® Core ™ i9-13900 with 128 GB RAM. The SD model normally completes 5000 iterations in 30 seconds, while a single POLARIS simulation for 100% synthetic population takes 4.5 hours.

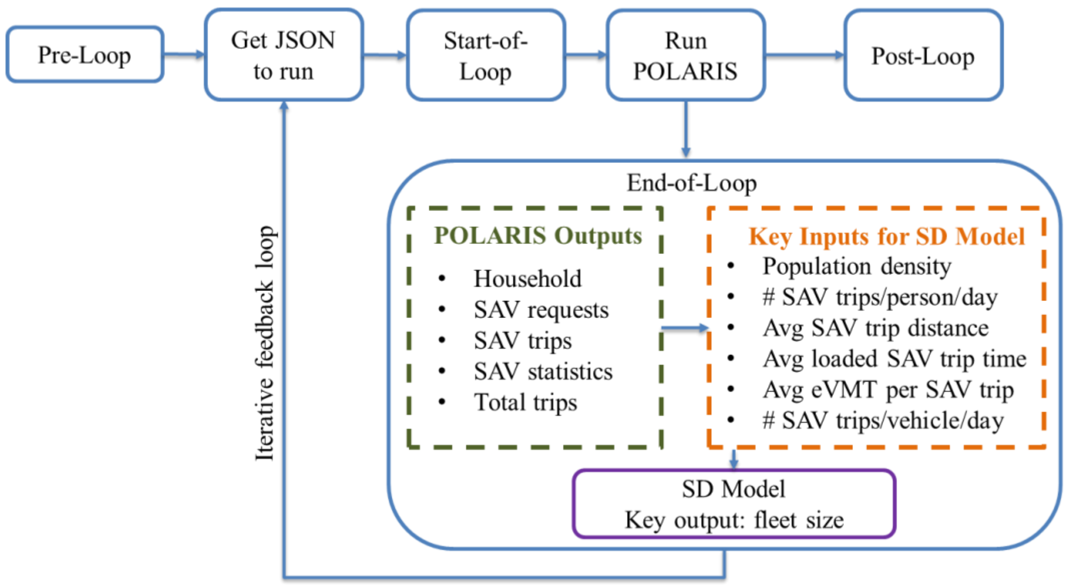

Figure 2. Integrated POLARIS + SD Framework

3. FINDINGS

Figure 3 illustrates changes in the metro area's SAV fleet size and SAV use fraction over 5,000 iterations in the SD model (before feedback into POLARIS). Starting with 15,000 SAVs, the SD model ultimately stabilizes at a recommended fleet size of 5,654 SAVs (for 1.8M travelers), considering cost, fleet performance, and supply-demand feedback. The fleet-use fraction rises from 0.28 to 0.90, reflecting improved efficiency as the system converges. Table 2 summarizes POLARIS-simulated fleet performance metrics using an exogenous fleet size in the initial POLARIS iteration versus the SD model-derived endogenous fleet size approach in the subsequent iteration.

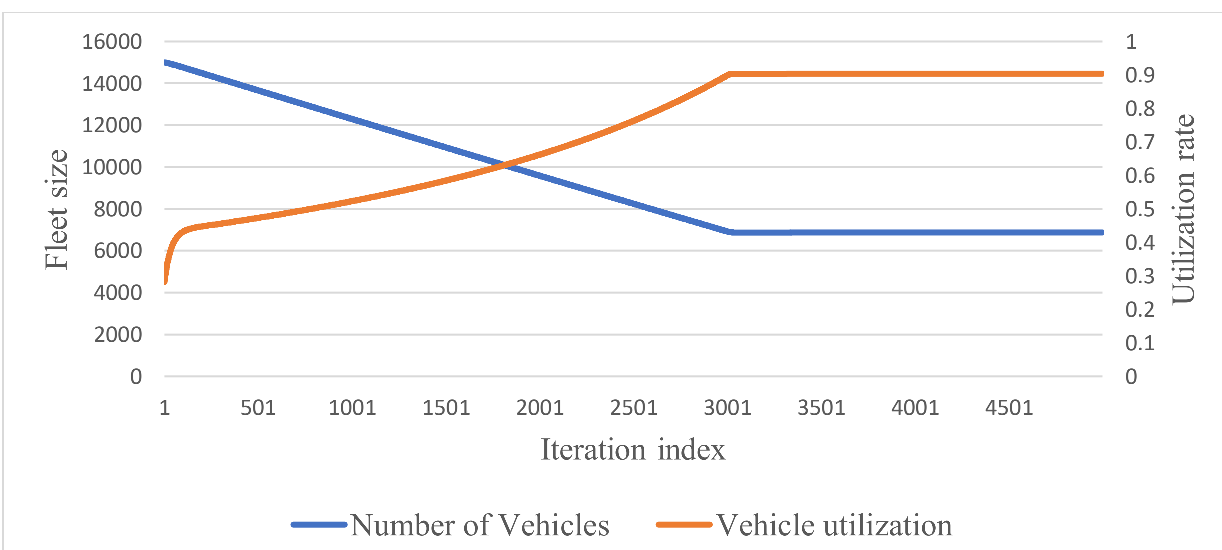

Figure 3. Fleet Size and Fleet Vehicle Utilization over SD Model Iterations

Table 2. POLARIS Simulated SAV Fleet Performance

Parameters	**Fixed fleet size (exogenous)**	**SD model-driven fleet size (endogenous)**
Fleet size	15,000 vehicles	6,875 vehicles
Served demand	418,767 trips	197,259 trips
SAV VMT on simulated day	2,840,893 miles	1,352,599 miles
SAV loaded VMT	2,129,910 miles	1,010,512 miles
Avg daily VMT per SAV	189.4 mi/day/SAV	198.4 mi/day/SAV
Avg daily pickups per SAV	29.0 pickups/day/SAV	30.7 pickups/day/SAV
SAV Fleet eVMT%	25% empty VMT	25% empty VMT
Avg. wait time for traveler	9.9 minutes	9.5 minutes
Median wait time for traveler	6.5 minutes	6.6 minutes
Avg. SAV trip fare	$8.5/trip	$8.6/trip
Avg. repositioning distance per SAV trip	3.5 miles	3.5 miles
Avg. vehicle occupancy (AVO) per revenue-mile	1.8	1.8
SAV fleet cost ($)	$2,304,536/day	$1,108,884/day
SAV fleet income ($)	$3,576,582/day	$1,724,214/day
Daily profit per SAV ($/SAV/day)	$84.8/SAV/day	$89.5/SAV/day

The SD-driven fleet size model achieves a better balance between operational costs and demand. Average daily VMT per SAV is higher under the endogenous fleet model (198.4 miles vs 189.4 miles). There is also a rise in average daily travel-party pickups per SAV, showing 30.7 vs 29.0 party-trips served per day per SAV. This highlights the SD model's ability to intensify SAV fleet use, benefiting sustainable businesses amid fluctuating demand.

While maintaining a similar service level, as indicated by median traveler total wait time (6.6 minutes vs 6.5 minutes), the SD model reduces TNC operating cost by 52%. Net profit per SAV rises to $89.50, compared to $84.80, in the exogenous fleet scenario. These findings highlight the SD model's capability to efficiently scale fleet size in response to dynamic demand, making it a promising approach for simulating future complex mobility systems and supporting sustainable business operations.

While the SD model effectively balances supply and demand and enhances resource use, notable limitations are its reliance on aggregated (average) inputs and a reduced ability to track agent-level data. Future research could bridge these gaps by incorporating finer simulation scales and enhancing optimization settings.

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