Synergies Between Repositioning and Charging Strategies for Shared Autonomous Electric Vehicle (SAEV) Fleets

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1. Introduction

Shared autonomous electric vehicles (SAEVs) are expected to create both positive and negative externalities. Reclaimed urban space [1, 2, 3], lower per-mile costs relative to ride-sourcing thanks to full automation, and a greener environment from electric powertrain technology can begin to address persistent issues of inequity that affect transportation disadvantaged communities and low-income neighborhoods [4, 5, 6, 7, 8, 9]. On the other hand, municipalities will need to manage competing interests at the curb and may even create dedicated pickup/dropoff zones [2, 10, 11, 12]. Furthermore, potential gains in mobility and accessibility will be offset by empty vehicle miles traveled (eVMT), that if left unregulated, could lead to worse congestion across cities [13, 14]. While some experts have argued for congestion-based pricing that would penalize eVMT [15, 16], SAEV fleet operators will inherently want to minimize eVMT given limited battery range and long charging time. In general, there are three sources of eVMT: travel to a pickup location, travel to a charging station (cVMT), and repositioning the vehicle after completing the final trip (rVMT) [17, 18, 19].

Early SAEV studies on a grid network used rule-based charging and low-impact repositioning to prevent oversupplying adjacent zones, resulting in 2.1-11.1% eVMT [20, 21]. Others explored rebalancing idling non-electric SAVs with time-varying demand flow across arcs [22]. A repositioning algorithm based on greedy assignment found that repositioning can lead to a 20% increase in the share of served SAV requests [23]. Even a 3-6% increase in eVMT, as observed by an assignment strategy study using a fixed-trip dataset [24], can shorten the range of SAEVs to serve passenger trips. Even if Level 3, or direct current fast charging (DCFC), chargers are used for SAEVs, a drop in the supply of vehicles may increase pick-up eVMT, reduce fleet operation revenue, and create a cycle of diminished average fleet state of charge (SOC).

To minimize the negative effects of charging downtime and rVMT, fleet operators can couple charging and repositioning activities. Previously unexplored for SAEVs, this study introduces an optimization framework to manage charging and repositioning activities jointly. This synergy

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is explored for the Bloomington, Illinois, region using POLARIS, an agent-based model [25, 26, 27]. The synergy is evaluated on its ability to improve operational efficiency (rider wait times), externalities (rVMT and cVMT), and operations (average daily trips per SAEV).

2. Methodology

For each zone, j, the supply of vehicles, s_j, accounts for: (i) vehicles idling at that zone j with SOC higher than $SOC^{\min}$, and (ii) non-idle vehicles doing different operations that are expected to eventually idle at zone j (i.e., dropoff in which the last customer is at zone j, repositioning to zone j or repositioning to and then charging at zone j). The minimum supply at zone j is f_j, which is adjusted in agreement with the expected demand for each zone. The slack variable, δ_j, indicates the unmet demand at zone j. In addition, the number of EVCS plugs available at zone j is denoted as C_j.

With respect to variables associated with each vehicle, $\mathcal{I}$ is the set of idle vehicles. For each vehicle $i \in \mathcal{I}$ the binary variable $x_{i,j}$ takes the value 1 if the vehicle i will perform a repositioning trip to zone j and 0 otherwise. Likewise, $a_{i,j}$ represents whether the vehicle i will perform a repositioning trip and then charge at zone j. For each idle vehicle, the current SOC is denoted as SOC_i. In the formulation that follows, the binary variables $x_{i,j}$ and $a_{i,j}$ are continuous variables between zero and one. Since each vehicle can undertake only one operation at a time, the sum of $x_{i,j}$ and $a_{i,j}$ cannot exceed one. To avoid queuing at the EVCS, the number of vehicles sent to each zone to charge cannot exceed the number of available plugs. Finally, the goal is to keep the supply in each zone higher than the estimated demand f_j. The variable $v_{i,j}$ is an indicator variable that takes value of 1 if vehicle i has $SOC_i \geq SOC^{\min}$ and $\mathcal{I}_j$ is the set of idle vehicles that is currently at zone j. The current supply s_j must balance with the vehicles coming to and leaving from zone j. In cases where it is not possible to serve all zones, the variable δ_j has the supply deficit at that zone. The complete formulation is as follows:

$$
\begin{aligned}
\min_{a_{i,j},x_{i,j},\delta_j} J = \sum_{i\in\mathcal{I},j\in\mathcal{Z}} t_{i,j}\Big(x_{i,j}+a_{i,j}\Big) - \sum_{i\in\mathcal{I},j\in\mathcal{Z}} \alpha a_{i,j}\Big(SOC^{\max}-SOC_i\Big) + \beta\sum_{j\in\mathcal{Z}}\delta_j,& \\
s.t.,& \\
0 \leq x_{i,j} \leq 1 \quad i\in\mathcal{I}, j\in\mathcal{Z},& \\
0 \leq a_{i,j} \leq 1 \quad i\in\mathcal{I}, j\in\mathcal{Z}& \\
0 \leq \sum_{j\in\mathcal{Z}} a_{i,j} \leq 1, \qquad i\in\mathcal{I}& \\
\sum_{i\in\mathcal{I}} a_{i,j} \leq C_j \quad j\in\mathcal{Z}& \\
f_j+\delta_j \geq s_j + \Big(\sum_{i\in\mathcal{I}} a_{i,j}+x_{i,j}\Big) - \Big(\sum_{i\in\mathcal{I}_j} a_{i,j}+x_{i,j}\Big)v_i \quad j\in\mathcal{Z}.&
\end{aligned}
\tag{1}
$$

The objective function J attempts to reduce travel cost, increase charging, and ensure enough supply in each zone with parameters α and β to be specified. The value of α weights the charge priority (CP) and β the demand priority (DP). Due to a particular structure of the problem, the Mixed Integer Linear Programming (1) can be solved as a Linear Programming and therefore with reduced computational cost.

This framework is tested on the mid-sized Bloomington, Illinois region. The network has 185 TAZs, 7000 links, and 2500 nodes. The baseline SAEV demand is 68.1k trips, or a 10.6% mode split (when there is 1 SAEV per 75 residents). Figure 1 shows a layout of the network, zones, and EVCS. Table 1 summarizes the SAEV fleet parameters, EVCS network, and optimization parameters used in the scenarios.

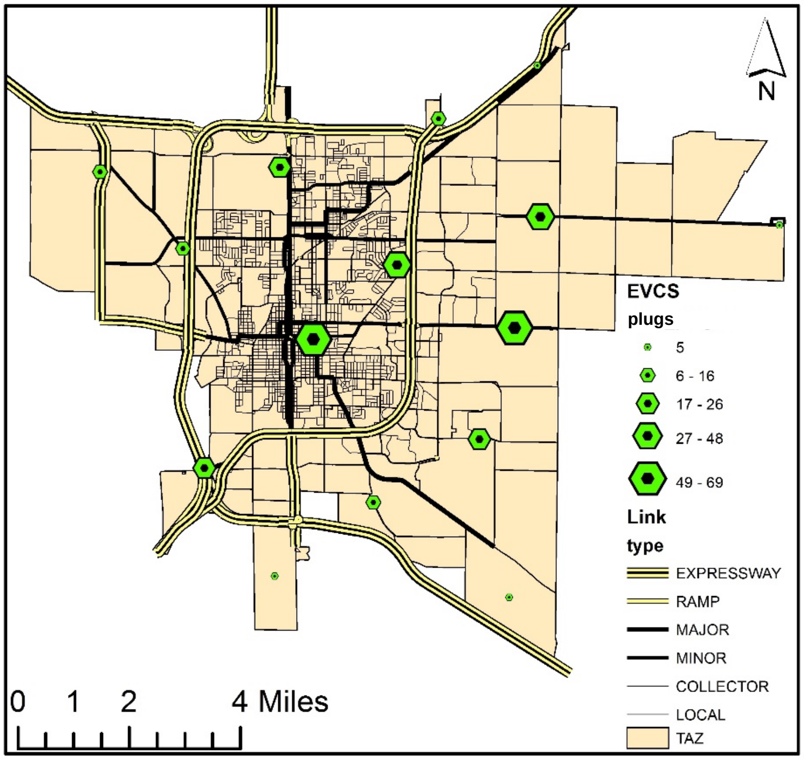

Figure 1: Bloomington Network

Table 1: Summary of model inputs

Parameter	**Value**
EVCS DCFC Stations (50kW)	15
EVCS DCFC Plugs	334
SAEV Theoretical Range	100 mi
SAEV Fleet Size	1600
SAEV Starting SOC	Normal($\mu = 70$, $\sigma = 5$)
SAEV Vehicle Efficiency	30 kWh/100 mi
SAEV Max SOC	90%
SAEV Min SOC	20%
Time trade-off (β)	1200s
Charge weight (α)	25s/SOC(%)

3. Results

The first scenario is the baseline scenario of rule-based charging without repositioning (1-Baseline). The second scenario seeks to fulfill all requests and improve passenger wait times by allowing repositioning (2-Repositioning). The third scenario seeks to optimize the two events jointly with a focus on meeting demand (3-Joint DP). A fourth scenario examined the trade-off between the two events to prioritize charging (4-Joint CP) by considering a minimum supply f_j 25% lower.

Table 2 presents the changes between all four scenarios with respect to the following metrics: total VMT, average daily trips (ADT) per SAEV, cVMT, rVMT, %eVMT, average pickup wait times, and average charging time. Figure 2 presents the differences in average wait times (2a) and average fleet SOC throughout the day (2b).

Table 2: Summary of the results for the four different scenarios. Waiting time is in minutes. ATC is short for Average Time in Charging operation per vehicle (in hours).

Case	**VMT**	**ADT**	**cVMT**	**rVMT**	**%eVMT**	**Avg. Wait time**	**ATC**
1-Baseline	394K	42.3	13.5K	0	23.2	6.1	2.3
2-Repositioning	422K	42.7	15.5K	39.1K	39.3	4.6	2.8
3-Joint-DP	417K	42.8	20.7K	31.4K	29.1	3.7	1.7
4-Joint-CP	421K	43.1	20.3K	20.0K	27.3	4.9	1.7

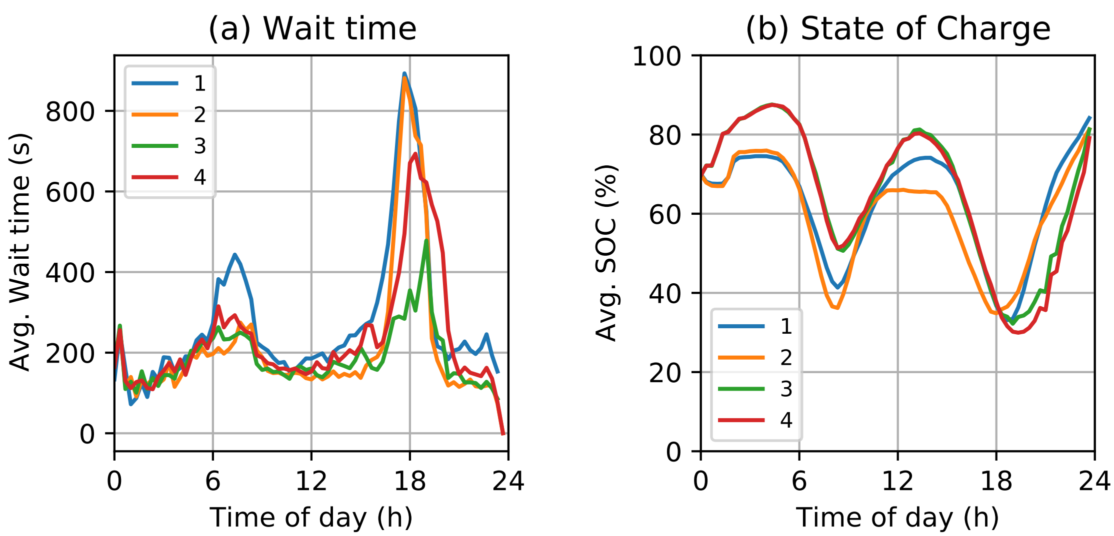

Figure 2: Wait time (a) and State of Charge (b) for the four different scenarios.

4. Conclusion

The coupled framework reduced ATC by strategically charging during periods of low demand and avoiding large queues that rule-based charging exhibits. Since charging was prioritized when demand-to-supply was largely met, the coupled scenarios outperformed baseline scenarios during the PM peak hours when repositioning to meet higher demand was prioritized. Average wait times for the joint strategies were marginally higher than baseline repositioning for the AM peak but were nearly 3 and 9 minutes shorter during the PM peak for Joint-DP and Joint-CP strategies, respectively. The corresponding average SOC was lower after the PM peak, even though it started 5%-15% higher. The joint strategies reduced %eVMT compared to the baseline repositioning scenario and served more trips per SAEV, on average. The Joint-DP had the lowest average wait time of 3.7 minutes, a 40% time savings to the base.

This paper reveals how fleet operators can exploit the synergy of jointly modeling repositioning and charging to increase revenue-generating opportunities, especially in the PM peak, and lessen eVMT externalities. Future work should ascertain synergies under charger-abundant settings, EVCS queuing costs versus the charger availability constraint, and time-dependent joint optimization.

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