Electric vehicle charging recommendation considering voltage deviation

1st Wenlei Chen
Department of Automation
Tsinghua University
Beijing, China
3484782071@qq.com

2nd Junqi Liu
Department of Automation
Tsinghua University
Beijing, China
liu-jq24@mails.tsinghua.edu.cn

3rd Junwei Cao
Beijing National Research Center for Information Science and Technology
Tsinghua University
Beijing, China
jcao@tsinghua.edu.cn

***Abstract*—In recent years, the quiet and environmentally friendly characteristics of electric vehicles (EVs) have made them increasingly popular, driving the construction of charging infrastructure. However, the large amount of charging access and the promotion of fast charging technology have led to an increasing total power demand for charging. If the charging behavior of EVs is not regulated, it will inevitably affect the stable operation of the power distribution network. This paper proposes a charging recommendation method that considers the voltage deviation of power distribution network nodes, keeping the node voltage deviation within 10%. We formulate the problem as a Markov Decision Process and solve it using a graph reinforcement learning algorithm. The simulation results show that our algorithm can maintain the voltage deviation within the limits and improve the level of obtaining charging services.**

***Index Terms*—charging recommendation, graph reinforcement learning, power distribution network**

I. Introduction

With the increasing global emphasis on environmental protection and sustainable development, electric vehicles (EVs) are playing a crucial role in reducing carbon emissions and promoting energy transition. As a result of the unprecedented rapid development, EVs are experiencing a surge in popularity due to the continuous technological advancements and gradually decreasing costs. This has not only transformed traditional modes of transportation but also posed new challenges and opportunities for energy systems, grid operation, and urban infrastructure [1].

In the wave of EV popularization, the rapid growth of charging demand has put significant pressure on the existing power infrastructure. Especially during peak hours, charging a large number of EVs simultaneously may cause the grid to overload, affecting power quality and stability, and even posing the risk of power outages [2]. At the same time, due to the flexibility of charging time and charging place, by conducting reasonable charging scheduling, the grid pressure be effectively alleviated [3].

Existing studies that consider the impact of EV charging on the power system can be divided into two categories. The first category schedules EVs in the time dimension. Reference [4] develops an actor-critic based charging algorithm to schedule EVs in order to reduce peak load and lower charging costs. The second category is known as charging recommendation, it will dispatch EVs to different charging stations (CSs), and attract more owners to charge in locations closer to distributed energy by reducing electricity prices and other ways. Reference [5] introduces a two-stage method for determining the optimal path for EVs and managing their active and reactive power within the distribution network. This method reduces the loss cost of the distribution network and benefits the owners of EVs. Reference [6] designs a smart grid system that allows dynamic interaction between EVs / plug-in EVs and the grid, thereby minimizing costs and preventing damage caused by excessive loads. In [7], an online learning based algorithm is proposed to solve the multi-stage Markov decision process model, which greatly shortens the time of system convergence. Reference [8] proposes a multi-objective system-level fast CS recommendation method to dynamically assign EVs to suitable CSs. Here, the average voltage deviation rate of each node is regarded as one of the objective of optimization. Although the aforementioned studies have considered the impact of EV charging on the power system, the voltage deviation limits of the distribution network has not been taken into account. If EVs are concentrated at certain CSs, it may cause the node voltage deviations in the distribution network to exceed the limits, affecting the safe and stable operation of the distribution network. Some studies [9], [10] have considered the limits of voltage deviation, but they all achieve this by shifting the charging demand to other times, lacking research on maintaining voltage deviation within limits by recommending EVs to charge at different CSs.

All the previous research has provided corresponding solutions for charging guidance and control scenarios. However, in scenarios where EVs have a high penetration rate, EVs with charging demands must be promptly allocated to avoid disrupting subsequent EV guidance processes. Additionally, to cater to the urgent need for charging, guidance strategies need to respond to user demands online within dynamic and complex environments. Traditional optimization algorithms or heuristic methods often suffer from low computational efficiency, making it challenging to meet the real-time requirements of a large number of EVs. Reinforcement learning (RL), on the other hand, does not require an explicit model. It can acquire effective strategies through interactions with the environment and continuous learning from relevant experiences and has been proven suitable for complex sequential decision-making problems, such as charging recommendation [11]. To this end, this paper addresses the issue of node voltage deviation from the limit values in the distribution network by utilizing charging recommendations from the perspective of reinforcement learning.

The rest of this paper is organized as follows: Section II introduces the problem we are studying. Section III first formulates the problem as a Markov Decision Process and then introduces the reinforcement learning methods used. Section IV is an analysis of the simulation results. Section V is the conclusion.

II. Problem Formulation

In our charging recommendation scenario, the entities involved include: EVs, CSs, the power distribution network, and the intelligent traffic center. All CSs within a certain area are powered by the power distribution network. If an EV traveling in that area has a SoC lower than the threshold during its journey, the driver will send a charging request to the intelligent traffic center. After receiving the request, the intelligent traffic center, considering the operation states of the EV, CSs, and power distribution network, recommends a CS for the EV. Subsequently, the EV follows the recommendation, charges at the CS for a certain period, and then continues on to its destination.

However, the rapid growth in the number of charging infrastructures and the widespread adoption of fast charging technology have posed unprecedented challenges to the stable operation of the power distribution network.

Let the active power for each EV charging be denoted as P^{ch}, and the corresponding reactive power be denoted as Q^{ch}. The relationship between the two is:

$$Q^{\mathrm{ch}} = \sqrt{(P^{\mathrm{ch}}/\cos\phi)^2 - (P^{\mathrm{ch}})^2} \tag{1}$$

where $\cos\phi$ is power factor.

The total active power for CS i at time t is:

$$P_{i,t} = P^{\mathrm{ch}}(N_i^{\mathrm{p}} - N_{i,t}^{\mathrm{i}}) \tag{2}$$

where N_i^{p} represents the number of charging piles at CS i, $N_{i,t}^{\mathrm{i}}$ indicates the number of idle charging piles at CS i at time t.

At time t, there is the following relationship between the power at node i of the distribution network and the voltage:

$$P_{i,t} = V_{i,t}\sum_{j=1}^{n} V_{j,t}(G_{ij}\cos\theta_{ij,t} + B_{ij}\sin\theta_{ij,t}) \tag{3}$$

$$Q_{i,t} = V_{i,t}\sum_{j=1}^{n} V_{j,t}(G_{ij}\sin\theta_{ij,t} - B_{ij}\cos\theta_{ij,t}) \tag{4}$$

where n is the total number of nodes, and $P_{i,t}$ and $Q_{i,t}$ are the active power and reactive power at node i at time t, respectively, $V_{i,t}$ is the voltage magnitude at node i at time t, $\theta_{ij,t}$ is the voltage phase angle difference between nodes i and j at time t, and G_{ij} and B_{ij} are the conductance and susceptance between nodes i and j, respectively.

It can be seen from the above equation that the number of charging vehicles will affect the node voltage of the distribution network. The unregulated charging behavior of EVs leads to an imbalance in load among various CSs, exacerbating this issue. Therefore, when making charging recommendations, our main goal is to ensure the stable operation of the power distribution network and to keep the voltage deviations of the nodes connected to the CSs within a certain range, that is:

$$V_{\min} \leq V_{i,t} \leq V_{\max}, \forall i \in \{1, 2, \cdots, n^{\mathrm{CS}}\}, \forall t \tag{5}$$

where $V_{i,t}$ represents the voltage of node i in the power distribution network at time t, $V_{\min}$ and $V_{\max}$ are the upper and lower bounds of the set voltage deviation, and the total number of CSs is n^{CS}.

Although simply directing vehicles to CSs that are already in a queue can delay charging demands and prevent voltage deviations from exceeding the specified values, the long wait for charging services can also render the charging recommendation meaningless. Therefore, the charging recommendation should, under the premise of ensuring the stable operation of the power distribution network, make full use of idle charging piles to provide charging services for EVs.

III. Methodology

A. Formulation of Markov Decision Process

State space $\mathcal{S}$: The state of the environment at step t is denoted as s_t. When there is no charging request at a certain moment, it is considered as a state. When there are N_t charging requests at the actual moment t, each charging request is regarded as a state. Therefore, the subscript t in s_t refers to the environment step, not the actual time.

There is a significant delay between making a charging recommendation and the EV starting to charge. To reflect the node voltage when the EV is connected to the charging pile and to mitigate the impact of the delay on the agent, we use the estimated node voltage upon the vehicle's arrival rather than the current node voltage. When estimating the node voltage, we consider the worst-case scenario, where vehicles that requested charging before the current EV will arrive at the CS earlier than it. Upon the vehicle's arrival at the CS, the estimated active power of the vehicles currently charging is:

$$\boldsymbol{P}_t = \min\{\boldsymbol{N}^{\mathrm{p}}, \boldsymbol{N}_t^{\mathrm{EV}} + \boldsymbol{N}^{\mathrm{p}} - \boldsymbol{N}_t^{\mathrm{i}}\} \cdot P^{\mathrm{ch}} \tag{6}$$

where $\boldsymbol{N}^{\mathrm{p}}$ represents the number of charging piles at each CS, bold symbol means it's a vector. $\boldsymbol{N}_t^{\mathrm{EV}}$ represents the total number of EVs that are about to go to each CS and those already queuing at the CSs at time t, $\boldsymbol{N}_t^{\mathrm{i}}$ indicates the number of idle charging piles at each CS at time t, and p^{ch} denotes the charging power.

Additionally, the agent should also be aware of the utilization status of each CS, in order to recommend vehicles to underutilized CSs when congestion occurs at some stations.

The indicator reflecting the utilization of CSs is defined as follows:

$$\boldsymbol{N}_t^{\mathrm{u}} = (\boldsymbol{N}_t^{\mathrm{EV}} - \boldsymbol{N}_t^{\mathrm{i}})/\boldsymbol{N}^{\mathrm{p}} \tag{7}$$

The state is defined as follows:

$$s_t = \begin{cases} [0.1, \mathbf{-0.1}, \mathbf{1}], & \text{no request} \\ [-0.1, \boldsymbol{V} - \mathbf{0.9}, \boldsymbol{N}_t^{\mathrm{u}}], & \text{otherwise} \end{cases} \tag{8}$$

where $\boldsymbol{V}$ is the voltage (per unit) of the nodes connected to the CSs, which can be calculated by (1), (3), (4) and (6). Since we want to keep voltage deviation within 10%, the voltage was uniformly reduced by 0.9.

Action space $\mathcal{A}$: The action space includes an action of making no recommendations and actions recommending to each CS. The action at time t is denoted as a_t.

Reward function $\mathcal{R}$: The reward function consists of two parts: one part reflects the impact of the recommendation results on node voltage, denoted as r_{vol}, the other part represents the utilization of the charging piles, denoted as r_{util}.

When EVs head to the recommended CS for charging, there may be situations where the voltage of the node connected to the recommended CS is already lower than the threshold upon the vehicle's arrival. Besides, since each CS is connected to the same power distribution network, the voltages of the nodes will affect each other. After a vehicle starts charging at the recommended CS, it may cause some nodes connected to the CSs to first fall below the threshold voltage or further decrease the voltage of the nodes that were already below the threshold. All of the above situations should be avoided when making recommendations, so the reward should be negative in these cases, and r_{vol} is defined as:

$$r_{\mathrm{vol}} = \begin{cases} -10, & \boldsymbol{V}[a_t] \le 0.9 \\ -10, & \boldsymbol{V}'[\boldsymbol{V} \le 0.9] < \boldsymbol{V}[\boldsymbol{V} \le 0.9] \\ -10, & \mathrm{len}(\boldsymbol{V} \le 0.9) < \mathrm{len}(\boldsymbol{V}' \le 0.9) \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

here, $\boldsymbol{V}'$ represents the estimated node voltages after current EV is added to $\boldsymbol{N}_t^{\mathrm{EV}}$.

To improve the utilization rate of charging piles, a higher reward should be given for choosing CSs with lower predicted utilization rates when vehicles are estimated to arrive, so the reward r_{util} is defined as:

$$r_{\mathrm{util}} = \begin{cases} 0, & \text{no request} \\ -\boldsymbol{N}_t^{\mathrm{u}}[a_t], & \text{otherwise} \end{cases} \tag{10}$$

B. Graph Reinforcement Learning Algorithm

We utilize the reinforcement learning algorithm named Dueling DQN(λ), which is the same as the one used in our previous work [12].

However, for the problem studied in this paper, the topology of the distribution network is known, and the network structure used in our previous work cannot take advantage of this information. Therefore, based on [12], we have made certain modifications to the algorithm. Inspired by [8], we use multi-head graph attention layers instead of full connected layers to transform the voltage components in the state. The transformed features are defined as follows [13]:

$$\boldsymbol{h}_i' = \sigma\Big(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in\mathcal{N}_i} \alpha_{ij}^k \boldsymbol{W}^k \boldsymbol{h}_j\Big) \tag{11}$$

where K represents the number of heads in multi-head attention, $\mathcal{N}_i$ represents the neighboring nodes, α_{ij}^k represents the attention coefficient between the current node i and the neighboring node j, $\boldsymbol{W}^k$ is the weight matrix, and σ is the activation function.

The attention coefficient includes the relationships between adjacent nodes, so the transformed features utilize the topological structure of the power distribution network, aggregate information from adjacent nodes, and reflect the interdependent relationship between node voltages.

IV. Simulation

A. Scenario and Parameter Settings

To validate the effectiveness of the algorithm, we employ the SUMO simulation platform to emulate the driving behavior and charging process of EVs. It offers a TRACI interface, enabling us to obtain traffic information in real-time and direct vehicles to specific CSs. Additionally, we utilize the pandapower module to perform power flow calculations, forming an integrated transportation-power simulation environment with SUMO. The algorithm is implemented using Python-PyTorch and is executed on an Ubuntu server.

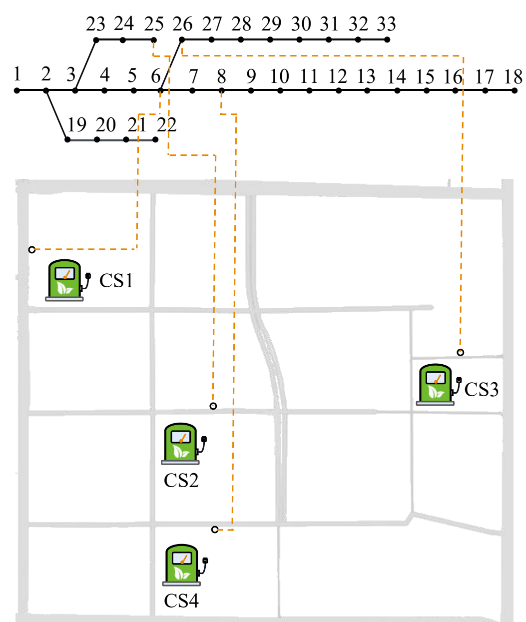


Fig. 1. Joint transportation-power simulation scenario.

An area in Beijing is utilized as the simulation road network, equipped with four CSs that have a limited number of charging piles, all of which are powered by the distribution network. A modified IEEE 33-node distribution network model is adopted in our simulation scenario. CS 1 to CS 4 are connected to node 6, 25, 26, and 8 of the distribution network, respectively, with power factors of 0.7, 0.65, 0.71, and 0.88. It is assumed that the voltage at each node connected to the CSs must not be lower than 0.9 U_N. The simulation scenario is shown in Fig. 1. The battery capacity of all EVs in the road network is set to 20 kWh, with an average power consumption of 10 kW during travel. We design a high-load scenario where trips are generated every 0.84 seconds with random starting points and destinations. Before departure, the EVs have a certain initial battery capacity, with the SoC uniformly distributed between 0.2 and 0.4. During the journey to the destination, once the SoC of the EV drops to a threshold (uniformly distributed between 0.14 and 0.17), the driver issues a charging request and proceeds to the recommended CS by the algorithm for a 10-minute charge before continuing the trip.

B. Simulation Results

1) Validation of graph reinforcement learning algorithm: We utilize 10 random seeds to compare the average returns of our algorithm, which incorporates graph attention layers, against the algorithm that does not employ graph attention layers (it uses conventional Multilayer Perceptron instead). The results across the training process are illustrated in Fig. 2.

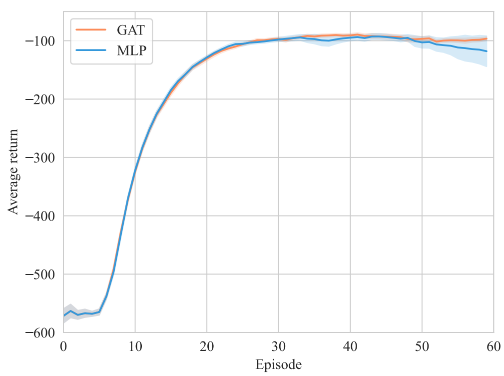


Fig. 2. The average return curves of the two algorithm.

From Fig. 2, it can be observed that although the two algorithms exhibit similar performance in the early stages of training, the algorithm without graph attention layers experiences a decline in performance in the later stages of training, while the algorithm with graph attention layers maintains stable performance. Fig. 3 shows the results after excluding the random seed 60, where the performances of the two algorithms are comparatively close. The reason for this outcome is that reinforcement learning algorithms are sensitive to random seeds, and under certain seeds, the algorithm may fail to converge. The use of graph attention layers, however, fully leverages the prior knowledge of the power distribution network topology, thereby making the algorithm more robust. Note that the 10 random seeds used here are not carefully selected but are evenly spaced within the range of 10 to 100.

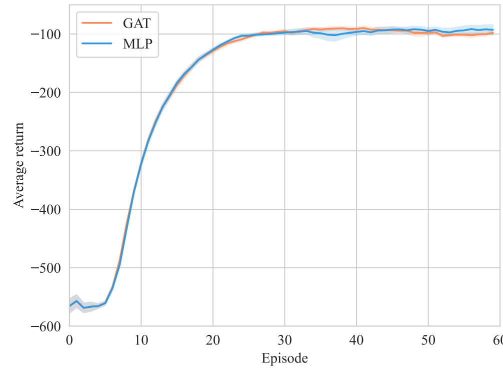


Fig. 3. The average return curves of the two algorithm (excluding random seed 60).

2) Validation of the effectiveness in avoiding voltage constraint violations : We compare the model trained in IV-B1 with the distance greedy method and the random CS selection method. The results are shown in Fig. 4. From Fig. 4a and Fig. 4b, it can be found that without effective measures, the voltage at some nodes may drop below the pre-set threshold due to excessive electrical load, which is detrimental to the safe and stable operation of the power distribution network. Our method estimates the worst-case voltage deviation when vehicles arrive at CSs and recommends CSs for EVs accordingly, thereby avoiding violations of node voltage constraints.

3) Validation of the effectiveness in enhancing charging pile utilization rates: We compared two methods: one that considers only voltage constraints in the reward function (denoted as Method I) and another that takes into account both voltage constraints and CS utilization rates (denoted as Method II). The results are shown in Fig. 5, where the power at each CS is used to reflect the utilization of the charging piles.

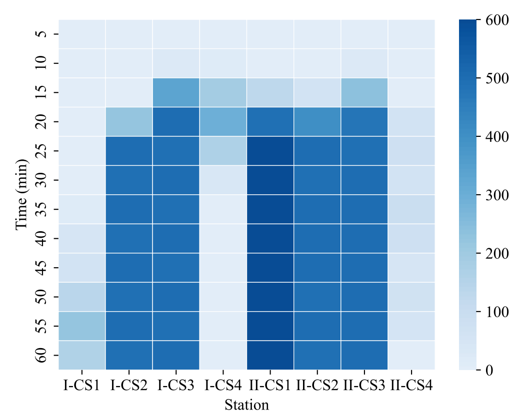
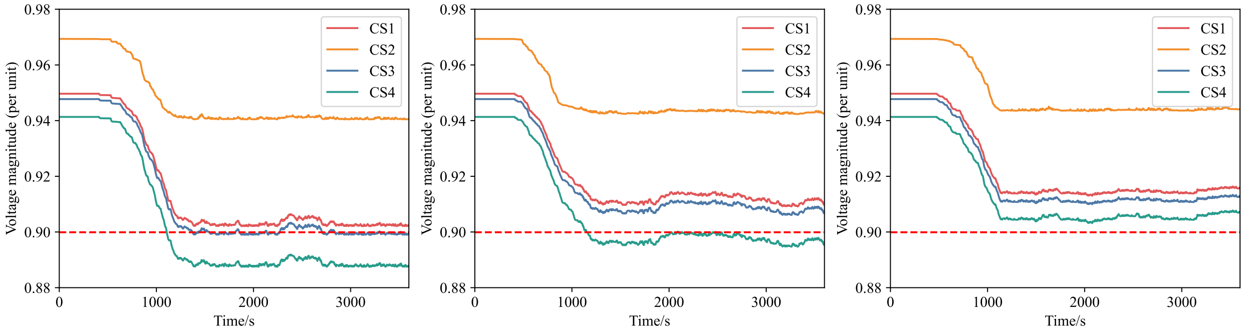


Fig. 5. Power heatmap under two different reward function.

From Fig. 5, it can be observed that when only voltage constraints are considered, the policy learned by the algorithm simply recommends vehicles to go to CS 2 and CS 3, which are already in queue, to delay charging access and avoid



(a) Random selection method (b) Distance greedy method (c) Our method

Fig. 4. Voltage curves under different methods.

violating voltage constraints. However, when the utilization rate of charging piles is taken into account, the algorithm can identify the idleness of CS 1 and utilize it to serve EVs without violating voltage constraints. Therefore, our algorithm is effective in enhancing the utilization rate of charging piles. It should be noted that since the voltage deviation of CS 4 is relatively high even without additional charging load, to avoid violating voltage constraints, its utilization rate remains low in both cases.

V. Conclusion

This paper design a graph reinforcement learning based EV charging recommendation algorithm to address the issue of voltage deviation exceeding limits at power distribution network nodes, while also considering the utilization rate of charging piles. The results show that using graph attention layers can fully leverage the topological information of the power distribution network, thereby enhancing the robustness of the reinforcement learning algorithm. Moreover, compared to distance greedy and random selection algorithms, our algorithm can maintain voltage deviations within the specified limits. Finally, the design of the reward function considering the utilization rate of charging piles has improved the level of timely charging services for EVs. When deploying in practice, it is necessary to improve the design of the state space and reward function to reduce unnecessary power flow calculations and speed up response times, which will also be the focus of our future work.

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