Agent-Based Modeling of Smart Sustainable Mobility Services, Markets, and Policy

Doctoral Consortium

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ABSTRACT

The transportation system is undergoing several transformations at once: The pressing need to become environmentally sustainable, reflected by the increased uptake of electric vehicles. The intertwined trends of transportation servitization and platformization that often culminate in user-facing applications that bundle all mobility-on-demand offers together. This dynamic system comprises heterogeneous services that interact with each other. Uncertainty is imposed by competition and regulation from policy, as actors behave self-interested. I explore the use of agent-based modeling and multi-agent simulation, configured with empirical data, for realistic scenario analysis of services, markets, and policy. In this piece, I dive deeper into one example of that research agenda: The coordination of a scarce resource (charging infrastructure) among competitors (ride hailing operators).

KEYWORDS

agent-based modeling; discrete event simulation; mobility-on-demand; electric vehicles; electronic markets; resource allocation

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1 INTRODUCTION

Transportation systems are undergoing fundamental changes [26] and the future of urban mobility is likely to be centered around fleets that offer mobility-on-demand (MoD) services to their customers [20]. This includes, but is not limited to, vehicle sharing with micro-mobility modes and cars, ride hailing, and ride pooling in van-like vehicles. Such MoD systems offer greater efficiency in sustainability and urban space, as well as operator profitability [25], without compromising user convenience. Still, researchers have identified challenges associated with the operations of such services [22], specifically related to service and charging [12, 15, 17], especially when the fleet consists of electric vehicles (EV). Not only that, but it is accompanied by the possibility for completely new business models, each with their own set of problems to solve, including acceptance [2, 5, 23].

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While research has tackled a multitude of such problems, including customer allocation, relocation, and charging [4, 9, 14], the set of unsolved problems remains large, and grows with advances in technology like the emergence of smart markets [7]. Additionally, the sphere of urban mobility is regulated to a varying degree of strictness, and recent examples show that the absence of well implemented regulation has a detrimental effect on the system [6, 21, 24]. These three factors, services, markets, and policies together form a complex construct of interactions that have a major impact on the urban mobility system and its inner workings. Understanding the impact of any change to the system on other actors and on system-wide metrics such as environmental impact, cost, or social inclusion is crucial. Prescriptive analytics can be a real game changer [8], and yet, the system's large-scale, dynamic, and stochastic nature often makes it unsuitable for analytical methods [19].

1.1 Smart Sustainable Mobility Models and Simulation Framework (SSMMS)

In my PhD I try to tackle the described problem with a mixture of agent-based modeling (ABM) and simulation of the environment and all relevant actors within [18]. For this, I develop a sophisticated multi-agent simulation (MAS), configured with empirical data, able to replicate the intricate interdependent processes in an urban mobility system. I then use the MAS as a test bed for any ABM of counterfactual service and policy interventions [27]. I model each problem through different agents that follow a programmed behavior according to information available in the environment, both from other agents and non-agentic, stateful objects. Stateful objects can include, for example, charging stations or vehicles (if not autonomous, that is). The agents interact with each other and the stateful objects, leading to emergent system-level behavior, which I can then use for scenario analysis.

The MAS takes a mesoscopic perspective, as it does not simulate microscopic travel itineraries of individual inhabitants (like MatSIM [16]) nor simply use stochastic outcome models for system-level metrics. Rather, it utilizes ephemeral user agents characterized by a spatio-temporal travel demand: The modelled city, is discretized into cells, and as time progresses, generator processes in each cell draw inter arrival times from a Poisson distribution. After waiting for that arrival time, a user agent is spawned at that origin cell and draws a destination cell for its transport task from a multinomial distribution of weekday, time bucket, and spawning cell [13]. The MAS software itself is highly modularized, parametrized, and configurable. To exemplify: Any service operator has a module that commands day-to-day operations like allocation of customer requests, relocation, and charging of vehicles. This module can be switched out for any agent that implements its interface. It could be a simple agent that follows a rule based agenda or it could be a learning agent, and if it is a learning agent, because the reinforcement learning (RL) interfaces are standardized as well, the underlying model can be switched out analogously. This is true for all agents in the simulation.

2 EXAMPLE: COORDINATION OF SCARCE RESOURCES AMONG COMPETITORS

Servitization and electrification are driving rapid growth in commercial EV fleets, but charging infrastructure (CI) is a scarce resource constrained by regulation and cost. This creates a challenge: coordinating fleet charging is essential [4, 11], but hindered when those fleets compete for the same business. This is the case we consider: Ride-hailing services that compete for users and a shared CI. We propose a privacy-conserving auction mechanism for coordinating a number of competitors on a shared, scarce resource, enabled by autonomous bidder and auctioneer agents.

2.1 Model and Simulation

We, again, employ ABM to construct what we call the *mechanism environment* within the described simulation environment described before, as depicted in Figure 1. We augment the CI with a new agent, the auctioneer, that owns and brokers information about the CI. Similarly, we replace the fleet objects and their rule-based operations with fleet agents that can interface with this auctioneer agent. Because we abstract from the travel demand that user agents create using charging demands that endogenously arise as a result, this environment does not need to have direct interaction with the rest of the simulation. The result of the agents bidding for capacity, possibly winning some, and incorporating this into their charging operations planning merely reflects in a changed capability to serve customer demands based on the fleet's state of charge.

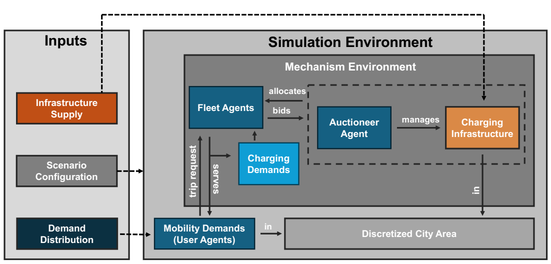

Figure 1: Simulation and Mechanism Environment

The vehicles drain battery during the fulfillment of travel tasks. The operator agents periodically check the fleets' vehicles SOC and informs its value function for the next round of the auction with this fleet state. Auctions run in parallel for each district, with a certain number of charging stations available in each district. The auctions run frequently for a specified period with a look ahead to that auctioned period. After auction results are announced, operators execute a configurable charging strategy based on the acquired reservations and their fleets' charging demands by creating *charging tasks*. Acquired reservations are subject to the bidding behavior of all other fleet operators. As a default, fleet operators consider a suite of heuristic methods for creation of these charging tasks, commonly employed in the literature, specifically a combination of greedy algorithms and rule-based heuristics [3].

2.2 Chicago Case Study

We configure the demand distributions and other parameters using real-world data from ride-hailing providers in the city of Chicago in the year 2022 City of Chicago [10]. We consider three benchmark cases: First, an uncoordinated shared CI with first-come first-serve coordination and myopic, optimistic charging task planning. Second, a private infrastructure for each operator with ahead-planning using next-period downtime minimization. Last, the proposed coordinate shared infrastructure with the same myopic charging task planning, but without the uncertainty revolving around charging station availability in the next period. Figure 2 shows customer service rate of a simulated week. These results indicate that the auction-based coordination outperforms first-come first-serve shared infrastructure and performs comparable to individual infrastructure, while keeping sensitive charging demand information private.

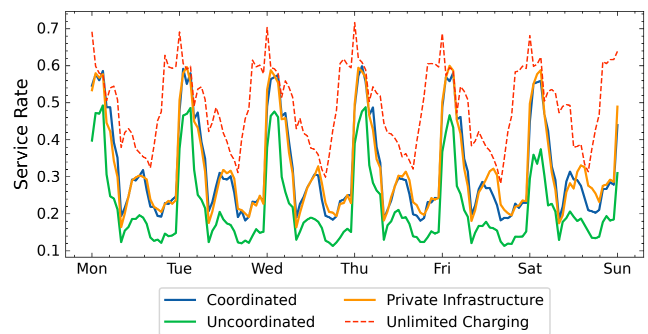

Figure 2: Service Fulfillment Rate, Opportunistic Users

3 CONCLUSION AND FUTURE WORK

This proposal highlights one instantiation of the described SSMMS research framework, the coordination of competing ride hailing fleets on shared CI through a market mechanism enabled by autonomous smart bidding agents [1]. We demonstrate the potential of ABM and simulation for tackling intricate real-world problems with approaches that cannot be evaluated theoretically or analytically only. The SSMMS framework is the cornerstone to all other research projects of my PhD: In one, I look at shared mobility service tenders in cities, which regularly need to balance cost, environmental concerns, and accessibility. I use a simulation-based evolutionary algorithm to generate a solution set for the multi-objective optimization problem that the potential fleet sizes of each mode (bike, scooter, moped, car) pose. In another, I model a public transport system where buses are common-goal oriented learning agents that can deviate from their planned route if they could serve more passengers along the alternative route. The SSMMS framework has also proven to be valuable for other researchers in my group, and I hope to open-source the software in the near future to provide this ABM-driven scenario analysis of urban mobility to a larger community.

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