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Intelligent Charging and Discharging Scheduling in Multistorey Car Park with Wireless Electric Vehicle Network

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Abstract

Multistorey car park outfitted with wireless charging infrastructures can offer space-efficient and charging-convenient solutions for electric vehicles (EVs) in urban areas. Serving as energy storages, numerous EVs parked for long periods hold substantial potential to alleviate transformer load stresses and yield considerable profits for drivers. To effectively realize dual benefits, this paper investigates the EV (dis)charging scheduling problem, aiming at maximizing the driver's profit while guaranteeing sufficient battery's state of charge upon departure, and avoiding transformer overloading. A multi-agent reinforcement learning method is utilized based on an actor-critic framework. Also, a revised centralized training and decentralized execution is designed based on a simple statistic global observation, which is able to address the time-variable number of agents problem. The computational simulation is conducted to verify the feasibility of the proposed algorithm.

Keywords: Electric vehicles, multistorey car parks, (dis)charging scheduling, reinforcement learning

1 INTRODUCTION

Electric vehicles (EVs) have been garnering widespread research attention due to their environmentally friendly advantages [1-4]. Over 20 countries have established broader and more ambitious policies to foster the growth of the electric vehicle (EV) industry. In order to align with the International Energy Agency's sustainable development scenario, it is necessary to have 230 million EVs on the road by 2030 [5]. However, in the urban area, the land is limited and expensive, which poses nonnegligible challenges to support EV batteries with adequate charging infrastructures. Comparing with conventional charging station parking lot, multistorey car parks offer compact and space-efficient solutions with the multi-layer structure [6].

Also, recently, the concept, wireless electric vehicle network (WEVN) is developed, where energy exchanging is achieved by wireless transfer technology, and information loading is supported through vehicular communication technologies [7-9]. WEVN makes multistorey car park a smart energy building which intelligently utilize the long-duration parking EVs, achieving goals such as peak load shaving, frequency regulation, renewable energy consumption, and energy trading profitability [10-14]. It also provides EV owners with a more convenient, flexible, and safe environment [15]. To achieve above benefits, charging and discharging scheduling is of great importance. On the one hand, the peak load issues might be exacerbated by the uncoordinated high EV popularization, thereby potentially threatening the local transformers, and even shortening their lifespan. On the other hand, as electricity price fluctuate over time, the long parking duration offers EV owners ample opportunities for earning profit by exploiting the difference between buying and selling.

There are extensive model-based studies with the topic of EV charging coordination, and a variety of optimization algorithms are applied, including linear programming, stochastic programming, evolution approaches [16-18]. Usually, the objectives are developed from drivers and operators' perspectives. From the EV owners' stand point, researchers emphasize on maximizing trading profit, reducing energy cost, and keeping healthy state of charging (SoC). From view of grid operator, studies mainly concern about minimizing power loss, decreasing load variance, and avoiding transformer overload [19]. However, the aforementioned researches require accurate model with uncertainties, which is difficult to obtain.

In recent years, the model-free approach, reinforcement learning (RL) techniques have been widely utilized in optimizing sequential decision problems, which learns the optimal strategy directly without requiring prior knowledge of the dynamic environment [20, 21]. The single-agent RL methods have demonstrated their success in charging coordination for individual EV [19]. Nevertheless, when involving a large number of EVs, their utilization is limited, since the action and state spaces will be expanded dramatically. To tackle these complexity and scalability problems, based on space decomposition, multi-agent ML is introduced. During the training process, multiple agents are learning concurrently. Consequently, the next state is determined by the joint actions of all agents, making the non-stationary environment. One setting commonly used is centralized training and decentralized execution (CTDE) framework. It is assumed that the centralized critic is able to access the complete observations and actions of all agents, and then evaluate the action value, updating the agent by the local information in a decentralized manner. However, it is not applicable in the practical scenario where the number of agents is time variable. In the context of multistorey car park, it is evident that parking EVs vary over time. If the input dimension of the critic is fixed as a concatenation of the observations of all agents, then it would not be capable of handling situation with an unfixed number of agents.

Motivated by the above discussions, the contributions are:

- A multi-agent RL-based approach is formulated for the EV (dis)charging scheduling in the multistorey car park with wireless EV network. The randomness of the EVs' arrival, departure time, and initial SoC are modeled by probability distributions. Different from the works formulate the optimization from single perspective, multiple factors are considered in our model, including minimizing the electricity cost, maximizing the trading profit, reducing the battery degradation, maintaining expected healthy SoC and preventing transformer overload.
- Develop a simple revised CTDE framework, which can be used when the number of agents changes. Instead of simply concatenating all observations as the existing literatures, the states' statistical values, such as mean and variance values, are regarded as input for the critic network, therefore it can be used when the number of agents is changed. The effective of the model is validated in the simulation experiments.

2 THE PROPOSED SYSTEM MODEL

2.1 Overview of the proposed model

The framework of the proposed model in shown in Figure 1. There are N EVs in the multistorey car parks which require intelligent agent for (dis)charging recommendation. According to the driver's preference, our system mainly consists of two types of agents: charging and trading agents. Charging agents serve EV owners who are unwilling to discharge their battery. These drivers wish charging their batteries economically and ensuring a satisfactory SoC level upon departure. Trading agents are designed for EVs which are willing to engage in energy trading. They are able to make profit by selling electricity while the electricity price is relatively high. Also, it can be noticed that in the system each EV is assigned with an agent, and the actor-critic architecture is employed. The input of actor network is the individual's local observation, while the input of critic is the designed global observation, which is elaborated in the subsequent part. Multiple agents learn their policies and decide their actions, thereby influencing the environment.

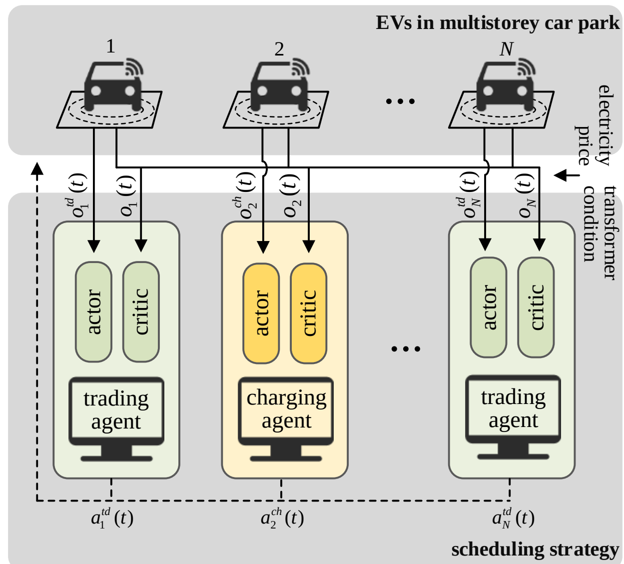

Figure 1. Framework of the proposed model

2.2 Problem Formulation

A) The Markov Decision Process

The (dis)charging scheduling in the time horizon $\mathcal{T}$={1, 2, …, T} can be formulated as Markov decision process, which can be represented as <$\mathcal{N}$, $\mathcal{S}$, $\mathcal{A}_1$, $\mathcal{A}_2$, …, $\mathcal{A}_N$, $\mathcal{P}$, $\mathcal{R}_1$, $\mathcal{R}_2$, …, $\mathcal{R}_N$>. The number of agents is $\mathcal{N}$ = {1, 2, …, N} with the actions of $\mathcal{A}_1$, $\mathcal{A}_2$, …, $\mathcal{A}_N$; the transition function is $\mathcal{P}$; the rewards of each agent are $\mathcal{R}_1$, $\mathcal{R}_2$, …, $\mathcal{R}_N$. A trajectory can be presented as the sequence of states, actions, and rewards: s_1, a_1, $r1$, s_2, a_2, r_2, … Specially, in the RL algorithm, the state transition function is not required for the highly-coupled environment.

B) RL Formulation

There are two types of agents: charging agent ch_n and trading agent tr_n. They share same observation and reward. In this paper, and the detailed formulation will be explained in this part.

- *Observation*: The local observation $o_n(t)$ of n-th EV at time t is defined as: $o_n(t) = (\lambda(t\text{-}23), \ldots, \lambda(t), \gamma(t\text{-}23), \ldots, \gamma(t), t_n^{dur}, c_n(t), soc_n(t), \Delta soc_n^{exp}(t), \Delta soc_n^{min}(t), \Delta\lambda_n^{exp}(t))$. $(\lambda(t\text{-}23),\ldots, \lambda(t))$ and $(\gamma(t\text{-}23),\ldots, \gamma(t))$ represent the electricity price and non-

EV load during past 24 hours; t_i^{dur} denotes the parking duration, which is updated with time; $c_n^b(t)$ is the capacity of battery; $soc_n(t)$ is the SoC; $\Delta soc_n^{exp}(t)$, $\Delta soc_n^{min}(t)$, and $\Delta\lambda_n^{exp}(t)$ are defined by (1)-(3), where soc_n^{exp}, soc_n^{min}, and λ_n^{exp} are the expected SoC, minimal acceptable SoC, and expected electricity price based on drivers personal preference.

$$\Delta soc_n^{exp}(t) = soc_n^{\exp} - soc_n(t) \tag{1}$$

$$\Delta soc_n^{min}(t) = soc_n(t) - soc_n^{min} \tag{2}$$

$$\Delta\lambda_n^{exp}(t) = \lambda(t) - \lambda_n^{\exp} \tag{3}$$

- *Action*: The action $a_n(t)$ denotes the charging power, and it is different for ch_n and tr_n. For agent ch_n, only charging is allowed, so the action ranges from $[0, p_n^{max}]$, where p_n^{max} is the maximum power. For agent tr_n, charging and discharging behavior are considered, hence the continuous action is from $[-p_n^{max}, p_n^{max}]$. Positive and negative values indicate charging and discharging, respectively. When there is no action, $a_n(t)=0$.
- *Reward*: In this article, there are multiples objectives: minimizing the charging expenses, reducing the battery degradation costs, maintaining expected SoC level when departure, and avoiding transformer overloading.

First is the charging expense reward, which is calculated by (4), where $\lambda(t)$ is the current price at t; Δt^{slot} is the length of time slot. When $a_n(t)>0$, the reward is positive only when current electricity price is lower than the expected price, since drivers charge their battery with a relatively lower cost. When $a_n(t)<0$, the reward is positive when electricity price is higher, meaning drivers sell their energy with a relatively higher price.

$$r_n^{elec,tr}(t) = \left(\lambda_n^{exp} - \lambda(t)\right) a_n(t) \Delta t^{slot} \tag{4}$$

Second is the degradation cost reward. The degradation loss in battery capacity resulting from SoC changes is described by (5), where k_w is the degradation coefficient. Then, the capacity in next time slot t+1 can be updated by (6). The degradation cost is calculated by (7), where $cost_n$ is the battery cost; $c_n^b(0)$ is the initial capacity; th^{life} is the threshold of battery life cycle.

$$\Delta e_n(t) \cong k_w c_n^b(t) \left| soc_n(t) - soc_n(t-1) \right| \tag{5}$$

$$c_n^b(t+1) = c_n^b(t) - \Delta e_n(t) \tag{6}$$

$$r_n^{de}(t) = -\Delta e_n(t) cost_n \big/ th^{life} c_n^b(0) \tag{7}$$

Third is the SoC satisfaction reward. Driver is required to upload SoC preference soc_n^{exp} and soc_n^{min} to the agents. It is formulated as the piecewise function as (8).

$$r_n^{soc}(t) = \begin{cases} 0 & \text{if } soc_n(t) \geq soc_n^{exp} \\ -\left(soc_n^{exp} - soc_n(t)\right) & \text{if } soc_n^{\min} < soc_n(t) < soc_n^{exp} \\ -1 & \text{if } soc_n(t) \leq soc_n^{min} \end{cases} \tag{8}$$

The transformer-related reward should be considered after obtaining the actions from all agents. The remaining load capacity of the local transformer can be calculated by subtracting the non-EV $l^{nonev}(t)$ and EV load from the transformer's capacity c^{tran} by (9). The reward can be express as (10). If the overall load exceeds the range allowed by the transformer, a negative penalty is calculated proportionally to the demand with charging behavior. Likewise, for discharging, a positive reward is given.

$$l^{remain}(t) = c^{tran} - l^{nonev}(t) - \sum_n^N a_n(t) \Delta t^{slot} \tag{9}$$

$$r_n^{trans}(t) = \begin{cases} 0 & \text{if } l_n^{remain}(t) \geq 0 \\ a_n(t) \Delta t^{slot} \big/ l^{remain}(t) & o.w. \end{cases} \tag{10}$$

Finally, the comprehensive reward for n-th EV at t can be formulated, where w_n^{buy}, w_n^{de}, w_n^{soc}, and w_n^{trans} are positive weights.

$$r_n(t) = w_n^{buy} r_n^{buy}(t) + w_n^{de} r_n^{de}(t) + w_n^{soc} r_n^{soc}(t) + w_n^{trans} r_n^{trans}(t) \tag{11}$$

2.3 Multi-agent RL Algorithm

Deep deterministic policy gradient (DDPG) algorithm is utilized in our paper as it is designed to address the challenges of learning in continuous action spaces. There are actor and critic networks in the algorithm. The actor learns from observation and updates the policy to make action. The critic network makes the value evaluation for the action assessment by considering long-term rewards. For actor network $\mu(o|\theta^{\mu})$, the objective is maximizing the scores by critic network by (12). The goal of critic network $Q(o,a|\theta^{Q})$ is to minimize the loss based on the Bellman equation as (13)-(14), where o is the observation/state; a is the action; o' means next state; subscript t indicates target network; γ is the discount factor.

$$J(\theta^{\mu}) = E\left[Q(o, \mu(o \mid \theta^{\mu}) \mid \theta^{Q}) \right] \tag{12}$$

$$y = r + \gamma Q_t\left(o', \mu_t\left(o' \mid \theta^{\mu_t}\right) \mid \theta^{Q_t}\right) \tag{13}$$

$$L(\theta^{Q}) = E\left[y - Q(o, a \mid \theta^{Q})^2 \right] \tag{14}$$

To expand single-agent DDPG to the multi-agent system, centralized training and decentralized execution (CTDE) paradigm is widely applied to deal with the non-stationary issue. The benefits of both centralized and decentralized methods are combined in this framework to leverage complete information during training while ensuring a private and scalable execution. In the centralized training, the central critic is accessible to the global observations of the environment, which allows the optimization considering the interactions among multiple agents and their collective impact on the dynamic environment. In the decentralized execution, each agent makes their own decisions based on their local observation by the actor policy.

A common way to implement centralized training is concatenating the local observation of all agents to form the global information. However, there are several issues are presented: (1) It is only applicable when the number of agents if fixed. In the parking building, the number of agents varies over time as the randomness in drivers' behavior, so this approach cannot be used directly. (2) Naïve concatenation brings redundant information. For instance, the electricity price and residential load at t remains the same for all agents.

Therefore, in response to these considerations, this paper designs a simple global observation based on statistic values for critic network. According to the designed states, the following features in (15) are different among individual agents. Therefore, for the n-th agent, the comprehensive input for critic includes its own local observation, as well as statistical measures of features specified in (15), which excludes those of their own value.

$$o_{\bar{n}}(t) = \{c_{\bar{n}}(t), soc_{\bar{n}}(t), soc_{\bar{n}}^{\exp}, soc_{\bar{n}}^{\min}, \lambda_{\bar{n}}^{\exp}, t_{\bar{n}}^{dur} \mid \bar{n} \in N, \bar{n} \neq n\} \quad (15)$$

$$o_n^{global} = \left[o_n, \text{mean}(o_{\bar{n}}), \text{variance}(o_{\bar{n}})\right] \quad (16)$$

3 EXPERIMENT RESULTS

3.1 Data Preparation

Our simulation is conducted in the context of a single day with the time interval of 1 hour. The maximum allowable number of parking EVs is 100. The probability distributions are utilized to model the randomness, including: initial SoC, arrival and departure time, hence the parking duration can be obtained [22, 23]. The electricity price is collected from [24]. The related visualization is shown in Fig. 2. In our setting, there are 50 EVs stay in the parking for 24 hours, and the rest 50% follows the probability distributions. It can be seen that the parking of EVs begins to increase around 6 am, peaks around noon, and then gradually declines. The initial SoC of these EVs is given in Fig. 2 (b), which mainly ranges from 30% to 100%, and the peak is around 50~60%. The electricity price and the non-EV load are given in Fig.2 (c) and (d), respectively. They exhibit similar trends, and there are two peaks, around 10 am and 20 pm, respectively. The battery capacity is 80 kwh; the maximum power is 20 kW; the expected and minimum acceptable SoC are 0.8 and 0.4, respectively; the expected price is the average electricity price.

In this part, the proposed model is compared with several algorithms:

1) SoC-driven method, where drivers' behavior is solely driven by driving anxiety. Namely, the battery is charged when the $soc_n(t) < soc_n^{exp}$, while discharging occurs exclusively when $soc_n(t) > soc_{exp}$.
2) Price-driven approach, where drivers' behavior is decided by the electricity price. Drivers charge the battery when the $price(t) < price_n^{exp}$, while discharge when $price(t) > price_n^{exp}$.
3) The independent DDPG (IDDPG) algorithm, which is decentralized training for critic network. The input of both critic and actor networks are local observations. The framework and related hyperparameters of the networks are the same with the proposed model.

There are 4 indicators used to compare the performance of methods, where $cost_n^{elec}$, $cost_n^{degrad}$, and $profit_n^{elec}$ are electricity cost, degradation cost, and electricity profit of n-th EV, and p^{soc} is the percentage of EVs' final SoC is over expectation. These cost or profit related indicators present the average unit cost or profit per kWh.

$$cost_{mean}^{elec} = \sum_n^N cost_n^{elec} / a_n(t)\Delta t^{slot} \quad (17)$$

$$profit_{mean}^{elec} = \sum_n^N profit_n^{elec} / a_n(t)\Delta t^{slot} \quad (18)$$

$$cost_{mean}^{degrad} = \sum_n^N cost_n^{degrad} / a_n(t)\Delta t^{slot} \quad (19)$$

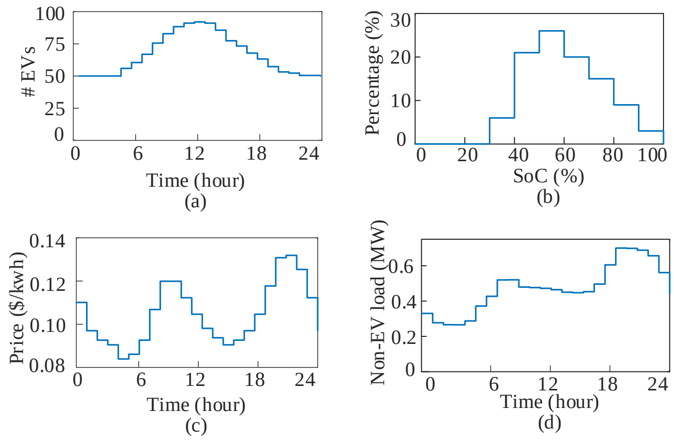

Figure 2. Simulation curves. (a) the number of EVs. (b) electricity price

3.2 Performances

The performances of the EV groups in multistorey car park is discussed in this part. The training curves of rewards are shown in Fig. 3. It can be seen that with the increasing of episodes, the rewards keep increasing. Compared with IDDPG algorithm, it achieves higher rewards throughout the whole training process.

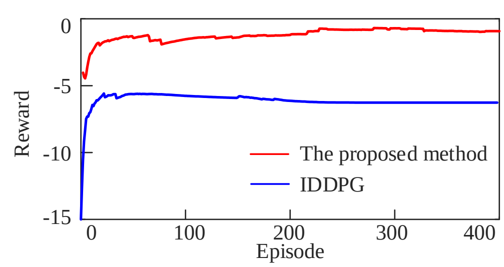

Figure 3. The training curves of the proposed method and IDDPG.

The load conditions are shown in Fig.4, including the EV and the allowable load, which is calculated by the transformers' capacity minus the corresponding non-EV load. It is observable that only the SoC-driven method exceeds the allowable load range introduced by transformer. The peak load is easily introduced since charging occurs immediately as long as the SoC is below the expectation. The peak is generated when there are a certain number of low-SoC EVs with charging requests. Also, discharging is inactive under this method. The price-driven approach exhibits a curve inversely correlated with price trends. It shows the highest overall discharge volume, which in turn impacts the final SoC levels. The RL-based methods, including IDDPG and the proposed method, adopt a more balanced consideration, wherein charging and discharging behaviors are conducted comprehensively rather than being driven by a singular focus, such as price and current SoC level. Their generated EV loads are below the allowable load.

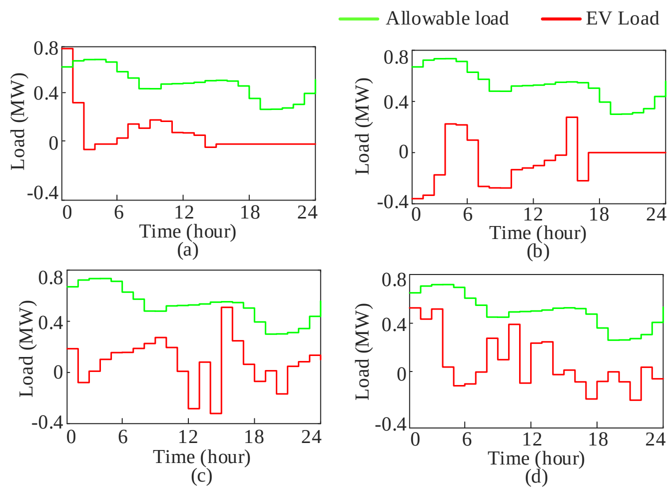

Figure 4. Load curves. (a) SoC-driven method. (b) Price-driven method. (c) IDDPG. (d) The proposed method.

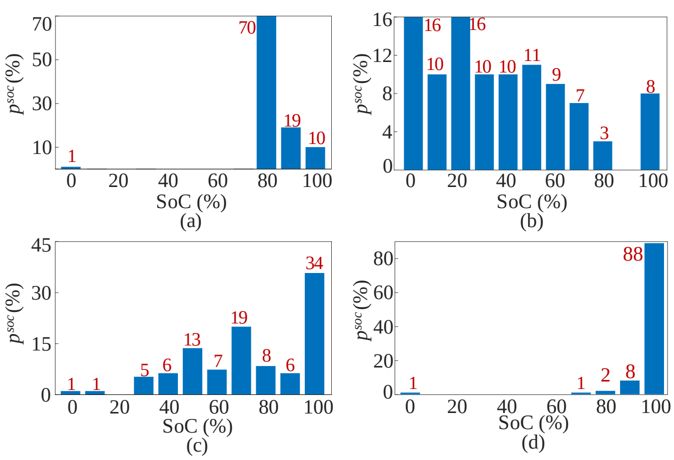

Figure 5. The distribution of SoC when departure. (a) SoC-driven method. (b) Price-driven method. (c) IDDPG. (d) The proposed method.

The visualizations of final SoC distributions are provided in Fig. 5. For the SoC-driven approach, the 99% SoC is maintained at a relatively high level with an expectation SoC threshold set at 80%. Among them, 70% have their SoC close to the 80%. In contrast, the distributions of SoC for the price-driven method and IDDPG is not satisfactory comparatively. The price-driven method exhibits the worst p^{soc} among 4 approaches. The proposed method, while p^{soc} is slightly lower than SoC-driven method as 1%, 88% of vehicles achieve a 100% SoC upon departure.

The results of indicators are concluded in the Table.1. For SoC-driven method, the best p^{soc} is achieved. 99% EVs can reach or above their expectation threshold of 0.8 after departure. However, a notable issue is that $cost^{elec}_{mean}$ is higher than $profit^{elec}_{mean}$, so drivers are not able to earn the financial gain by energy trading and cause battery degradation at the same time. For the price-driven approach, it realizes lowest $cost^{elec}_{mean}$, meaning drivers can purchasing electricity at an economical price and sell at a relatively high price. Nevertheless, since in this scheme, SoC level is out of the scope, the p^{soc} is only 11%, rendering it less appealing to drivers concerned with range anxiety. The IDDPG model, compared to the aforementioned methods, not only facilitates profitability but also enhances p^{soc} to certain extent. It can be concluded the proposed method achieves most satisfactory performance from a comprehensive consideration. Electricity can be purchased at a reasonable price and possesses the ability to sell the energy at a relatively highest price. Also, the p^{soc} is 98%.

Table 1. Comparison of four indicators

Method	$cost^{elec}_{mean}$	$cost^{degrad}_{mean}$	$profit^{elec}_{mean}$	p^{soc}
SoC-driven	1.07e-1	1.5e-3	1.04e-1	**99%**
Price-driven	**0.90e-1**	1.5e-3	1.03e-1	11%
IDDPG	1.02e-1	1.5e-3	1.04e-1	48%
Proposed	1.04e-1	1.5e-3	**1.07e-1**	98%

4 CONCLUSIONS

In the context of multistorey car park, this article has addressed the problem of optimal (dis)charging scheduling by multi-agent deep deterministic policy gradient (DDPG) method. Different from the literatures focusing solely on unilateral goal, the optimization is formulated considering drivers' cost, profit, driving anxiety, and transformer overloading. Also, a simple centralized observation is designed to address the problem of time-varying number of agents.

In the experiment, the proposed method is compared with 3 baseline methods. For SoC-driven method, our model facilitates profit earning. Although p^{soc} is 1% lower, the final SoC distribution in our model is closer to 100% rather than the expected SoC threshold. For price-driven method, our model presents a significantly compelling advantage with the concern of range anxiety. For IDDPG, which also considers scheduling from a comprehensive perspective, our method demonstrates superior performance both in making profit and ensuring a high final SoC. The superiority of the proposed method is demonstrated with the benchmarks.

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