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Charging Pricing Strategy of Fast Charging Station Considering Electric Vehicle Charging Right Trading Mechanism

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ABSTRACT

The zero-carbonization trend has accelerated the popularity of EVs due to their low-carbon emissions and energy-efficiency advantages. FCS act as both charging service operator and load aggregator. They need to benefit from providing charging service to electric vehicle users while also coordinating the charging power of EVs to prevent overloading. This paper proposes a novel approach that integrates charging right trading and charging pricing using reinforcement learning algorithms. The proposed framework takes into account the influence of charging right prices on charging demand of EV users. It employs a reinforcement learning algorithm to learn the optimal charging pricing strategy and EV charging schedule for FCS, with the aim of maximizing the benefit of FCS. Numerical experiments are conducted to demonstrate the effectiveness of the proposed method.

Keywords: Charging right, Electric vehicle (EV), Fast charging station (FCS), Pricing strategy

NONMENCLATURE

Abbreviations	
EV	Electric Vehicle
FCS	Fast Charging Station
CR	Charging Right
CRM	Charging Right Trading Mechanism
RL	Reinforcement Learning
Symbols	
Ω_t	The set of EVs waiting to be charged in the FCS at time *t*
I_t	The set of EVs arriving at the FCS at time *t*
Φ_t	The set of EVs that are already at the station at time *t*.
d_i	Charging demand of the *i* th EV
φ_t^{cs}	Charging price at time *t*
φ_t^{cr}	Charging right price at time *t*
φ_t^{e}	Electricity price at time *t*
p_{it}	Charging power of the *i* th EV at time t

1. INTRODUCTION

In the context of carbon neutrality, EVs are playing a crucial role in the global transportation system. The number of EVs is increasing dramatically worldwide, leading to a growing demand for EV charging. In China, it is estimated that by 2030, about 80% of EVs will be charged at public charging stations, where fast charging will play an important role. Fast charging stations are critical infrastructure for emergency EV charging and will be rapidly developed to meet the increasing demand. However, fast charging behavior is characterized by short charging cycles and high charging power, which can threaten the safety of the distribution network and lead to a loss of social welfare if not properly coordinated. The limited number of charging piles and the sharp increase in EVs will exacerbate the charging coordination problem for fast charging stations and pose challenges to charging management.

Under an appropriate demand response mechanism, EVs can adjust their charging demand based on the charging prices announced by FCS or utility companies. With the application of more reliable and privacy-protecting technologies, such as blockchain, EVs can access the real-time status of the FCS, which enables the real-time model to match the actual situation. From the perspective of the FCS, effective pricing and scheduling policies are needed to ensure their revenue while

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enhancing the charging experience of EV users. Previous studies [3-6] have examined EV charging scheduling and FCS optimal pricing problems from different perspectives but did not consider the variation of EV users' charging demand with price and relied on accurate EV charging forecasts. Reinforcement learning algorithms have been successfully applied to various EV scheduling problems, allowing for real-time stochastic and dynamic problems to be addressed without the need to understand the system model or technical parameters [7-11].

In contrast to existing studies, we investigate the impact of CRM on charging demand of EV users, as well as the optimal pricing and charging scheduling strategy for FCS under random EV arrival and departure. We formulate this problem as a Markov decision process. To address the challenge of time-varying state space and action space due to the random arrival and departure of EVs, we propose a model-free and on-policy RL algorithm. We verify the effectiveness of the proposed algorithm through simulation.

The remainder of this paper is organized as follows: Section II introduces the CRM and the FCS optimization model. Section III presents the Markov decision process and the improved SARSA algorithm. In Section IV, we present a case study. Finally, Section V concludes the paper and discusses future work.

2. MODEL FORMULATION

2.1 Charging right trading mechanism

To enhance the user charging experience and service guarantee capability of EV charging infrastructure in urban public fast charging systems, it is essential to accelerate the innovation of related technologies, models, and mechanisms. Literature [12] proposes a new charging right trading mechanism (shown in Fig. 1), which effectively reduces EV charging waiting time and alleviates congestion.

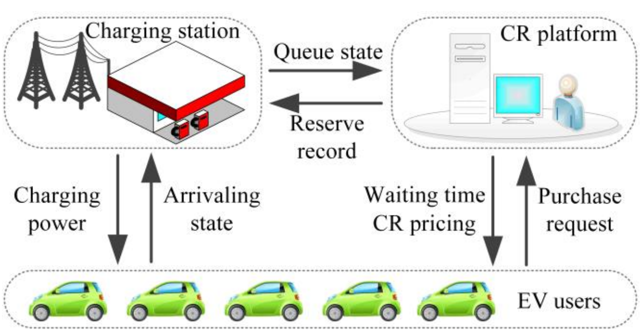

Fig. 1. Structure of CRM

In this mechanism, EV users can access the Internet to obtain estimated waiting times and charging prices, decide when and where to charge, and book or request to purchase charging rights on the CR platform. Prior to the introduction of the CRM, EVs charged at a certain power and paid a charging fee to the FCS based on the charging price and their own charging needs once they arrived at the FCS. However, some EV users may alter their charging demands and FCS choices due to excessively high charging right prices, assuming that these FCSs belong to different charging network operators or are independently priced. This makes it necessary for FCSs to set more reasonable charging prices and powers to safeguard their own interests.

2.2 FCS optimization model

When an EV arrives at a FCS, it submits a charging request to the energy management system of FCS, which includes the parking duration and charging requirements. Subsequently, the FCS needs to promptly respond by determining whether to accept the request and incorporate it into the charging schedule (assuming the charging capacity is sufficient; this paper does not consider cases where the FCS has to reject newly arrived vehicles due to full occupancy). Simultaneously, the FCS must establish charging prices for all EVs arriving at time t. These charging prices vary for EVs arriving at different times and remain constant throughout the charging process. It is assumed that EV users automatically accept the prevailing charging price upon entering the FCS. In practice, if the charging price at the current FCS is excessively high, price-sensitive EV users may opt for alternative FCSs, resulting in zero charging demand at that time. Taking into account the influence of both CR price and charging price, the EV charging demand can be described by the following equation:

$$d_i = \alpha_1(\varphi_t^{cs} + \varphi_t^{cr}) + \alpha_2 \tag{1}$$

where d_i is the charging demand of the i th EV; φ_t^{cs} and φ_t^{cr} is the charging price and CR price at moment t, respectively; and α_1 and α_2 denote the price elasticity coefficients of the EV charging demand.

At time t, the FCS engages in the charging process for EVs and compensates the electric utility for the consumed electricity. However, due to the uncertainty surrounding EV arrivals and electricity prices, the FCS is only aware of the EV charging requests that have already arrived, as well as the historical and current electricity prices. The scheduling problem for the FCS can be formulated as an optimization problem with the objective of maximizing FCS profit while adhering to operational constraints.

$$\max R_t = \sum_{i \in \mathrm{I}_t} \varphi_t^{cs} d_i - \varphi_t^{e} \sum_{i \in \Omega_t} p_{it} \tag{2}$$

$$p_{it} \le p^{\max}, i \in \Omega_t, t \in \mathrm{T} \quad (3)$$

$$\sum_{i \in \Omega_t} p_{it} \le e^{\max}, t \in \mathrm{T} \quad (4)$$

$$\sum_{t=t_i^a}^{t_i^d} p_{it} \ge d_i, i \in \Omega_t \quad (5)$$

where R_t is the profit of the FCS at time t. φ_t^e is electricity price at time t. I_t is the set of EVs arriving at the FCS at time t. Ω_t is the set of EVs waiting to be charged at the FCS at time t. T is the set of FCS dispatching times. p_{it} is the charging power of the *i* th EV at time t. $p^{\max}$ is the maximum charging power of the EV. $e^{\max}$ is the maximum charging capacity of the FCS. And t_i^a and t_i^d denote the arrival time and the departure time of the *i* th EV respectively.

3. METHODOLOGY

3.1 Markov decision process

In this section, the FCS decision-making process is formulated as an Markov decision process (MDP) model. When the EV arrives at the FCS, it will be connected to the charging post, and the FCS can get the information of EV's charging demand and departure time through the charging post, and at the same time, the FCS can get the real-time electricity price through the Internet. The FCS is regarded as an intelligence that coordinates the charging power of the EV and the charging price. The MDP model consists of the states, actions, rewards, and transition functions, which are defined as follows.

(1) State: the system state at time *t* includes the set of EVs already at the station, the remaining charging demand of EVs already at the station, and the departure time of EVs already at the station.

$$S_t = (\Phi_t, d_i \,|\forall i \in \Phi_t, t_i^d \,|\forall i \in \Phi_t) \quad (6)$$

where Φ_t is the set of EVs that are already at the station at time *t*.

(2) Action: the decision of the agent FCS is the charging price and EV charging power at time *t*, and the action space is described as a high-dimensional vector.

$$A_t = (\varphi_t^{cs}, p_{it} \,|\forall i \in \Omega_t) \quad (7)$$

Because the monolithic EV decision makes the dimension of the action space too high and difficult to solve, the problem is changed from the original monolithic EV charging power optimization to the aggregated EV charging power optimization, so as to cut down the action space, and the dimensionality of the action space is reduced from $|\Omega_t| + 1$ dimensions to two dimensions after the cut.

$$A_t = (\varphi_t^{cs}, e_t) \quad (8)$$

where, $e_t = \sum_{i \in \Omega_t} p_{it}$ is the total charging power of the EV to be charged at time *t*.

(3) Reward function: the design of the reward function is closely related to the goal of FCS, then the reward function at time *t* can be calculated by equation (2).

(4) Transfer function: the new state of the environment is affected by the arrival and departure of the EV, and the state transfer function at the moment *t*+1 as follow:

$$S_{t+1} = (\Phi_{t+1}, d_i \,|\forall i \in \Phi_{t+1}, t_i^d \,|\forall i \in \Phi_{t+1}) \quad (8)$$

where Φ_{t+1} is the set of EVs that are already on station at the time *t*+1.

3.2 SARSA algorithm

State-Action-Reward-State-Action(SARSA) algorithm is an on-policy reinforcement learning algorithm based on a state-action value function, whose basic idea is to find the optimal policy by continuously learning a state-action value function through interaction with the environment. At each time step, it selects an action and executes it based on the current state and the state-action value function, and then updates the state-action value function based on the feedback from the environment and the next state. This process iterates until it converges to the optimal state-action value function and policy. However, since the dimension of the state space keeps changing with the random arrivals and departures of EVs and is proportional to the number of EVs already at the station, for this reason, a SARSA algorithm that approximates the original state-action value function by a linear combination of multiple eigenfunctions is proposed. The feature functions are described in detail in [13] and will not be repeated in this paper.

4. NUMERICAL EXPERIMEN

In this section, numerical simulations are performed to verify the validity of the proposed model and methodology. All calculations were performed in Python on a computer with an Intel Core i7-10400 2.90 GHz CPU and 16 GB of RAM.

The simulations were based on hourly historical data, including the California ISO's open-source San Francisco day-ahead electricity prices and the number of vehicle arrivals (total number of vehicles passing through) at the Richards Avenue station near downtown Davis. The time span of the electricity price dataset is from January 1, 2017 to June 30, 2017, and the time period length is one hour, as shown in Fig. 2. The time span of the vehicle dataset was from October 1, 2016 to October 12, 2016, with a time period length of 30 seconds, and the number of EVs entering the CS was modeled using the scaled number of arrivals, which were categorized into three types: emergent, normal, and residual, as shown in Fig.3.

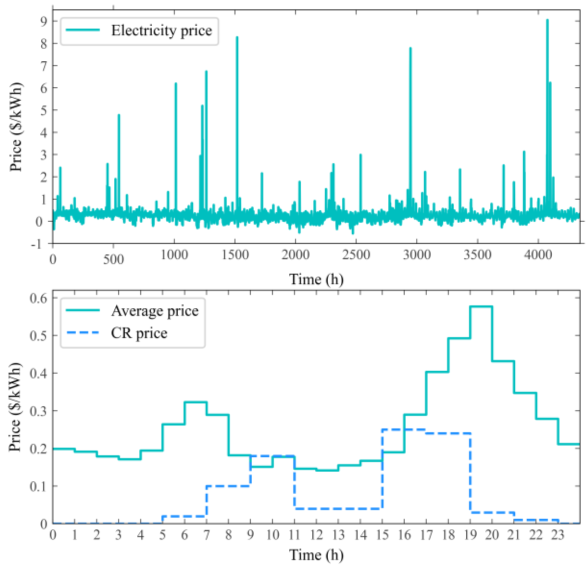

Fig. 2. Electricity price data

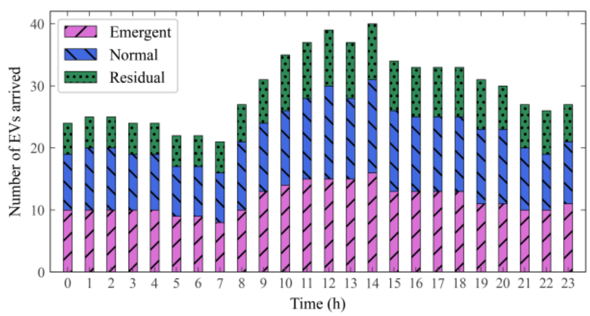

Fig. 3. Average number of arrivals per hour for different types of EVs

During the training process, we test and evaluate the strategy periodically. Fig. 4 shows the performance curve of the algorithm, and it can be seen that the proposed algorithm has good convergence and gradually reaches a stable state as the number of iterations increases.

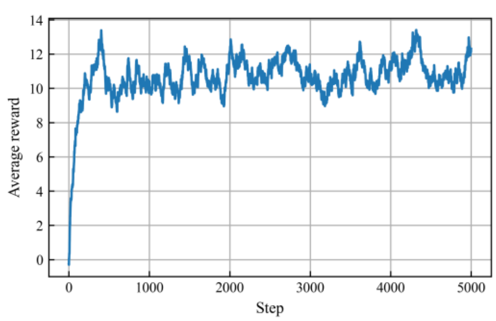

Fig. 4. Algorithm performance curve

5. CONCLUSIONS

In this paper, considering the impact of the charging right trading mechanism on EV users' charging demand, an optimization model of FCS pricing and scheduling strategy is constructed with the objective of maximizing the profit of FCS. Then, a model-free reinforcement learning algorithm is proposed to solve the MDP problem, which approximates the state-value function using linear weighting of the eigenfunctions to further improve the solution efficiency of the proposed algorithm, and the effectiveness of the proposed algorithm is verified by simulation with real data. In future work, charging network operators with multiple FCSs and queuing models are considered to further enrich the model, while attempting to use a more stable deep reinforcement learning algorithm to solve the problem.

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