June 2024

Managing Electric Vehicle Charging Hubs Through Dynamic Capacity-Based Pricing

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Completed Research Paper

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Abstract

As electric vehicles (EVs) become more prevalent, demand for charging infrastructure is growing. This paper explores the operational management of electric vehicle charging hubs (EVCHs) with a focus on service pricing. Specifically, we design a data-driven decision support system for the EVCH operator that dynamically publishes multiple prices for capacity-based charging services. In capacity-based services users pay based on the charging rate they choose. The goal is to exploit heterogeneous user preferences, taking into account time-dependent and stochastic factors, by offering dynamic charging services. We address this problem by implementing reinforcement learning agents that learn optimal price setting policies through interaction with the EVCH environment without prior knowledge of user characteristics. Our findings indicate that the proposed pricing model outperforms existing benchmark policies. Furthermore, our analysis reveals that the system is responsive to exogenous factors, including electricity contracts and user behavior, and that our model successfully adapts to these changes.

Keywords: Sustainability, Dynamic Pricing, Charging Management, Agent-based Modeling, Reinforcement Learning.

1 Introduction

Transportation significantly contributes to climate change (Pal, Gopal, and Ramkumar, 2023). One solution to mitigate its effects is through the use of electric vehicles (EVs) for a more sustainable transportation system (Nanaki and Koroneos, 2016). The widespread adoption of EVs faces technological challenges, including prolonged charging sessions, which necessitates access to charging locations in various places like shopping malls (Egbue and Long, 2012). Therefore, substantial funding must be allocated for non-residential charging infrastructure, including those in workplaces, to facilitate the shift towards electric mobility (Z. J. Lee, Li, and Low, 2019). These systems, which enable high-density EV charging use cases, are referred to as EV Charging Hubs (EVCHs).

With the rapid development of EVs, charging stations are needed to be widely deployed. One barrier to the development of charging stations is financial viability due to the need for significant upfront investment (Engel et al., 2018). To encourage stakeholders to invest, an appropriate pricing scheme (e.g. dynamic pricing) that increases profits could prove effective (Lin, Shang, and Sun, 2023). Moreover, a significant number of EVs connected to the power grid may cause supply shortages and extreme overload issues. Although time-of-use (TOU) pricing can somewhat ease the impact of charging load on the power grid, it is not a comprehensive solution to the problem (Yang et al., 2021). More effectively, novel dynamic pricing policies are promising, as they can shift some loads to off-peak hours (Valogianni, Ketter, Collins, and Zhdanov, 2020). Finally, dynamic pricing schemes could offer extra advantages, such as the flexible reshaping of charging loads to a desirable load profile. This is becoming increasingly important due to the rising use of renewable energy sources.

We analyze the operations management of a EVCH [1] with a focus on the pricing problem. Pricing acts as a connection between charging providers and EV users. Charging providers aim to increase prices to maximize profits, whereas EV users are sensitive to prices and adjust or cancel their demand accordingly. From the perspective of the EVCH operator, we propose a decision support system (DSS) to identify near-optimal pricing policies for diverse situations. The EVCH operator is modeled as self-interested agents with the goal of profit maximization. To incorporate environmental considerations, we follow new electricity tariffs for large-scale charging facilities. These tariffs are designed to minimize the adverse effects of significant EV loads on the grid by using high peak charge costs. Therefore, to maximize profits, EVCH operators must reduce their environmental costs, such as the peak of their consumption loads. Although we aim for profit maximization, our proposed DSS is flexible enough to accommodate other objective functions. For instance, some public charging facilities may want to shape their consumption to a desired pattern to cooperate directly with grid operators.

Dynamic pricing has been implemented as a means of decreasing load peaks (Valogianni, Ketter, Collins, and Zhdanov, 2020), addressing uncertainties in energy demand and renewable energy production (Soares et al., 2017), and enhancing the profitability of charging services in parking areas (Zanvettor et al., 2022). Recently, researchers have examined the benefits of menu-based [2] charging services, where users pay different prices based on adjustments to their departure times (C. Lu et al., 2023). We combine these advantages to design a learning agent that identifies optimal dynamic pricing policies for different charging powers[3]. We refer to our proposed approach as a capacity-based dynamic pricing model that assigns varying prices to multiple charging options with different maximum rates (e.g., 0.3 and 0.5 $\$/kWh$ for 22 and 55 kW, respectively). The goal is to incentivize users to request their true demand and offer more flexible services to account for stochastic and heterogeneous charging preferences. Some charging stations already use fixed (time-independent) capacity-based pricing, but it has not been thoroughly researched in scientific literature. Our study aims to investigate this pricing scheme and exploits its advantages when integrated with dynamic pricing.

We also model EV users reaction toward the price of charging services. EV users show varying price sensitivity depending on their access to charging facilities, such as home charging (Babic et al., 2022). Therefore, it is crucial to analyze user behavior for our proposed model. Compared to previous works, EVCHs customers exhibit less flexibility with regards to time rather than energy demands. This is supported by Daina, Sivakumar, and Polak (2017), who suggest that EV charging is activity-based, meaning that users typically charge their vehicles during other activities, such as working or shopping. Therefore, EV drivers who are shopping might decrease their energy request but rarely change their departure time to marginally reduce their costs. Plus, EV users' heterogeneity and preferences for charging powers have not been investigated in previous works. We add to the current knowledge of dynamic pricing of charging services by answering the following research question.

How can dynamic capacity-based pricing for electric vehicle charging facilities enhance environmental and economic performance under varying user characteristics?

Methodologically, we use agent-based modeling (ABM) to create a digital representation of an EVCH with advance operations management considering user behavior and smart multi-plug charging stations. Our ABM is equipped with a variety of operational decision algorithms for resource allocation, load management, and dynamic pricing. Optimizing dynamic capacity-based pricing is a sequential stochastic decision-making problem, as decisions (prices at each time step) are interconnected and demand exhibits stochastic patterns with respect to arrival time and price sensitivity. Therefore, we formulate the problem as

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[1] Our approach is applicable to public charging stations, but we focus on EVCHs due to their importance in the future.

[2] By menu-based, we refer to the option for users to select more affordable services by staying more time slots.

[3] Charging power refers to the rate at which electric energy is delivered to a device or system during the process of charging, usually measured in watts (W) or kilowatts (kW).

a Markov decision process (MDP) and employ deep reinforcement learning (RL) algorithms to determine nearly optimal pricing policies.

We contribute to the literature in multiple ways. First, we offer a digital replica of large-scale EVCHs that includes a set of demand and supply features (e.g., charging management, pricing strategies, and user patterns). We calibrate our ABM using two different data sources of parking providers in Germany (around 3.8M parking events) and charging stations in California to estimate user arrival/departure times and energy demand. Secondly, we develop a DSS that utilizes advanced RL algorithms to determine the most efficient dynamic pricing strategies for varying charging levels. Our dynamic pricing approach responds to user behavior and can learn to recognize patterns in real-time without requiring for mathematical intricacies. There is great value in not requiring a mathematical model in practical scenarios where estimating user behavior is prohibitively expensive. Our findings indicate that the combination of dynamic and capacity-based pricing models results in superior performance compared to existing models. The proposed DSS substantially enhances the profitability (23% increase) of charging providers and can also reshape charging loads as desired. Our agent is trained for various user behavior parameters, and we demonstrate the model's robustness against different user characteristics and the significant impact of user behavior on system performance. These findings offer valuable insights for both EV charging providers and grid operators to make informed decisions about their operational pricing and strategic investment.

In the forthcoming sections, we contextualize our paper within the existing literature and conduct a review of related studies. We also provide a concise description of the problem and model. Finally, we present numerical examples and thoroughly discuss our results.

2 Literature Review

This study contributes to two streams of literature: (i) Green Information Systems (IS) and sustainable energy management, and (ii) electric vehicle charging facility operations management. We explore the link between sustainable electric mobility and IS research and investigate how a user-interactive DSS design can overcome the barriers to a sustainable charging network. Second, we examine the management of operations at large-scale charging stations with an emphasis on service pricing.

2.1 Green IS and sustainable electric mobility systems

Green IS is rooted in the recognition that information systems (IS) research can make a significant contribution to enabling environmental sustainability in a variety of sectors (Brocke et al., 2013; Corbett and Mellouli, 2017). IS have been shown to promote sustainable practicing by consumers (Seidel, Recker, and Brocke, 2013), to enable smart electricity grids (Watson, Boudreau, and A. J. Chen, 2010) or assist green policy design. While there has been considerable involvement from IS researchers in the field of sustainable energy (Dedrick, 2010; Melville, 2010), the call to action by Ketter, Schroer, and Valogianni (2023) highlights the necessity for greater engagement of the IS community in intelligent sustainable transportation systems. Our research examines a socio-technical challenge situated at the intersection of sustainable energy and smart mobility, requiring both technical algorithmic methodologies and large-scale behavioral toolbox provided by IS approaches (Sarker et al., 2019). Green IS has also been embraced by the design science (DS) community (Hevner and Gregor, 2013; Rai, 2017). Examples that are broadly related to our work include decision support systems for activating demand response and load shifting in electricity markets (Fridgen et al., 2016), data-driven operations of microgrids (Gust et al., 2021), or decentral management of EV charging processes (Valogianni, Ketter, Collins, and Zhdanov, 2020).

Our research contributes to Green IS stream by focusing on EV integration and adoption, a core driver of sustainability in the transportation sector. Specifically, we propose a DSS to optimally price capacity-based charging services at EVCHs (workplaces, malls, depots, etc.) with heterogeneous user behaviors. Our contribution falls into the computational and optimization field of IS, as specified by Rai (2017). The use of data analytics and artificial intelligence techniques links our work to the field of Information Technology (IT) engineering (Jenkin, Webster, and McShane, 2011; Valogianni, Ketter, Collins, and Adomavicius, 2019). Indeed, we position our work at the intersection of Green IS and IT engineering sciences, where we develop a DSS through IT solutions to promote sustainability by paving the way for mass adoption of EVs. Our approach uses machine learning techniques and ABM that have been recently applied in IS to tackle intricate socio-technical tasks (Haki et al., 2020). We provide a detailed agent-interactive simulation of EVCHs. We calibrate our ABM using data analysis and model service pricing decisions as a dynamic learning problem. Additionally, we analyze the impact of varying demand characteristics on the user price sensitivity model based on existing literature.

2.2 Electric vehicle charging hub operations management

EVCHs exhibit several unique features that distinguish them from other charging use cases. First, EVCHs typically represent large, locally concentrated loads that may require significant local electricity grid extensions and load management (Z. J. Lee, Li, and Low, 2019). Second, integration with building loads and generation units (renewable energy production, storage) may be possible/desirable (Nunes, Figueiredo, and Brito, 2016) to reduce induced peak loads. Third, they experience different user (i.e., charging) behavior compared to other charging use cases. User behavior can vary substantially depending on the use case of the attached facility (workplace, mall, etc.).

According to our contributions, we briefly review state-of-the-art operations management approaches in the realms of (1) smart charging and (2) pricing EVCHs. In terms of EVCH operations, we acknowledge the extensive work on EV smart charging (see e.g., Mukherjee and A. Gupta (2015) for a recent review) that most EVCH operations-focused research is based on. A notable differentiator from the traditional smart charging literature is the inclusion of building/cluster-level constraints and optimization opportunities. Early examples include the development of a mixed-integer optimization framework for workplace charging strategies that takes into account different eligibility levels (Y. Huang and Zhou, 2015), and coordinated charging management models with solar energy production (Z. J. Lee, Li, and Low, 2019).

EV charging price design is massively investigated to integrate EV loads into the grid. Auction mechanisms have been used to coordinate EV charging (Hou, C. Wang, and Yan, 2019). Pricing mechanisms attract more attention because they are easier to implement and are preferred by customers (Valogianni, Ketter, Collins, and Zhdanov, 2020). Cui, Hu, and Duan (2021) propose a charging price optimization to coordinate the demand between multiple EVCHs. To integrate the uncertainty of charging demand, Luo, Y.-F. Huang, and V. Gupta (2017) propose a stochastic dynamic pricing that also deals with renewable energy generation volatility. Mao et al. (2017) propose vehicle-to-grid pricing regulatory to utilize the EV batteries as storage systems in EVCHs. M. Lu, Z. Chen, and Shen (2018) consider the competitions among multiple EVCHs while designing a price scheme. Also, due to high uncertainty and computational complexities, many dynamic pricing related works employ deep RL algorithms to enable the implementation of their works in large-scale problems (S. Lee and Choi, 2021).

In more similar works, researchers design pricing models as a function of service quality. For example, Lin, Shang, and Sun (2023) includes the waiting time to dynamically determine the price for fast charging services in public charging stations, optimizing manage the queue for limited resources. Valogianni, Ketter, and Collins (2015) develop a capacity-based pricing model from the grid operator's perspective with the goal of reducing additional peak from EV loads. Some closer related works study the menu-based EV charging services to utilize the flexibility of EV charging demands. For example, Moradipari and Alizadeh (2019) investigate optimal pricing mechanism to assign users with higher priority to charging stations with lower waiting time in order to maximize social welfare. Zeng et al. (2021)'s model provides pricing options for flexible and inflexible charging demands, taking into account EV behaviors. The authors assume that users do not alter their requested energy, but only choose between flexible and urgent charging options. C. Lu et al. (2023) design a deadline differentiated (i.e., users get discount if they park longer) dynamic price model to reveal the real departure time of EV users. To expand on the existing literature, we have developed interrelated dynamic pricing models for multi-power (capacity-based) charging services. In the case of EVCHs, where users engage in other activities (e.g., working and shopping), it is unlikely that they will wait for charging services or alter their plans (departure time) based on varying prices. Supporting by the results of Daina, Sivakumar, and Polak (2017) and Z. J. Lee, Li, and Low (2019)'s work, we assume that charging demands at EVCHs are activity based and EV users do not change their departure time for marginal cost differences. We assume, EV users might adjust their charging demand according to the price signals based on their charging access in other occasions. reTo the best of our knowledge, our work is the first study that design dynamic capacity-based pricing for charging services when the energy request is a function of price. We use deep RL algorithms that do not require prior information about EV user utility functions (price responsiveness) while having scalability and computational advantages for large-scale problems. This allows us to analyze heterogeneous utility functions for EV users since the model learns the optimal pricing policies by interacting with the EVCH environment. Finally, our model allows for parallel use of charging infrastructure (multi-plug stations) which significantly boosts asset efficiency at the expense of higher operational complexity.

3 Model

Our approach is outlined in Figure 1. Our goal is to create a DSS that can identify nearly optimal pricing policies for capacity-based charging services in EVCHs. The model's core is an agent-based digital simulation of an EVCH that includes unique features and operating methods. While our primary focus is on pricing, we must also model a comprehensive operations management package to test our pricing strategies in a realistic simulation. This system learns profitable pricing schemes by publishing capacity-based prices that vary according to charging power and by observing EV users' behavior towards the published prices. The simulation platform requires essential inputs, such as objective function, constraints, demand patterns, and facility configurations, which are separately obtained using data preparation techniques and operator expertise. This feature allows the operator of EVCH to interact with the DSS, enabling them to verify the relationship between pricing models and other parameters, such as the objective function and EVCH configuration. Once the pricing agent is trained, it can output a fully automated agent capable of making dynamic pricing decisions in other simulation and real-world scenarios while updating itself with new exogenous information. Furthermore, it provides offline pricing policies and high-level managerial insights. For example, the EVCH operator can assess the effect of capacity-based pricing in various scenarios. Subsequently, we examine the acquired pricing policies for the EVCH environment and compare them to current pricing models. We also perform additional sensitivity analysis to observe the impact of user price elasticity and EVCH configurations. Each block is described individually in the following section.

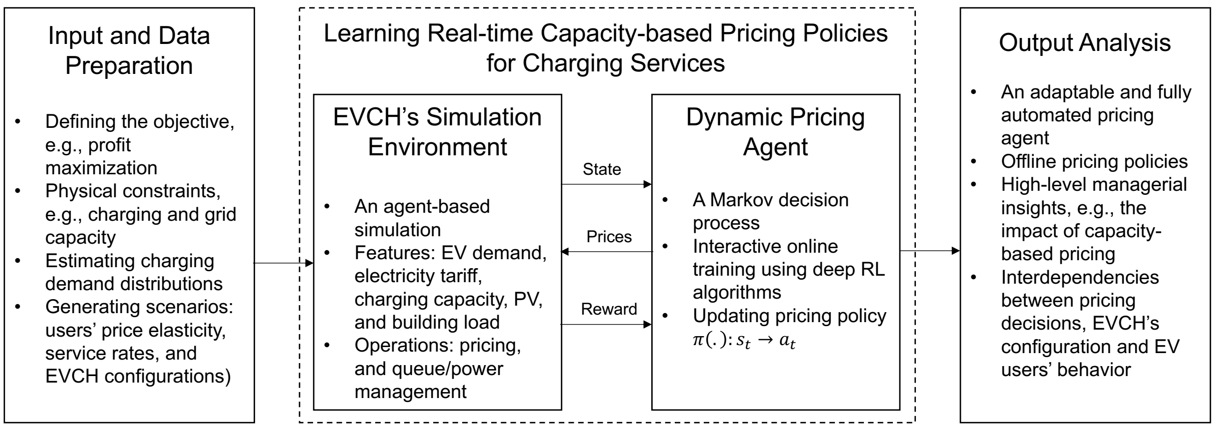

Figure 1. A decision support system for pricing charging services in EVCHs.

3.1 Input and data preparation

This section outlines the preparation of inputs for the EVCH environment. The three primary data inputs include EV user demands for arrival, duration of stay, and requested energy, building energy consumption patterns, and on-site energy generation via solar photovoltaic (PV). Note that our proposed DSS can work with either raw sensor data or abstract charging and parking distributions. Additionally, demand data is only necessary for the simulation-based training phase. Once trained, the agent interacts directly with real-time demand and other parameters to keep policies updated.

3.1.1 Parking and charging behavior

Our simulation's core input is parking and charging behavior of the EVCH. Charging patterns of EV users are mostly activity-based and depend on identified socio-demographic data, vehicle type, traveling behavior, and charging availability (e.g., home charging) (Z. J. Lee, Li, and Low, 2019). Therefore, charging management of EVCH such as pricing schemes should be aligned with these patterns to optimize system performance. User preferences (of an individual i) in an EVCH context are described by the three-dimensional vector $v_i = (A_i, \delta_i, e_i^d)$. The three individual components are: (1) time of arrival (A_i), (2) duration of stay δ_i and (3) requested energy (e_j^d). Following Z. J. Lee, Li, and Low (2019), we define laxity as $lax_i = \delta_i - \frac{e_i^d}{\kappa}$. Here, the term laxity means the remaining parking time after finishing the charging demand with maximum charging load; e.g., $lax = 0$ means that a vehicle needs to charge at the maximum available rate κ for the entirety of its stay, while higher laxity values indicate more room for active charging management.

We take advantage of a unique observational parking dataset that was provided by a major European real-estate investor, which includes transactions from seven large-scale parking garages (capacities range from 275 to 2200 parking spots) in Germany. A mix of workplace, inner-city, and shopping center facilities is available. Each row in this dataset represents a single parking event (user i) with corresponding arrival and departure preference information. For privacy reasons, individual users cannot be identified. We use a full year of data to capture daily, weekly and yearly seasonality. 2019 is chosen to filter out pandemic-related effects. In total, our data comprises 3.84M parking events. The dataset for observational parking is not publicly available, and we have obtained access to it through collaboration with our industrial partners.

For estimating the requested energy per vehicle e_i^d. We employ a recently published real-world dataset by Z. J. Lee, Li, and Low (2019) containing $>$25,000 charging transactions for the year 2019 at the Cal Poly San Luis Obispo campus in California. Per each charging transaction the full preference vector $v_i = (A_i, \delta_i, e_i^d)$ is available. Assuming that charging demands do not significantly vary across regions, we combine the charging data (which only contains served sessions that are constrained by the available infrastructure) with our parking dataset. We train a prediction model on the labeled Z. J. Lee, Li, and Low (2019) dataset and use the resulting model to predict charging demand in the parking dataset. Specifically, we train a kNN-model on the charging transaction dataset using the set of clustering variables from before as predictors and the requested energy in kWh as outcome variable. Cross-validation reveals k=12 neighbors to be a good value. We use the fitted kNN-model to predict charging demand per transaction in our unlabeled parking dataset. Using this approach, we obtain an exponentially distributed charging demand across the entire population of EVs with average demand of 26.46 kWh (σ = 17.20 kWh) per parking session.The distributional shape of charging demand is consistent with the one seen in other empirical EV charging settings (e.g., Ferguson et al., 2018). In Figure 2 we show core population characteristics for an exemplary mixed-use parking facility. Notice the long laxity values, a measure of charging flexibility, that indicate scope for leveraging vehicle flexibility for EVCH charging management.

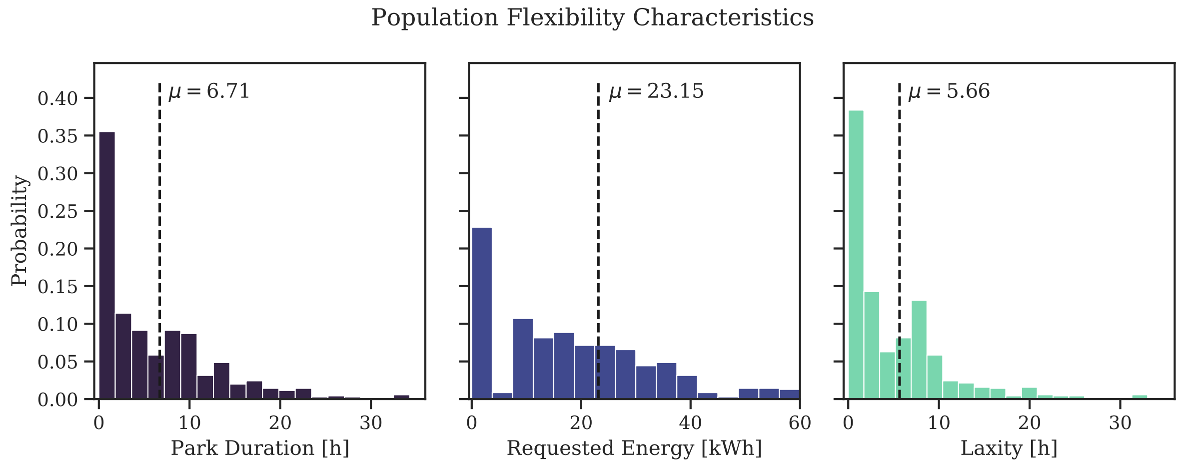

Figure 2. Parking and charging characteristics of electric vehicle users.

3.1.2 Building energy consumption patterns

We use real-world building consumption data to model peripheral base loads that are served by the same grid connection, thus influencing total available grid capacity and peak energy consumption. Contrary to EV loads, we assume building load to be exogenous, i.e., it cannot be dynamically managed or even curtailed. Given the absence of smart energy management hardware in most extant building stock, this is a reasonable assumption.

3.1.3 Electricity (PV) production patterns

We use real-world PV load factors to model PV production from the regions corresponding to the facility locations. Load factors are a measure of real PV panel power output as a ratio of installed capacity and depend on local solar irradiation conditions. We compute these load factors by dividing real PV infeed by the total installed PV capacity in the facility locations. This data is available via local transmission system operators (TSOs) and generally comes in 15-minute intervals.

3.2 Agent-based simulation

In this section, we present the agent-based modeling of EVCHs' digital representation, incorporating supply and demand specifics.

3.2.1 Supply side

First we briefly describe the EVCH equipment and the operational processes including charging dock allocation and power management.

3.2.1.1 Physical equipment

In EVCHs, both the building and the chargers receive power from the same grid connection point, which is constrained to a certain capacity. The integrated facility may have additional on-site behind-the-meter generation (e.g., PV). We assume that PV generation can be scaled and is limited by local facility space constraints, such as roof space. Naturally, the actual available PV capacity at any given time will depend on local weather and solar irradiation conditions, which we capture by means of a time-dependent load factor. The EVCH could equipped with different types of EV charging docks (22kW AC or 50kW DC docks) and the number of connectors per dock. Crucially, for charging docks with multiple connectors, we allow for simultaneous charging of EVs meaning the rated power per dock can be shared dynamically and flexibly by all connected vehicles.

3.2.1.2 Operations processes

We implement realistic operational policies that simulate real-world operations in the simulation environment. Service pricing is a crucial component of the operations management of EVCHs as price signals could indirectly adjust the charging demands and significantly impact profits. Additionally, since we allow for multi-connectors charging docks with simultaneous charging capability, the initial assignment of vehicles to charging stations becomes an important factor. It affects not only the charging capacity available for that EV but also for the current and future arrivals at the same dock. Since EVs cannot be relocated while connected to a charging dock, it is crucial to make well-informed initial assignment decisions. In practice, it is common to make routing and charging decisions separately for the sake of simplicity (Ferguson et al., 2018). We follow the same approach, as routing is not the focus of our paper.

Pricing scheme The (EVCH) operator provides multiple charging power services with varying prices. For instance, the options could include 11 kW or 22 kW charging, indicating the maximum charging power available. The prices may be fixed throughout the day or updated regularly. By implementing dynamic, capacity-based pricing, the operator can achieve various objectives, such as maximizing profits or reducing peak usage. In this paper, we assume that the operator aims to maximize profits. We must consider that there is a trade-off between prices and demand, wherein higher prices lower demand. Additionally, it is worth noting that EVCH has a time-of-use electricity contract, which encompasses peak charges. Therefore, determining optimal prices for different charging powers is a complex problem due to stochastic charging demand patterns, including arrival times, duration of stay, and price sensitivity, as well as time-based electricity costs.

Vehicle routing and charging algorithms Vehicles are assigned to a connector upon entering the EVCH.We use the lowest-laxity-to-highest-capacity matching algorithm. It categorizes incoming vehicles as having low, medium, or high laxity (using bins derived from historical data) and then pairs low-laxity vehicles with charging docks that have high remaining capacity, and vice versa. This way, the strategy implicitly prepares for future arrivals that may require more or less charging capacity. For managing the power of charging vehicles, we employ a model predictive control. This model utilizes mathematical optimization to compute charging schedules that are cost-optimal and meet charging demand for the planning period Δ in scope. We employ a standard cost-optimal charging framework (e.g., Ferguson et al., 2018) and plan $\Delta = 12$ periods in advance. We also implement a smoothing constraint through restricting the maximum charging ramp rate. Since the preference vectors of future arrivals are unknown during the planning stage, a calibrated safety margin is employed to allow for their accommodation in future periods.

3.2.2 Demand side

This subsection explains the assumptions made regarding modeling the decision-making process of EV users to adjust their energy request.

3.2.2.1 Electric vehicles

EVs enter and exit the EVCH according to a schedule driven by real-world sensor data. When entering, EV users are presented with prices for multiple charging power options and are prompted to provide estimates for their intended duration of stay and the desired amount of energy (if any) to be charged during that period. These are common assumptions in the literature (Z. J. Lee, Chang, et al., 2018; Z. J. Lee, Li, and Low, 2019). In most trials, it is assumed that users remain for the duration they indicated at the beginning, although this assumption is not necessary for our model. Upon arrival, and only if they desire to charge, the operator connects the EVs to the designated connector. It is critical to note that EVs cannot be moved or relocated during their stay, occupying both the parking spot and connector assigned to them for the entire period, even if the charging process has already ended. Once EVs reach their scheduled stay, any charging in progress is terminated, the connector is released, and the parking space is vacated and becomes available for the next period.

3.2.2.2 EV user decision-making

We assume that EVs arrive with raw charging demand (e_i^d) and adjust their demand according to capacity-based prices published by the EVCH operator. Prices change dynamically, such as on an hourly basis, but users pay based on the price they selected upon arrival. We assume users are price-takers, selecting the option that maximizes their utility, and they have heterogeneous price elasticity in different situations. For instance, a customer who needs to undertake long-distance travel may incur higher costs for a higher power charging option. Additionally, we presume a standard utility value for an alternative option (a reference of charging prices for users), such as charging at home or neighbor charging service providers. Therefore, users may decline all prices and refrain from charging at this facility. As a result, we define user i's utility function for charging option j.

$$U_{ij} = U_i - p_j d_{ij} - \beta_i f(e_i^d - d_{ij}) \tag{1}$$

U_i represents the baseline utility for user i when charging at this EV charging hub. For the reference charging option, U_i is set to zero. The charging price for option j is denoted by p_j ($\$/kwh$), and the requested/adjusted energy $d_{ij} = max\{\delta_i \kappa_j, e_i^d\}$ is a function of the charging rate (κ_j) of option j and the duration of stay (δ_i), which cannot exceed the raw demand (e_i^d). The charging price has a negative impact on the utility (C. Lu et al., 2023), and users exhibit individualized stochastic tendency ($\beta_i > 0$) of charging up to their raw demand. Thus, any requested charging amount below the raw demand results in a negative value in the utility function. The function, $f(\cdot)$, may take different forms, including linear, polynomial, or exponential, based on the difference between the requested energy and the raw demand.

Finally, each EV user chooses an option (a pair of price and charging rate) among the services offered by the EVCH and a virtual reference charging availability j', so that her utility is maximized. Note that users have various reference charging options based on their access to charging at home or other locations. For instance, users who have access to home-charging are more likely to decline services with high prices.

$$j^* = \arg\max_{j \in J} U_{ij} \tag{2}$$

3.3 Capacity-based dynamic pricing problem

Dynamic pricing for charging services presents a sequential stochastic problem. Each decision has an impact on the following system state and depends on the previous actions (prices) and the stochastic load demands, which are affected by the prices. We assume that the configuration of the EVCH including the number of charging stations, power capacity, and energy contracts are predetermined. EV users enter the parking facility at uncertain times of the day with stochastic demand preferences. Furthermore, renewable energy production constitutes an additional source of stochasticity. In addition to the pricing scheme, there are additional operational decisions, including power management of charging vehicles, which have an impact on the system. Because of the problem's high complexity, we formulate it as a Markov decision process (MDP) and employ approximate solutions to determine optimal pricing policies.

3.3.1 Markov decision process

The state at time t $s_t = \{t, EP, PT, PV, GC, AE, AP\}$ includes the time information t, the purchase price of electricity from the grid (EP), the current threshold for electricity peak (PT), the current generation of PV (PV), the current capacity of the power grid (GC), the current average energy (AD) and power demand (AP). Note that EVCH purchases electricity through a time-of-use contract from the grid. A peak charge is induced when electricity consumption exceeds the peak threshold in the electricity contract. The peak costs depend on the amount of power that exceeds the peak threshold. The facility is restricted by a certain grid capacity, and the total energy consumption, including EV charging and building load, cannot exceed that capacity. The operator can access all connected EVs information, including their unserved energy demand and departure time. Based on our model evaluation, we have determined that providing an approximation (average) of this information to the pricing agent is sufficient. The action consists of a vector of prices $a = (a_1, a_2, ..., a_J)$ for various charging powers. We discretize the action space to five price options by a fixed step size (e.g., $a_1 \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$). The reward function is fully aligned with our objective function and is formulated as the profit gained between two successive decision time steps (see Eq 3). The profit of choosing action a in state s is the revenue obtained from selling electricity to EVs, which is dependent on the published prices and user characteristics, minus grid costs, including the cost of purchasing electricity from the grid and additional peak charges (if applicable).

$$r(a,s) = \sum_i d_{ij^*} p_{j^*} - c_{grid}(s,a) \tag{3}$$

Finally, the objective function maximizes the cumulative reward over the operational period.

3.3.2 Solution: deep reinforcement learning algorithm

Estimating user behavior distributions is a costly and dynamic process, leaving pricing agents unaware of the environment's dynamics. To tackle this issue, we utilize model-free algorithms (Reinforcement Learning) that learn optimal policies through interaction with the environment. These algorithms do not require knowledge of the users' behavioral distribution or and other source of stochasticities. Additionally, due to the enormity of the state space in our problem, traditional tabular RL algorithms are insufficient to solve it. Thus, function approximation techniques are employed to generalize the state space and solve the problem for large-scale state and action spaces. Neural networks aid in estimating the action-value function for such immense problem settings. We employ a DDQN algorithm that utilizes a deep-dueling Q-network to determine optimal action-value states and policies through iteration. Please refer to the original study for a more detailed explanation of the algorithm (Z. Wang et al., 2016).

4 Numerical Experiments

We conduct various benchmark and sensitivity analyses to evaluate the benefits of incorporating capacity-based and dynamic pricing for EVCHs. We select a mixed-use facility with attached parking, for which we have access to both building load data and transaction-level parking and estimated charging demand. We consider a facility that has 200 parking spaces, with a minimum building load of 74kW and a maximum building load of 110kW. With 50% EV adoption rate, the facility is equipped with 40 single-plug and 20 double-plug DC fast chargers. Additionally, there are 80 square meters of installed PV and the maximum grid capacity power is 900 kW. Energy costs are calculated using electricity tariffs from California, the same region where the charging data was collected. Table 1 presents an overview of the tariff structure applied in all experiments. The default parameters entail a peak charge threshold of 500 kW, beyond which the EVCH operator must pay a fee for exceeding power usage at the end of each month.

Regarding the user price sensitivity characteristics,we use uniform random distributions to parameterize utility function of EV users. This is a common assumption in the literature as EV users have heterogeneous preferences for the prices of charging services with different charging speeds (Babic et al., 2022; Valogianni, Ketter, Collins, and Zhdanov, 2020). The base utility of users to charge in this EVCH (U_i) is uniformly generated between $[0, 1]$. The tendency (β) of users to charge up to their raw demand is heterogeneous among the users and randomly generate between $[0.8, 0.9]$. We also consider that EV users might have access to alternative charging stations with heterogeneous power and prices. We fixed the reference charging power ($c_{j'}$) to 11 kW but the reference price is varied among users and depends on the arrival time (A_i) and raw charging demand (e_i^d). The Equ 4 shows the reference price value generation in

	Summer (Jun - Sep)	**Winter** (all other months)
Super Off-Peak (8am-4pm)	0.08 USD/kWh	0.06 USD/kWh
On-Peak (4pm to 9pm)	0.23 USD/kWh	0.23 USD/kWh
Off-Peak (9pm-8am)	0.08 USD/kWh	0.08 USD/kWh
Peak Charge (monthly)	15.48 USD/kW	

Table 1. Time-of-use tariff for large-scale EV charging customers (> 500 kW).

the simulation. The base of the reference price ($p^0_{j'}$) is uniformly generated between $[0.8, 0.9]$. We include a negative time-dependent value ($\frac{A_i^{hourly}}{100}$) and a positive energy-dependent value ($\frac{e_i^d}{100}$) to the reference price ($p_{ij'}$) of user i for reference j'. We argue that the users that arrive earlier and have higher raw energy demand have access to reference charging with higher prices. Note that calibrating the parameters of users utility function is beyond the scope of this paper. Thanks to our proposed model-free deep reinforcement learning DSS, we can identify optimal power-based charging without relying on actual utility distribution. These assumptions only reflect the characteristics of a random user, and therefore do not generalize user behavior in the real world.

$$p_{ij'} = Max(p^0_{j'} - \frac{A_i^{hourly}}{100} + \frac{e_i^d}{100}, 0) \tag{4}$$

For finding the closest-to-optimal dynamic pricing policies, we use grid search to set the hyperparameters of our deep reinforcement learning algorithm. For the above-mentioned simulation the grid search leads to 10^{-4} learning rate with Adam optimizer, 64 batch size, and a neural network with 2 hidden layers of (256, 256) number of nodes. We exclude the replay buffer size and soft update parameter from the grid search and set them to 10^5, and 5^{-2} as suggested by the developers.

4.1 Results

We first benchmark our proposed model (dynamic multi-power pricing with 11, and 22 kW maximum power options) against 3 different pricing schemes: a) a dynamic single-power pricing model with 22 kW maximum power, b) a dynamic single-power pricing model with 11 kW maximum power, and c) a static multi-power pricing model. For the dynamic single-power models we use the same algorithm as our proposed model (deep RL). For the static multi-power benchmark policy we use a simple genetic algorithm to find the optimal fixed prices for different charging power (i.e., these prices are time-independent). As explained below, our proposed method can increase EVCH profits by 23% while simultaneously covering 39 % more charging demands. Figure 3 shows the benefits of our proposed model against the benchmark policies. We train the dynamic models for 1000 episodes (five working days) [4]. The learning agents converge after about 300 episodes for the single-power pricing model, and after 500 episodes for the multi-power case. Our proposed model significantly outperforms the benchmark policies as it leverages time-varying pricing and offers more power options to users that can deal with heterogeneous user characteristics. Among the benchmark policies, the static multi-power model outperforms the dynamic single-power models. Additionally, in this numerical setting, if the EVCH offers single-power services, it is more profitable to offer a 22 kW charging pricing model. Note that the model is compared with static single-power models, but they are excluded from Figure 3 as they cannot be better than other benchmark policies. Static single-power pricing models with 11 kW and 22 kW respectively result in average profits of $1763 and $2837 over the operation time.

[4] Since we use a genetic algorithm for the static multi-power pricing model, we show the trained agent for this pricing model in Figure 3.

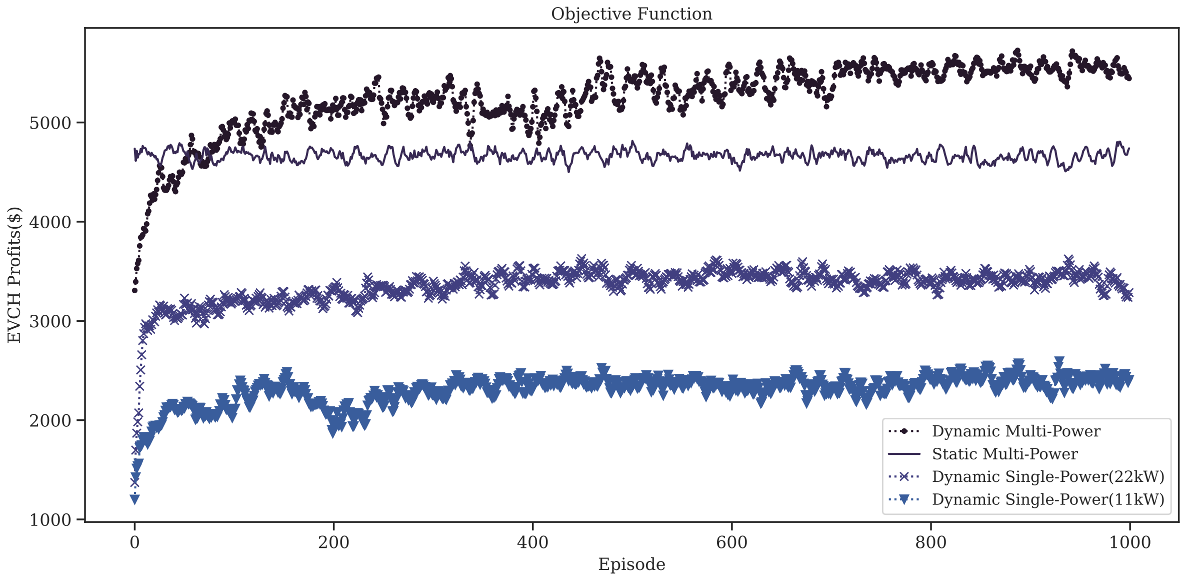

Figure 3. Benchmark evaluation of the proposed dynamic capacity-based pricing model.

After training, we run 50 episodes for using the trained pricing agents and report the results. Both multi-power pricing policies cover considerably higher charging demands, 31697 and 22578 kWh, respectively for dynamic and static models. This means that in addition to higher profitability, they serve more EV charging requests. We also see that using dynamic pricing has service quality advantages since with almost the same peak electricity consumption, the dynamic multi-power approach covers more demands. The single-power pricing policies perform not as good multi-power models since they cannot cover users heterogeneity. The single-power with maximum 22 kW pricing serves 19373 kW charging demand while this is reduced to 16347 hWh for the single-power pricing model with the maximum 11 kW power.

Our proposed model responds to different electricity contracts. In order to check if we can reshape the charging load of EVCHs using our pricing model we run the simulation for higher peak charge cost (doubles compared to the default setting). As you can see in Figure 4 the peak load considerably reduces when we double the peak charge cost. However, peak usage is still higher than the threshold (500 kw), meaning that even with high peak costs, it is still profitable to exceed the peak threshold.

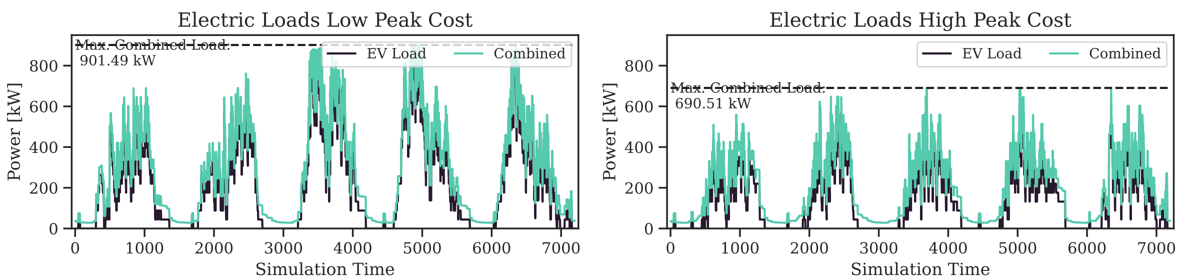

Figure 4. Electric load consumption for different peak load costs.

To show the importance of users price sensitivity level we train our proposed pricing agent for different values of charging to the maximum demand (β) and the reference charging price (p^0). The results are shown in Table 2. For instance, if the reference charging price (p^0) and the willingness to fully charge (β) are generated using a uniform distribution of $U(0.4, 0.5)$ and $U(0.6, 0.7)$, respectively, the EVCH profit is 3655\$. We vary these parameters from four different range of uniform distributions. As expected, both parameters have a positive effect on the objective function (total profits). It means that if users reference charging options are expensive, the EVCH can make more profits. Similarly, if users have more tendency to charge up to their maximum demand, they request higher charging demand even for relatively high charging prices. Another point is the non-linear relation of profitability to these parameters.

β/p^0	U(0.2, 0.3)	U(0.4, 0.5)	U(0.6, 0.7)	U(0.8, 0.9)
U(0.2, 0.3)	2615	2832	3042	4430
U(0.4, 0,5)	3252	3513	3747	4615
U(0.6, 0.7)	3449	3655	4184	5366
U(0.8, 0.9)	3976	4320	4783	5746

Table 2. Sensitivity analysis: EVCH profits for different user characteristics.

5 Discussion and Conclusion

In this paper, we present a Green IS artifact to improve the management of large-scale EVCHs through dynamic capacity-based pricing. Our goal is to promote sustainable mobility systems by providing EVCH operators with a DSS that aids in profitability and reduces stress on the power grid. To achieve this, we introduce a dynamic capacity-based pricing model that offers time-dependent rates for varying charging capacities. We consider varying user preferences and attributes, such as price sensitivity, reference charging options (e.g., home charging), and stochastic arrival time and energy demand. Our proposed pricing model increases the profitability of EVCHs by accounting for the stochasticity and heterogeneity of charging demands.

To determine nearly optimal pricing policies based on dynamic capacity, we solve a sequential stochastic decision problem. This problem is complicated by multiple sources of uncertainty, including user arrival times, their energy demand and price sensitivity, as well as PV energy production. The pricing decisions have temporal dependencies, as each decision impacts the charging demand at the next decision step and consequently affects the pricing decision. We define the problem as a Markov decision process. Since obtaining information regarding the dynamics of the environment is not practical (e.g., estimating the behavior of EV users is costly and fluctuates over time), we use a model-free approach (deep RL) to approximate the optimal pricing policies. Through interaction with the environment, these models learn the policies over multiple episodes. Therefore, we create a digital representation of the EVCH environment using agent-based modeling and calibrate the charging demand using real-world parking and charging observational data.

We find that the proposed approach outperforms benchmark policies (around 23% higher profits), including dynamic single-capacity pricing and static multi-capacity pricing models. This finding addresses a part of our research question, demonstrating that the proposed pricing model has a significant positive impact on the economic performance of EVCHs. Our model is capable of learning time-dependent factors, such as price sensitivity and grid costs, to optimize overall profits. Even users arriving at the same time may have different preferences, so a single service with dynamic pricing is insufficient to capture the full heterogeneity of users. The EVCH operators can enhance their profits by providing multiple capacity-based services. For instance, they can charge a relatively higher price for fast charging services which is suitable for customers with a low price sensitivity, while offering low power services at a fair price that caters to highly price-sensitive users. Additionally, due to the high grid costs during some periods, high prices for fast charging could avoid extreme peak loads. This is a major benefit for grid operators as the need for grid expansion reduces significantly. It is important to note that our proposed model only has positive environmental impacts if the energy providers have significant peak costs due to the profit maximization objective function. Our analysis indicates that the pricing model is sensitive to peak costs, and EVCHs could use it to reduce their environmental costs in the future.

To address the final part of our research question, we conduct a sensitivity analysis to determine the impact of user characteristics on the results. We show that EVCH profits are significantly affected by user characteristics such as the cost of their alternative charging options and their willingness to fully charge. Although accurate measurements of user behavior were not obtained in our research, our model-free approach eliminates the need for user input in real-world implementation and instead learns through environmental interactions. Therefore, the discussed assumption about user behavior serves only to analyze our model and offer managerial insights for EVCH and grid operators.

The literature supports our results, as related works have been found. Lin, Shang, and Sun (2023) show that dynamic pricing for fast public charging stations can improve profitability, which aligns with our finding that our approach outperforms static policies. Valogianni, Ketter, Collins, and Zhdanov (2020) demonstrate that dynamic pricing of EV charging services can control their adverse additional loads on the power grid. Similarly, our results demonstrate that our pricing scheme can reduce negative environmental effects by including peak costs in the objective function. Additionally, studies on menu-based pricing of charging services, such as Zeng et al. (2021), support our findings that offering multiple options to EV users can decrease the likelihood of service rejection and increase profits.

One challenge of deep RL models is the uncertainty of learned policies to be optimal. To validate such models, lower benchmarks such as naive or straightforward policies, which are static single-power pricing models in our problem, can be used. Our approach outperforms these lower boundaries. Another validation check is the comparison with a higher bound, which could be perfect information optimization in our case. Formulating a complex problem involving smart charging and limited charging capacity can be challenging. Additionally, pricing and operational decisions are highly dependent on this. The mathematical problem can become intractable due to the need for mixed integer programming and the size of the problem. In future works, we aim to create a perfect information model for a simple numerical example. Relating the learned policies to the objective function could increase the algorithm's explainability. However, due to the large number of factors influencing the learned policies, it is difficult to relate them to different elements of the state, such as time, demand, and energy price. Because RL explainability analysis is beyond the scope of this paper we just added some insights here. The pricing for faster charging services is consistently higher for learned policies, resulting in increased profits. While there may be some EV drivers with lower price elasticity who are more likely to accept cheaper services, the heterogeneity of users must be taken into account. Our validation tests demonstrate that our model can learn temporal patterns for the price elasticity of EV users and electricity costs, outperforming static policies by adjusting prices over time.

Our research is not without limitations. Methodologically, we decouple the load scheduling and pricing problems and treat them separately. In future works, there may be values in solving both scheduling and pricing jointly. To tackle the problem in discrete action spaces, we implemented value-based RL algorithms, but a continuous action space may exploit more user flexibility. In future research, we also aim to validate our assumptions of user price sensitivities through survey experiments. We expect that this will increase the robustness of our results.

References

Babic, J., A. Carvalho, W. Ketter, and V. Podobnik (May 2022). "A data-driven approach to managing electric vehicle charging infrastructure in parking lots." *Transportation Research Part D: Transport and Environment* 105, 103198. ISSN: 13619209.

Brocke, J. vom, R. T. Watson, C. Dwyer, S. Elliot, and N. Melville (2013). "Green Information Systems: Directives for the IS Discipline." *Communications of the Association for Information Systems* 33, 509–520. ISSN: 15293181.

Corbett, J. and S. Mellouli (2017). "Winning the SDG battle in cities: how an integrated information ecosystem can contribute to the achievement of the 2030 sustainable development goals." *Information Systems Journal* 27 (4), 427–461. ISSN: 13652575.

Cui, Y., Z. Hu, and X. Duan (2021). "Optimal pricing of public electric vehicle charging stations considering operations of coupled transportation and power systems." *IEEE Transactions on Smart Grid* 12 (4), 3278–3288.

Daina, N., A. Sivakumar, and J. W. Polak (2017). "Electric vehicle charging choices: Modelling and implications for smart charging services." *Transportation Research Part C: Emerging Technologies* 81, 36–56.

Dedrick, J. (2010). "Green IS: concepts and issues for information systems research." *Communications of the Association for Information Systems* 27 (1), 11.

Egbue, O. and S. Long (2012). "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions." *Energy policy* 48, 717–729.

Engel, H., R. Hensley, S. Knupfer, and S. Sahdev (2018). "Charging ahead: Electric-vehicle infrastructure demand." *McKinsey Center for Future Mobility* 8.

Ferguson, B., V. Nagaraj, E. C. Kara, and M. Alizadeh (2018). "Optimal Planning of Workplace Electric Vehicle Charging Infrastructure with Smart Charging Opportunities." *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC* 2018-Novem, 1149–1154.

Fridgen, G., L. Häfner, C. König, and T. Sachs (2016). "Providing utility to utilities: the value of information systems enabled flexibility in electricity consumption." *Journal of the Association for Information Systems* 17 (8), 1.

Gust, G., T. Brandt, S. Mashayekh, M. Heleno, N. DeForest, M. Stadler, and D. Neumann (2021). "Strategies for microgrid operation under real-world conditions." *European Journal of Operational Research* 292 (1), 339–352. ISSN: 03772217.

Haki, K., J. Beese, S. Aier, and R. Winter (2020). "The Evolution of Information Systems Architecture: An Agent-Based Simulation Model." *MIS Quarterly* 44 (1).

Hevner, A. R. and S. Gregor (2013). "Positioning and Presenting Design Science Research for Maximum Impact." *MIS Quarterly* 37 (2), 337–355. ISSN: 02767783. arXiv: z0022.

Hou, L., C. Wang, and J. Yan (2019). "Bidding for preferred timing: An auction design for electric vehicle charging station scheduling." *IEEE Transactions on Intelligent Transportation Systems* 21 (8), 3332–3343.

Huang, Y. and Y. Zhou (2015). "An optimization framework for workplace charging strategies." *Transportation Research Part C: Emerging Technologies* 52, 144–155. ISSN: 0968090X.

Jenkin, T. A., J. Webster, and L. McShane (2011). "An agenda for 'Green' information technology and systems research." *Information and organization* 21 (1), 17–40.

Ketter, W., K. Schroer, and K. Valogianni (2023). "Information systems research for smart sustainable mobility: A framework and call for action." *Information Systems Research* 34 (3), 1045–1065.

Lee, S. and D.-H. Choi (2021). "Dynamic pricing and energy management for profit maximization in multiple smart electric vehicle charging stations: A privacy-preserving deep reinforcement learning approach." *Applied Energy* 304, 117754.

Lee, Z. J., D. Chang, C. Jin, G. S. Lee, R. Lee, T. Lee, and S. H. Low (2018). "Large-scale adaptive electric vehicle charging." *2018 IEEE Global Conference on Signal and Information Processing, GlobalSIP 2018 - Proceedings*, 863–864.

Lee, Z. J., T. Li, and S. H. Low (2019). "ACN-Data: Analysis and applications of an open EV charging dataset." *e-Energy 2019 - Proceedings of the 10th ACM International Conference on Future Energy Systems*, 139–149.

Lin, C.-A., K. Shang, and P. Sun (2023). "Wait time–based pricing for queues with customer-chosen service times." *Management Science* 69 (4), 2127–2146.

Lu, C., J. Wu, J. Cui, Y. Xu, C. Wu, and M. C. Gonzalez (Jan. 2023). "Deadline Differentiated Dynamic EV Charging Price Menu Design." *IEEE Transactions on Smart Grid* 14 (1), 502–516 (1). ISSN: 19493061.

Lu, M., Z. Chen, and S. Shen (May 2018). “Optimizing the Profitability and Quality of Service in Carshare Systems Under Demand Uncertainty.” en. *Manufacturing & Service Operations Management* 20 (2), 162–180.

Luo, C., Y.-F. Huang, and V. Gupta (2017). “Stochastic dynamic pricing for EV charging stations with renewable integration and energy storage.” *IEEE Transactions on Smart Grid* 9 (2), 1494–1505.

Mao, T., W.-h. Lau, C. Shum, H. S.-H. Chung, K.-F. Tsang, and N. C.-F. Tse (2017). “A regulation policy of EV discharging price for demand scheduling.” *IEEE Transactions on Power Systems* 33 (2), 1275–1288.

Melville, N. P. (2010). “Information Systems Innovation for Environmental Sustainability.” *MIS Quarterly* 34 (1), 1–21.

Moradipari, A. and M. Alizadeh (2019). “Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network.” *IEEE Transactions on smart grid* 11 (2), 1489–1499.

Mukherjee, J. C. and A. Gupta (2015). “A Review of Charge Scheduling of Electric Vehicles in Smart Grid.” *IEEE Systems Journal* 9 (4), 1541–1553. ISSN: 19379234.

Nanaki, E. A. and C. J. Koroneos (2016). “Climate change mitigation and deployment of electric vehicles in urban areas.” *Renewable energy* 99, 1153–1160.

Nunes, P., R. Figueiredo, and M. C. Brito (2016). “The use of parking lots to solar-charge electric vehicles.” *Renewable and Sustainable Energy Reviews* 66, 679–693. ISSN: 18790690.

Pal, P., P. Gopal, and M. Ramkumar (2023). “Impact of transportation on climate change: An ecological modernization theoretical perspective.” *Transport Policy* 130, 167–183.

Rai, A. (2017). “Diversity of Design Science Research.” *MIS Quarterly* 41 (1), iii–xviii.

Sarker, S., S. Chatterjee, X. Xiao, and A. Elbanna (2019). “The sociotechnical axis of cohesion for the IS discipline: Its historical legacy and its continued relevance.” *MIS quarterly* 43 (3), 695–720.

Seidel, S., J. Recker, and J. vom Brocke (2013). “Sensemaking and Sustainable Practicing: Functional Affordances of Information Systems in Green Transformations.” *MIS Quarterly* 37 (4), 1275–1299. ISSN: 02767783.

Soares, J., M. A. F. Ghazvini, N. Borges, and Z. Vale (2017). “Dynamic electricity pricing for electric vehicles using stochastic programming.” *Energy* 122, 111–127.

Valogianni, K., W. Ketter, and J. Collins (2015). “A multiagent approach to variable-rate electric vehicle charging coordination.” In: *Proceedings of the 2015 international conference on autonomous agents and multiagent systems*, pp. 1131–1139.

Valogianni, K., W. Ketter, J. Collins, and G. Adomavicius (2019). “Heterogeneous electric vehicle charging coordination: A variable charging speed approach.” *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 756–773.

Valogianni, K., W. Ketter, J. Collins, and D. Zhdanov (2020). “Sustainable Electric Vehicle Charging using Adaptive Pricing.” *Production and Operations Management* 29 (6), 1550–1572. ISSN: 19375956.

Wang, Z., T. Schaul, M. Hessel, H. Hasselt, M. Lanctot, and N. Freitas (2016). “Dueling network architectures for deep reinforcement learning.” In: *International conference on machine learning*. PMLR, pp. 1995–2003.

Watson, R. T., M.-C. Boudreau, and A. J. Chen (2010). “Information Systems and Environmentally Sustainable Development: Energy Informatics and New Directions for the IS Community.” *MIS Quarterly* 24 (4), 665–694. ISSN: 02767783.

Yang, M., L. Zhang, Z. Zhao, and L. Wang (2021). “Comprehensive benefits analysis of electric vehicle charging station integrated photovoltaic and energy storage.” *Journal of Cleaner Production* 302, 126967.

Zanvettor, G. G., M. Casini, R. S. Smith, and A. Vicino (2022). “Stochastic energy pricing of an electric vehicle parking lot.” *IEEE Transactions on smart grid* 13 (4), 3069–3081.

Zeng, T., S. Bae, B. Travacca, and S. Moura (2021). “Inducing human behavior to maximize operation performance at PEV charging station.” *IEEE Transactions on Smart Grid* 12 (4), 3353–3363.