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Multi-Agent Game-Theoretic Modelling of Electric Vehicle Charging Behavior and Pricing Optimization in Dynamic Ecosystems

Pei Jia, Pok[a], Hwasoo Yeo[a], Soomin Woo[b,*]

[a]*Department of Civil and Environmental Engineering, Faculty of Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, 34141, Korea*
[b]*Smart Vehicle Engineering, Konkuk University, Seoul, 05029, Korea*

Abstract

This research investigates the dynamic interactions between electric vehicles (EVs) and electric vehicle charging stations (EVCSs) through a multi-agent simulation over 30 days. The simulation models EV commuting behavior, charging decisions, and dynamic pricing strategies to analyze their impact on station utilization and energy distribution. EVs operate with unique parameters, including State of Charge (SOC), SOC thresholds, and weighted preferences for cost, wait time, and distance. Each vehicle follows a logistic urgency model and a utility function to evaluate trade-offs between charging at home or office stations. Dynamic pricing at office stations adjusts costs based on demand, encouraging cost-sensitive EVs to charge during off-peak hours, while time-sensitive EVs prioritize shorter queues despite higher costs. Vehicles with critically low SOC exhibit urgency-driven behavior, prioritizing the nearest available station to prevent depletion. The simulation models 101 EVs, distributed across three home locations (50 at Home1, 50 at Home2, and 1 at Home3), capturing diverse charging behaviors and station interactions. The results demonstrate that dynamic pricing effectively mitigates congestion at high-demand stations during peak hours while improving resource utilization. These findings emphasize the importance of personalized decision-making frameworks and flexible pricing strategies in optimizing EVCS operations. The study provides insights for integrating real-time pricing and adaptive charging infrastructure in smart cities, with future work exploring real-world traffic patterns, renewable energy integration, and vehicle-to-grid (V2G) interactions to enhance system sustainability.

Keywords: Electric Vehicles; Charging; Electric Vehicle Charging Behaviour; Pricing; Game theory

* Corresponding author. Tel.:(+82) 02-450-3675.
E-mail address: soominwoo@konkuk.ac.kr

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1. Introduction

Transportation is responsible for around one-fifth of global carbon dioxide (CO_2) emissions from energy sources (Ritchie, 2020). To mitigate climate change, electric vehicles (EVs) have emerged as a promising alternative to traditional automobiles, supported by improvements in battery technology, declining costs, and widespread commitments to emissions reduction. Recent statistics show that EV sales reached 14 million in 2023, increasing the global total to 40 million, with projections indicating a surge to nearly 130 million by 2030 (IEA, 2024). This rapid expansion underscores the need for effective strategies to manage EV charging behavior and ensure the development of robust infrastructure. Charging patterns substantially affect electrical grid operations. In countries such as New Zealand, the UK, and Australia, many EVs are plugged in during early evening hours, aligning with existing peak electricity demand (Department of Climate Change, Energy, the Environment and Water, 2023). Although certain vehicles rely on algorithms to schedule off-peak charging (Tesla, 2023), user convenience and individual habits can limit the success of such measures. Consequently, dynamic pricing strategies and queue management have been proposed to balance charging loads more evenly, an approach supported by studies indicating reduced grid strain, lower emissions, and improved station efficiency (White et al., 2022; Sanchari et al., 2017).

Timing is particularly important, as it shapes total electricity demand and infrastructure wear (Leemput et al., 2014; Veldman & Verzijlbergh, 2015). Incentives to stagger charging times may alleviate demand peaks, mitigating potential risks to grid stability. International experience has demonstrated the feasibility of these policies, although implementation challenges persist (Williams et al., 2024). Shifting charging from peak to off-peak hours benefits both network providers—by lowering the load on grid components—and EV owners, who may see reduced costs and shorter waiting times (Tesla, 2023).In this context, dynamic pricing aligns electricity rates with real-time demand, while queue management optimizes station utilization to limit congestion. This research applies a multi-agent, game-theoretic simulation over two days to investigate EV charging behavior and station operations, offering insights for grid load optimization, efficient energy use, and cost-effective EV adoption.

2. Literature Review

The integration of electric vehicles (EVs) into power systems has prompted innovative strategies to address pricing optimization and user behavior. Effective pricing mechanisms balance grid stability, ensure user satisfaction, and improve the profitability of charging stations, while charging behavior—encompassing location preferences, timing, and frequency—directly affects infrastructure utilization and energy demand. An integrated approach that combines pricing strategies with insights into user behavior is therefore crucial for a sustainable EV ecosystem.

Game theory has been widely employed to explore EV charging decisions. Malandrino et al. (2015) modeled charging station selection as a congestion game, enabling near-optimal solutions for minimizing trip time and costs. Du et al. (2023) introduced a mixed integer model inspired by game theory to guide charging station site selection, focusing on balancing user and investor costs. Liu et al. (2022) proposed a two-level scheduling method that minimizes load variance and maximizes revenue through a master-slave game involving EV users and agents, effectively reducing peak demand. Similarly, Han et al. (2024) developed a non-cooperative game-based EV aggregator framework, offering flexibility to a Distribution System Operator through profit-sharing mechanisms.

Other studies emphasize infrastructure design. Zhang and Li (2016) adopted a non-cooperative game with coupled constraints for parking-lot EV charging, using the Nikadio–Isoda relaxation algorithm (NIRA) to ensure equilibrium. Mirheli and Hajibabai (2023) employed a bi-level optimization framework integrating user-equilibrium decisions to minimize facility deployment and operating costs. Meanwhile, Solvi Hoen et al. (2023) and Xing et al. (2021) examined user preferences in station placement, applying stochastic programming and queuing theory to handle demand variability.

Collectively, this body of work underscores the interplay between pricing mechanisms and user charging behavior, indicating that dynamic pricing and game-theoretic models can manage demand while robust infrastructure design accounts for behavioral dynamics. Future research should seek hybrid frameworks that incorporate economic, technical, and behavioral factors to ensure sustainable EV growth.

3. Objective

This study aims to analyze the charging behavior of electric vehicles (EVs) and the operational performance of electric vehicle charging stations (EVCSs) using a 30-day simulation of 101 EVs. It investigates EV decision-making in selecting charging stations based on a utility-based model that considers charging cost, wait time, SOC levels, and station distance. The study also examines dynamic pricing strategies, particularly at office stations, assessing how cost-sensitive EVs minimize expenses while time-sensitive EVs prioritize shorter queues despite higher costs. Another key objective is to model EVCS resource management, including slot allocation, queue dynamics, and demand-based utilization. The study evaluates how dynamic pricing reduces congestion, balances station loads, and improves efficiency by redistributing demand between peak and off-peak hours. By simulating daily commuting and charging behaviors, this research provides insights into optimizing EVCS infrastructure, including strategic station placement, load balancing, and adaptive pricing policies. The findings contribute to the development of scalable, efficient, and sustainable charging solutions for smart cities. Future work may incorporate real-world traffic patterns, renewable energy sources, and vehicle-to-grid (V2G) technologies to further enhance system resilience and sustainability.

4. Methodology

This study employs a simulation-based framework to analyze the charging behavior of electric vehicles (EVs) and the operational management of electric vehicle charging stations (EVCSs) over a 30-day period. The simulation models 101 EVs, each with unique parameters including initial State of Charge (SOC), SOC thresholds, and decision-making preferences for charging. EVs follow a predefined commuting pattern, traveling between home and office locations, while EVCSs dynamically manage charging slots, queue times, and pricing mechanisms.

4.1. EV Commuting and SOC Dynamics

Each EV follows a daily routine, departing from home to reach the office by 8:00 AM and returning home between 4:00 PM and 7:00 PM. SOC depletes during each commute based on travel distance and battery capacity, computed as:

$$EnergyLoss(\%) = \frac{DistancetoOffice}{BatteryCapacity(kWh)} \times 100 \tag{1}$$

If an EV's SOC falls below a predefined threshold, it evaluates the need to charge using a utility-based decision model.

4.2. Charging Decision Model

EVs select charging stations based on a utility function incorporating multiple factors: charging cost (C), total waiting and charging time (T), SOC urgency (S), and distance to the station (D):

$$U = -(w_c \cdot C + w_T \cdot T - w_S \cdot S - w_D \cdot D) \tag{2}$$

where w_c, w_T, w_S, and w_D are weight coefficients reflecting the relative importance of each factor.

The SOC urgency factor (S) follows a logistic function:

$$S = \frac{1}{1 + e^{-k \cdot (SOC - SOCthreshold)}} \tag{3}$$

where k is a sensitivity parameter controlling the rate at which urgency increases as SOC approaches the threshold. The distance factor (D) is computed using the Euclidean distance:

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{4}$$

where (x_1, y_1) and (x_2, y_2) are the coordinates of the EV and the EVCS, respectively. EVs evaluate all available charging stations and select the one with the highest utility if a charging slot is available. If no slots are free, the EV defers charging until a later time.

4.3. EVCS Operations and Charging Process

Each EVCS manages a limited number of charging slots. When an EV requests charging, it enters a queue if all slots are occupied. The estimated waiting time is determined by the queue length:

$$TotalWaitingTime = QueueLength \times 5 \ (minutesperEV) \tag{5}$$

Once a charging slot is available, the charging duration is determined based on the EV's current SOC and the station's charging speed:

$$ChargingTime(hours) = \frac{EnergyRequired(kWh)}{ChargingSpeed(kWh/hour)} \tag{6}$$

Charging continues until the EV reaches full SOC or completes the estimated charging time. EVCS stations track slot occupancy and manage queues dynamically.

4.4. Dynamic Pricing Mechanism

EVCSs implement dynamic pricing to balance demand. The price per unit of energy increases when demand is high and decreases when utilization is low. Specifically:

- If occupancy exceeds a threshold (e.g., morning and evening peak hours), the price increases to reduce congestion.
- During low-demand periods, prices decrease to attract more EVs.

This pricing adjustment encourages cost-sensitive EVs to charge at off-peak times, reducing waiting times and optimizing station utilization.

4.5. Simulation Execution

The simulation operates over a fixed horizon, divided into hourly increments. At each time step:

- EVs update their SOC based on commuting patterns.
- EVs evaluate charging station options based on their utility function.
- If required, EVs attempt to charge at an available EVCS.
- EVCSs allocate slots, manage queues, and dynamically adjust pricing.

Key performance metrics, including station utilization, queue lengths, and EV charging preferences, are logged for analysis. The results provide insights into optimizing EVCS infrastructure for efficient energy distribution and reduced congestion.

5. Discussion

The findings of this study provide valuable insights into the charging behavior of electric vehicles (EVs) and the operational performance of electric vehicle charging stations (EVCS). By analyzing office charging decisions, queue distributions, and overall waiting times, the research highlights the diverse priorities that guide EV charging choices and the dynamic station conditions that evolve throughout the day. Results show that while a significant portion of EVs opt to charge at the office, a considerable number prefer to rely on home stations, particularly when pricing strategies or anticipated queues make workplace charging less attractive. The distribution of queue lengths and waiting times underscores how stations with high traffic can still process vehicles quickly if equipped with sufficient capacity or faster charging speeds, whereas smaller or lower-capacity stations may experience prolonged waiting periods despite lower overall demand. These patterns emphasize that efficient EVCS management must account for not only the number of vehicles but also the timing and location of charging events, along with individual EV preferences for cost, proximity,

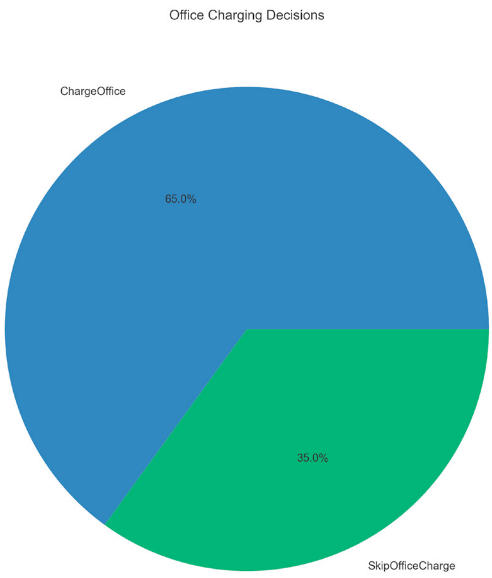

Fig. 1. Charging decisions

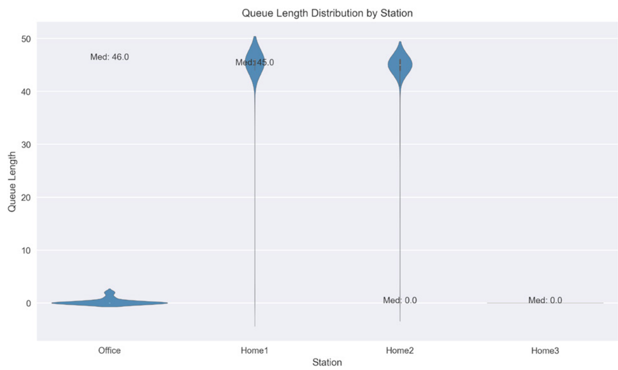

Fig. 2. Queue distribution

and state of charge (SOC) considerations. Consequently, the study illustrates how strategic station placement, dynamic pricing, and targeted capacity planning can optimize both user experience and operational efficiency, offering valuable guidance for future EV infrastructure development.

Figure 1 presents a pie chart illustrating how frequently EVs opt to charge at the office versus skip office charging. Approximately 65% of decisions fall into “ChargeOffice,” while the remaining 35% represent “SkipOfficeCharge.” Although a significant portion of vehicles choose to plug in at work—likely to maintain adequate state of charge for the return commute—a notable share refrains from doing so. Key factors influencing these behaviors include SOC thresholds, dynamic pricing at the office station, and anticipated queue lengths. Vehicles with higher SOC or lower cost sensitivity may choose to bypass office charging, instead relying on home stations with potentially more favorable pricing and availability. Conversely, EVs with urgent charging needs or minimal cost concerns tend to top up at the office. This split highlights the importance of location- and time-based strategies for managing charging demand. A carefully calibrated pricing scheme can encourage more users to shift to off-peak times or alternative stations, thereby reducing congestion at the office during peak hours.

Fig. 3. Wait times

Figures 2 and 3 together provide a more detailed view of how waiting times and queues vary across different locations in this simulation. Here, waiting time spans the entire interval from the moment an EV initiates a charging request until its battery is fully charged. This comprehensive metric integrates both the queuing duration—the time an EV spends waiting for a slot to become available—and the charging duration, during which the EV actually draws power. By consolidating these two stages, the box-plots in Figure 3 offer a more holistic perspective on station congestion compared to the queue length distributions shown in Figure 2.

Although some stations appear to accumulate moderate-to-high queues (as evidenced in Figure 2), they may still achieve relatively low total waiting times if they possess enough capacity or faster charging rates to process vehicles swiftly. For example, the Office station frequently records sizable queues yet avoids excessively prolonged waiting periods. This efficiency stems from multiple charging slots or higher throughput, allowing EVs to move through more quickly once they begin charging. In contrast, Home1 and Home2 frequently experience longer overall waiting times, even when their instantaneous queue lengths may not look as severe. These stations encounter demand surges at peak commuting hours, causing multiple vehicles to converge in a short span, which extends both the queuing and the charging phases.

By observing Figures 2 and 3 together, it becomes clear that station throughput and timing significantly influence an EV's total waiting experience, beyond what raw queue lengths alone might suggest. These findings underscore the need for carefully balancing station capacity, improving charging speeds, and managing load peaks—potentially through dynamic pricing or scheduling adjustments. Doing so can help mitigate the bottlenecks that lead to lengthy waits and enhance the overall efficiency of EV charging operations, ensuring a more streamlined experience for all users.

This study highlights the dynamic charging behaviour of Electric Vehicles (EVs) and the operational performance of Electric Vehicle Charging Stations (EVCS). EV charging decisions are driven by an interplay of factors, including State of Charge (SOC), waiting time, travel distance, and cost. Low-SOC vehicles often prioritize immediate access to nearby stations to avoid battery depletion, while cost-sensitive vehicles are more willing to wait in queue for cheaper charging opportunities. High-demand EVCS locations—such as workplaces or major commuting routes—tend to experience congestion and consequently offer lower utility to incoming vehicles. However, dynamic pricing and other load-balancing measures can help alleviate these bottlenecks by encouraging some EVs to shift to underutilized stations or to charge during off-peak hours. Overall, the findings underscore the need for strategic EVCS placement, capacity planning, and flexible pricing models to accommodate the growing diversity in EV user preferences and maintain an efficient charging ecosystem.

6. Conclusion

In conclusion, this study underscores the importance of understanding EV charging behavior and refining the operational strategies of electric vehicle charging stations (EVCS) to effectively manage increasing demand. Charging decisions are influenced by a combination of SOC urgency, cost sensitivity, waiting times, and proximity to charging locations, resulting in adaptive and context-dependent behaviors. High-demand stations, such as those near offices or along major commuter routes, tend to experience congestion and thus offer lower utility to EVs during peak hours. However, dynamic pricing and capacity optimization can alleviate these bottlenecks by encouraging vehicles to shift their charging to off-peak periods or underutilized stations.

Looking ahead, integrating real-world traffic data and renewable energy sources can enhance the sustainability and responsiveness of charging networks, particularly under fluctuating supply and demand conditions. Machine learning and predictive analytics could be employed to forecast EV arrivals and optimize charging schedules in real time, reducing both waiting times and energy costs. Expanding the simulations to account for heterogeneous EV types, battery capacities, and diverse user preferences would provide a more comprehensive view of charging behavior. These advancements would lay the groundwork for a more adaptive and robust EV charging ecosystem, capable of evolving alongside technological innovations and shifts in urban mobility patterns.

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