A Repositioning Method for Shared Autonomous Vehicles Operation

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Abstract

Shared fully-automated, or autonomous, mobility (SAVs) is anticipated to be the likely choice for future urban travel. SAVs boast many operational benefits but will add congestion in the form of unoccupied miles. The fleet's success further depends on service measures like the wait times for pickup trips. Agent-based simulation tools have closely looked at SAV operations but typically lack the integration between the supply and demand sides when simulating a population at scale. This paper focuses on the impact of SAV relocation on traveler wait times using a novel algorithm for repositioning. POLARIS, an agent-based tool, is used for a case study of Bloomington, Illinois to quantify the benefits of allowing SAV repositioning. On average, the wait times were lower with repositioning for all adequate fleet sizes. SAVs were available more uniformly across the region's zones, and proportional to trip-making at different times of day. In addition, with repositioning enable a higher share of demands were served. Finally, the increase in empty fleet miles from SAV repositioning may be justified with more trips being served, and an overall improvement in SAV wait times.

Keywords— Shared Autonomous Vehicles Repositioning Agent-Based Simulation POLARIS Bloomington

1 Introduction

In recent years, mobility services provided by Transportation Network Companies (TNC) have established themselves as a convenient option for door-to-door transportation in urban areas. For example, the number of trips made per day using a TNC vehicle in New York City increased from 60,000 in 2015 to around 600,000 in 2018 [1] . This trend will probably be reinforced with the emergence of Autonomous Vehicles (AVs), and travelers may relinquish their personal vehicles to rely on a fleet of Shared AVs (SAVs) [2, 3, 4].

The shift to shared fleets is likely to impact urban mobility in different ways. Many studies have shown that the number of vehicles required for all trip making in a region may reduce drastically. A study on Singapore's travel showed that one SAV could replace about three conventional vehicles [2]. Fagnant and Kockelman found that one SAV can substitute about 10 personally-owned vehicles in the City of Austin, Texas [3]. When travelers were simulated to pool and share their rides (i.e., dynamic ride-sharing) in Stockholm, Sweden, each vehicle was found to be able to replace around 20 vehicles [5].

However, an on-demand service of SAVs can potentially increase the total distance traveled since vehicles need to travel empty to pickup passengers or when relocating to high demand areas. This empty vehicle miles traveled (eVMT) can potentially undermine the benefits of using SAVs for mobility. There is some uncertainty on the share of empty travel in previous studies, and the extent to which dynamic ride-sharing can help. Bischoff and Maciejewski modeled daily trips in the City of Berlin with a fleet of SAVs and approximated the share of empty travel time as 17% [4]. Austin studies, with and without DRS, averaged between 6 and 15% eVMT [6, 7]. Although these are low in comparison to current TNC operation statistics like 40.8% of empty miles for Uber and Lyft [8], the scale of future SAV operation may still add congestion overall and need to be controlled.

There are three sources to empty travel: (i) the distance traveled from the current vehicle location to the traveler location; (ii) the distance traveled in the beginning and end of a driver's shift (or depot in the case of a SAV) to and from the area being served, respectively; and (iii) a repositioning trip to a area with higher demand after dropping off a traveler in order to serve more trips (only in the case of human-driven vehicles) and reduce average customer waiting time. Repositioning trips made based on demand typically occur due to an imbalance between pickup and dropoff locations. This leads to a large number of vehicles accumulating in low demand areas while dearth of vehicles is observed in high demand areas at other times of day.

Recent literature has pointed out the importance of repositioning trips with fixed-trip datasets. One repositioning strategy lead to a 20% increase in the share of served requests [9]. Another study proposed an assignment strategy that concurrently assigns vehicles to travelers while also dispatching vehicles to areas with high demand based on the expected future demand [10]. The share of repositioning miles ranged from 3 to 6% across all the simulation scenarios while the pickup miles remained around 12% of total miles. In this study, the impact of SAV repositioning is studied at scale using an agent-based framework called POLARIS. A computationally efficient repositioning strategy for SAV operation was implemented, and the operational results for the entire region of Bloomington, Illinois is discussed. The next section discusses the simulation framework, SAV modeling methodology and the repositioning algorithm. This is followed by results and discussions for the case study of Bloomington, Illinois, and finally ends with a conclusion.

2 Simulation Framework

POLARIS [11], an agent-based framework, is used in this study to explicitly model the demand and supply aspects of SAV operation concurrently. POLARIS is a high-performance, open-source, agent-based modeling framework that can simulate large-scale multi-modal transportation systems. POLARIS has integrated travel demand, network flow, and traffic assignment models on the paradigm of agent-based-modeling.

The activity models are based on [12, 13] which defines each traveler's decision-making process for within-day, mid-term, and long-term time frames by taking into account activity types, and preferred modes and destinations. The mid-term and within-day travel behavior decisions include the process of individual activity episode planning and engagement. These decisions are constrained by long-term choices regarding home and workplace choice, and household vehicle choices, and, in turn, influence activity and travel planning.

The realized travel times and delays along the simulation period is an outcome of traffic flow and dynamic traffic assignment models. The underlying traffic flow model is based on the link transmission models [14] which in turn is based on Newell's kinematic wave model [15] with further adaptation to be able to track individual vehicles along their journey [16]. The dynamic traffic assignment algorithm [17] assign routes to individual vehicles using a time-dependent A* shortest path router [18] based on the prevailing traffic condition, as well as updated skim travel times. Traveler's routing behavior in response to delays is also captured by allowing re-routing.

The effects of real-time information and impacts of connected and automated vehicles - from both demand and supply sides - are also captured. This allows for exploratory studies on the impact of connected and automated vehicles in the overall transportation networks [19], as well as the impact of shared mobility services in the presence of connected and automated vehicles [20].

POLARIS uses three separate mode-choice models depending on the activity purpose: home-based work/school, home-based other and non-home based, similar to traditional modeling. The nested-logit formulation used to model mode choice include nine modes: drive alone, TNC use, ride as passenger, walk, bike, bus with walk access, bus with drive access, rail with walk access, and rail with drive access. Road-network density and activity density of the destination zone are used to capture the characteristics of land use and the transportation network. The TNC-specific LOS variables used in the model include in-vehicle travel time and wait time (obtained from the simulation), and input fare. The TNC fare comprises of a fixed cost per trip, a distance-varying component, and a time-varying component. The model is developed and calibrated against the household travel survey data collected from the local region's metropolitan planning organization.

3 SAV Simulation

Shared mobility simulation implemented in POLARIS [20] is extended here to test repositioning. SAVs are modeled to mimic operations that are currently observed in a TNC by using a central operator. The operator assigns requests to individual vehicles depending on the assignment strategy and monitors demand-to-supply ratio to determine if repositioning is required. SAVs execute the pickup, dropoff and repositioning tasks depending on the instruction received from the operator. SAVs are able to store requests that are being executed and those that need to be executed in the future.

3.1 Operator

When a SAV trip request is made, the fleet operator attempts to assign it to the closest available vehicle in order to reduce total eVMT, as well as to minimize the traveler waiting time. Two assignment strategies are included in POLARIS: a coordinate-based search, and a zone-based architecture similar to Bischoff and Maciejewski [4], the latter of which was used in this study.

The zone-based architecture is generated using the traffic analysis zones (TAZs) for the region which is available in POLARIS. The SAV operator constructs an array of all neighboring zones, for each zone in the region, in ascending order of travel times defined with respect to a reference zone. This array is truncated using a predefined threshold for wait times so that a minimum level of service is maintained by the SAV service. By definition, the first zone in each array is the reference zone itself, which would mean minimal wait time. When a trip is requested, the operator checks for any available vehicle, starting from the origin zone and in the same order defined by the array, and assigns an unoccupied vehicle from the first neighboring zone that has a vehicle available. Within a given zone array there is no distinction between the specific distance of each vehicle to the customer. Therefore, the assigned vehicle is not necessarily the closest. Nevertheless, the area of each zone is relatively small enough so the additional travel time is minimal if the assigned is not the closest.

3.2 Vehicle Operation

Once the request is assigned, the SAV handles the remainder of the request. Each vehicle stores a sorted list of tasks to be performed. A pickup and a dropoff operation is added to this list for every request assigned to the vehicle. Each task in the list involves the vehicle moving between its location to either the pickup point or the dropoff point. Depending on the task, the SAV identifies the path from its current location to the next operation location. At the end of each trip, the total trip distance, travel time and empty travel, are computed and recorded. At the SAV's destination after dropoff, it may receive a new set of tasks and repeat the same process again. If there is no task to be performed, the vehicle stays idle at the last task's destination and awaits new trip assignment.

3.3 Repositioning Strategy

Typically, the pattern of origins and destinations of trip requests are spatially uneven and varies by time of day. In the morning peak, trip requests tend to the end at the Center Business District (CBD) whereas in the evening peak the trip requests tend to end in the suburban areas. The areas that are common trip destinations accumulate vehicles whereas areas that are common trip origin have no vehicles around to serve future incoming requests. For this reason, it is necessary that vehicles located in low demand areas move to areas with higher demand to serve the incoming requests.

The repositioning strategy should balance two conflicting objectives. If vehicles are relocated to high demand areas, it reduces the waiting times for the customers. However, this additional trip can add significant eVMT which is not desirable. Therefore, the repositioning strategy should find an equilibrium between low wait times and low eVMT and avoid relocating vehicles to locations where vehicles will be idle for a long time due to low demand.

This strategy is in line with the assignment strategy, and is implemented based on the zone-level variables. For each zone i, the desired number of vehicles, d_i, is computed as:

$$d_i = \frac{D_i + \alpha A_i}{\sum_{\forall j}\left(D_j + \alpha A_j\right)} S, \tag{1}$$

where S is the available fleet size, D_i is the number of requests in zone i, and A_i is the area of zone i. The number of requests per zone is calculated as a moving average over the preceding K hours. The constant α is a weight variable to control the extent to which the repositioning strategy is enforced, that is a uniform relocation when α is large ($\alpha \to \infty$) or based on the past demand when α is small ($\alpha \to 0$). Similarly, when there is no information on prior demand at the beginning of simulation as D_i is close to zero, the controller will attempt to distribute the vehicles evenly in the network ($D_i << \alpha A_i$). As D_i increases, especially closer to the peak times, the controller will be more sensitive to the incoming demand.

Next, the supply of vehicles in a zone, s_i, is computed by counting the vehicles idling in a zone i or those performing a task (pickup, dropoff, repositioning) with their final destination in i. Note that $\sum_{\forall i} s_i = S$. Finally, for each zone the following ratio is computed:

$$r_i = \frac{s_i}{d_i}, \tag{2}$$

Vehicles in zones with high r_i and $\frac{s_i-1}{d_i} > 1$ are expected to reposition to zones with $r_1 < 1$. For each of these zones that have an excess of vehicles, a fixed set V_i of potential destination zones are generated. The number of elements in set V_i is equal to n_v, an input parameter. That is, instead of considering all the zones in the network, only a number of n_v zones will be considered. For each zone $j \in V_i$ a score to rank potential destinations is necessary, and is computed as:

$$u_j = \frac{1}{r_j t_{i,j}}, \quad j \in V_i \tag{3}$$

where $t_{i,j}$ is the estimated travel time from zone i to zone j.

In summary, all repositioning decisions are undertaken at fixed time step, T, at which the following tasks are performed:

1. Compute d_i, s_i, and r_i for each zone.
2. For all zones with $\frac{s_i-1}{d_i} > 1$, generate a set V_i of potential destination zones.
3. While $\frac{s_i-1}{d_i} > 1$, pick a destination zone j from set V_i from a random draw with probabilities proportional to u_j.
4. Update s_i, d_j, and u_j according to equations (1),(2), and (3).

The probabilistic assumption made here is designed to resemble the current TNC operation, and to serve as a baseline for more sophisticated strategies that are expected in the future. The strategy can be tuned through four parameters: the weight on the area of a zone, α, the update interval, T, and the number of elements, n_v, in the set V_i and the window size used as a moving average for aggregating requests, K.

4 Case Study of Bloomington, Illinois

The repositioning strategy outlined above was tested for the Bloomington region in Illinois. The network contains 185 zones, 7000 links, and 2500 nodes. The mode choice parameters are tuned to the current travel trends and yielded around 30,000 trip requests for the 24 hour simulation period. Three different fleet sizes of 650, 700, and 750 SAVs were tested with, and without, repositioning.

For all cases, the maximum waiting time is set to 10 minutes (i.e., the maximum pickup time for a SAV is 10 minutes as estimated before the start of the pickup trip. The realized travel time might be higher if traffic conditions changes). When

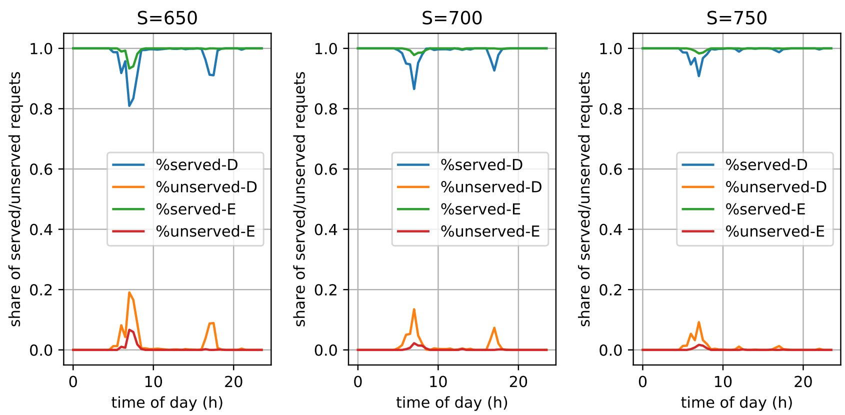

Figure 1: Share of served and unserved trips for the three fleet sizes with and without repositioning enabled.

repositioning is enabled, 36 potential destinations zones are considered ($n_v = 36$), with an update interval of 5 min ($T = 5$), a moving average window of 2 hr ($K = 2$) for aggregating requests, and a weight of $\alpha = 10^{-8}$ m^{-2}.

Table 1 presents the key metrics for each scenario. Without repositioning, the share of empty miles lies around 30% and it increased to around 40% in the cases in which repositioning was enabled. On the other hand, the share of served trips at peak time has increased for all fleet sizes. In addition, the repositioning algorithm also achieves lower average wait time by around 20% for the three different fleet sizes which confirms that the repositioning method is moving vehicles closer to the incoming demand.

Table 1: Summary of the results for the three different fleet sizes with and without repositioning. Pickup VMT is labeled as pVMT, repositioning vmt as rVMT and empty VMT as eVMT.

Fleet Size	VMT	% pVMT	% rVMT	% eVMT	% Requests Served at Peak	Wait Time (min)
Without Repositioning						
650	205,189	29.8	0.0	29.8	80.9	4.43
700	206,497	29.2	0.0	29.2	86.5	4.31
750	205,888	28.4	0.0	28.4	90.7	4.09
With Repositioning						
650	255,898	25.9	17.0	43.0	93.3	3.54
700	266,371	24.7	19.3	44.0	97.7	3.37
750	268,965	24.1	20.2	43.7	98.3	3.31

The share of trips that were served and unserved over the 24 hr time period for all fleet sizes is depicted in Figure 1. Blue and orange lines correspond to the scenario without repositioning, and the green and red lines correspond to the scenario with repositioning. The fleet sizes are 650, 700, and 750 from the left to right. In all cases, enabling repositioning led to an increase in the share of served trips with the difference being larger for smaller fleets.

The repositioning method also lowers waiting time. Figure 2 depicts the distribu-

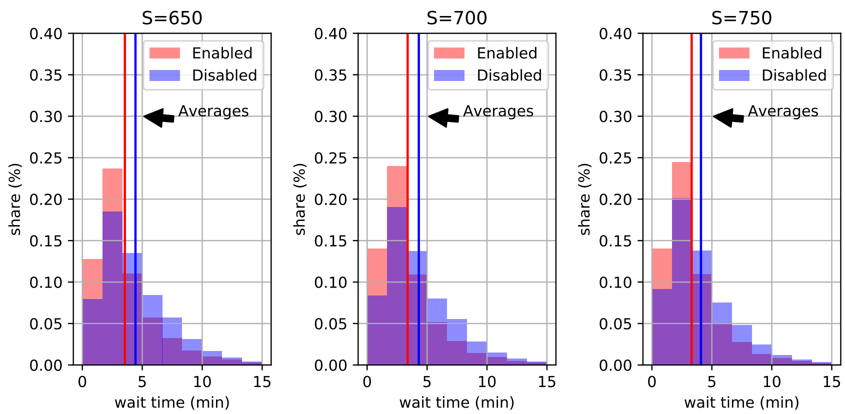

Figure 2: Histogram of waiting times for different fleet sizes with (red) and without (blue) repositioning.

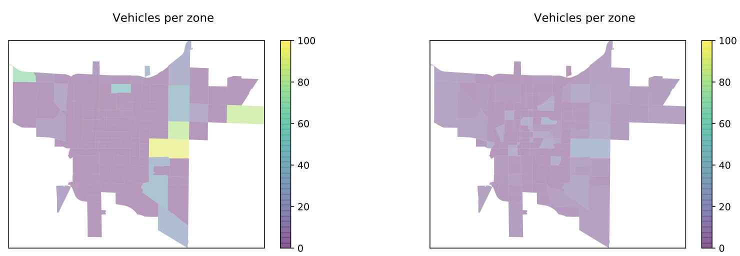

Figure 3: Distribution of vehicles by zone at the of the simulation period without (left) and with (right) repositioning.

tion of waiting time for fleet sizes of 650 (left), 700 (middle), and 750 vehicles (right) with (in red) and without (in blue) repositioning. The vertical lines in red and blue highlight the average waiting time for each case, respectively.

Figure 3 visualizes the spatial distribution of SAVs for the the scenarios without and with repositioning at the end of the simulation period. The use of a repositioning strategy shows a more uniform distribution of vehicles in the city, with a concentration of vehicles in the CBD. This directly impacts the reduction in wait times as SAVs are available in all zones that have had a sizable demand in the previous K hours.

The efficiency of an SAV fleet can be observed by assessing the daily operation profile. Figure 4 shows the share of SAVs idle, or performing pickup, dropoff or repositioning for the two scenarios with and without repositioning. When repositioning is enabled, the entire fleet is utilized at peak times of day, if necessary. This is not true in the absence of repositioning when SAVs are idling at low demand areas.

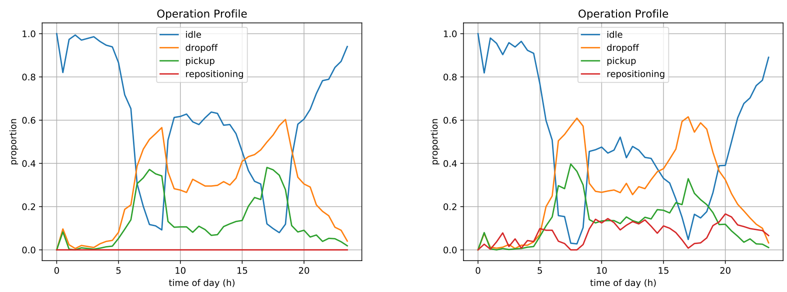

Figure 4: Fleet Operation Profile without (left graph) and with (right graph) repositioning enabled for $S = 650$.

5 Conclusion

A novel method for SAV fleet repositioning that uses the relationship between the supply and demand of each zone was presented. Vehicles in zones with larger supply compared to its past are repositioned to zones with lower supply. In experiments for a medium-sized network, enabling the repositioning strategy lead to an increase in the share of served requests as well as in a reduction in waiting times. The benefits occurs at expense of higher empty distance traveled. For future work, we plan to perform a thorough performance analysis using larger networks like that of the Chicago region.

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