# Coordinating Competing Electric Vehicle Fleets: An Agent-Based Charging Capacity Market

Extended Abstract

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## ABSTRACT

We use multi-agent simulation to design and test an auction-based coordination mechanism for the allocation of charging capacity among competing electric vehicle fleets.

## KEYWORDS

multi-agent simulation; electric vehicles; auction mechanism; resource allocation

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## 1 INTRODUCTION

The future of urban mobility will likely be centered around shared autonomous electric vehicle (SAEV) fleets providing on-demand mobility services to their users [17]. This is deemed to offer a balance of sustainability, efficient urban space utilization, and operator profitability while maintaining user convenience [12, 16]. A core task of operators is maintaining state of charge (SoC) levels sufficient for user service [13]. While previous research tackles the charging management of SAEV fleets [3, 6, 10], common limiting assumptions are a monopolistic fleet operator and unlimited charging infrastructure at its fingertips.

We thus consider an SAEV market under competition and argue that a shared charging infrastructure will lead to more efficient outcomes as fewer chargers are needed to satisfy charging demands [2]. In addition, an efficient coordination mechanism helps to manage these shared resources effectively and minimize prolonged waiting times. Few prior works have specifically considered the business case of a charging station operator (CSO) serving the charging needs of commercial fleets. Lu et al. [14] explore the pricing problem of multiple CSOs that compete for a monopolistic SAEV operator's business, and Zhao et al. [19] analyze the joint planning of a profit-oriented CSO and an electric fleet for charging and fleet configuration. We advance this emerging field by proposing a mechanism for a third-party CSO to coordinate the charging demand of multiple commercial fleets. Unlike existing studies that focus on the non-cooperative dynamics between one or more CSOs and a single customer, we address challenges stemming from uncoordinated charging of multiple fleets on a shared infrastructure.

Coordination problems are widely studied, and efficient outcomes have been repeatedly shown to be achieved using auction mechanisms [8, 11]. We propose a real-time auction system for allocating charging capacity facilitated by autonomous smart bidding agents [1] for efficient real-time allocation of scarce resources. Specifically, we suggest breaking down the charging capacity allocation into a spot market for reserving spatio-temporal charging capacity. To evaluate our proposed model, we use a multi-agent simulation, which is crucial to capture the endogenously emerging interactions between SAEV fleets and the CSO, reacting to stochastic mobility demand [5, 9, 13].

Our core contributions include developing a multi-agent simulation that replicates interdependent urban mobility processes, serving as a test bed for business and policy interventions [18]. We are the first to address the challenge of coordinating multiple competing fleets on the same capacitated charging infrastructure. Additionally, we propose an auction mechanism for allocating spatio-temporally dependent capacity reservations, demonstrating that it outperforms uncoordinated charging and competes effectively with private infrastructure scenarios.

## 2 METHOD

### 2.1 Mechanism and Environment Model

Competing SAEV operators serve the stochastic mobility demand of their customers. We assume opportunistic users whose utility function considers the competing services as perfect substitutes and inclines them to reject rides altogether if they don't fit their preferences. Trips are executed by vehicles belonging to the respective operator's fleet, thereby inducing charging demand. To this



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end, they observe their vehicles' SoC and dispatch them to charging tasks if their SoC drops below the heuristic recharging threshold.

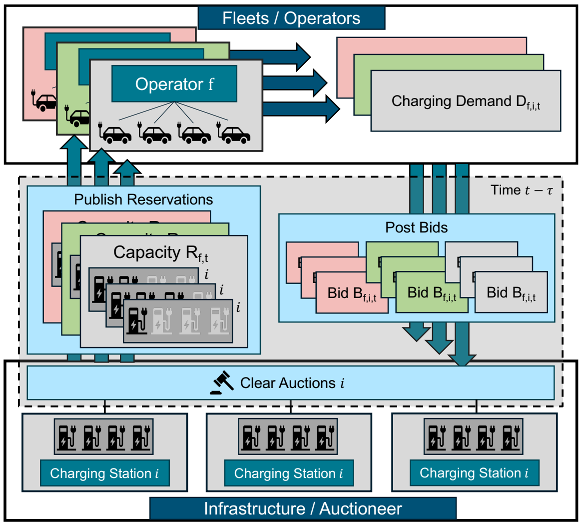


**Figure 1: SAEV Charging Coordination Framework**

All operators $f$ share a single charging network, consisting of charging hubs $i$ with multiple chargers per hub, placed at different locations in the city. Without coordination, the availability of chargers, and thus queue time, is uncertain for operators at the time of dispatch, as they observe current availability, but not the dispatch decisions of their competitors. While co-optimization of the charging schedules of all competitors would be theoretically feasible, this would require complete information sharing, revealing critical business information [15].

To address the inefficiency of uncertain availabilities, we propose a spot market auction for charging station reservations. For each charging location/hub at time $t$, the CSO posts the available chargers in a uniform sealed bid auction at $t - \tau$. Fleet operators submit their bid vectors for each location at that time $B_{f,i,t}$, based on their charging demand $D_{f,i,t}$ resulting from trip serving. Since we assume autonomous bidding agents, the auction is settled instantaneously and the CSO announces the individual allocations $R_{f,t}$ of all charging hubs to the respective fleets, where the clearing price at each $i$ is equal to the highest rejected bid. Fleet operators then plan charging tasks in accordance with their allocated reservations. Figure 1 provides an overview of the mechanism environment.

We evaluate the mechanism through a multi-agent simulation [4], which models the stochasticity and variable specifications of the fleets and the auctioneer.

## 2.2 Case Study

We configure the multi-agent simulation using real-world data from the city of Chicago [7]. We initialize the simulation with two SAEV fleets. Each of those fleets operates a total of 500 homogeneous vehicles with a usable battery capacity of 50 kWh. Their technical characteristics such as energy consumption and charging power follow industry standards. The charging infrastructure is strategically placed in high charging demand areas. We consider a charging infrastructure of ten 22 kW chargers at each of the nine charging locations, amounting to an installed capacity of roughly 2 MW, which can be considered scarce.

We analyze four scenarios: Two in which both fleets operate on the same shared charging infrastructure, and two sub-cases. Firstly, we examine the emergent behavior of fleet operators when they have to reserve charging capacity by auction, as described in Section 2.1. Secondly, we study a situation, in which the competing fleets dispatch vehicles to chargers without coordination or knowledge about the current decisions of the other fleet. We moreover analyze whether the shared infrastructure system can compete with operators who own their private infrastructure and dispatch their vehicles to it at will, without encountering congestion caused by other fleets. Since in this case operators can fully control the flow of vehicles to CS, we consider an optimization-based approach for their dispatch. To create a theoretical upper bound of which service rate could be achieved at most, we also benchmark our results against a scenario in which fleets have access to unlimited charging infrastructure.

# 3 RESULTS

We find that the proposed mechanism (32.05%) outperforms the uncoordinated benchmark (21.77%) in terms of service rate, while staying competitive with the fleets using private infrastructure and downtime-minimizing charging allocation (32.23%). Figure 2 shows the average hourly service levels throughout the experiment horizon. It becomes evident that the small performance difference between the coordination case and the private infrastructure benchmark is driven by a brief time window on the weekend. Note that fleet sizes and user utility inhibit service levels as high as 100 %, as is exemplified by the unlimited charging case.

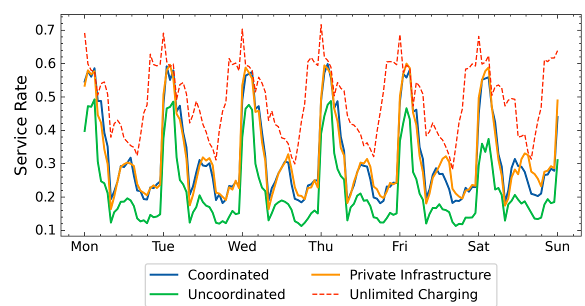


**Figure 2: Mean Hourly Service Levels**

Our experiments demonstrate that the employed coordination approach can improve operational outcomes under a constrained charging infrastructure without explicit multilateral coordination between competitors. In doing so, we demonstrate the potential of simulation for tackling intricate real-world problems with approaches that can't be evaluated only theoretically or analytically.

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