Journal of computer science and software applications
https://www.mfacademia.org/index.php/jcssa
ISSN:2377-0430
Vol. 5, No. 2, 2025

A Distributed Multi-Agent Reinforcement Learning Approach for Efficient Charging Station Recommendation in Large-Scale Environments

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Abstract:

The rapid growth of electric vehicles (EVs) and the increasing deployment of charging infrastructure have introduced new challenges in optimizing charging station recommendations. Current methods often fail to consider the dynamic and large-scale nature of charging environments, leading to increased waiting times and suboptimal user experiences. To address these limitations, we propose a distributed multi-agent reinforcement learning framework for EV charging station recommendations, with the objective of minimizing overall driving and queuing time. Our model leverages mean field theory to address the variable number of agents and uses a distributed decision-making approach, allowing each agent to select charging stations based on local observations while coordinating with others. Simulation results demonstrate that our proposed CSMF algorithm significantly outperforms conventional methods, such as Nearest, DQN, and MADDPG, by achieving lower mean waiting times. Future research will focus on incorporating personalized user preferences to further enhance recommendation accuracy.

Keywords:

Multi-agent Reinforcement Learning; Mean Field Theory; Distributed Decision Making; Real-Time Recommendation; Charging(Batteries).

1. Introduction

The development of electric vehicles has emerged as a crucial initiative for sustainable development and to relieve the pressure of the energy crisis and the environment in light of the global environmental degradation. According to the China Charging Alliance, there were 3.368 million electric vehicles on the road in 2019 and 516,000 public charging stations. The manufacturing of new energy cars surged by 194.9 percent yearly from January to July 2021. The number of charging piles will increase more quickly due to the rapid development of new energy vehicles and the national initiative to accelerate the building of charging piles for the "new infrastructure".

At the same time, many domestic charging station operators such as Tesco, Star Charging ,and third- party platforms such as Baidu and Amap have also introduced information of mainstream charging stations in the market. However, faced with numerous charging stations, drivers tend to make choices based on own habits or blindly, thus making charging completion take more time and charging costs. Electric vehicle users prefer charging platforms to guide them to make the best choice [1].

The recommendation of charging stations from the perspective of the user has been the subject of much research. They have taken into account a number of variables to improve the efficacy of the recommendations, such as user preference, travel cost, traffic conditions, and time. For example, in order to determine the user's preference for charging stations, Bu et al. [2] employed a collaborative filtering algorithm. This information served as the foundation for their recommendation. Wang et al. [3] used a factorization machine approach to predict recommendation results and combined federal learning to improve cross-platform data security. Jia et al. [4]'s method of cab trajectory prediction allowed them to select the charging station that would travel the least distance between the starting point and the intended destination. However, these studies do not take into account the impact between vehicles and charging stations at different times. Not considering the charging intentions of other users may lead to longer queues at charging stations for electric vehicles [1,5]. To address this problem, Wang et al. [1] used Pareto optimality to recommend charging stations for a group of EVs in a short period of time, resulting in an overall reduction in queuing time. The queuing up time prediction algorithm does not account for users who arrive at the charging station directly without sending a charging request although this method predicts numerous charging requests in a minute. A charging mechanism created by Zhang et al. [6] continuously monitors the condition of charging stations and changes the suggested stations list in real-time. In order to manage cars with various priority, Cao et al. [7] employed information on vehicle reservations. The information on electric vehicles and charging stations does, however, change frequently over time, making it extremely difficult for communication to continuously detect this information and feedback.

Recently, reinforcement learning (RL) has been applied to games, transportation, and other fields due to its ability to effectively solve sequential decision problems in complex environments, and has been effective in autonomous driving [8,9] and vehicle order scheduling [10,11]. In contrast to charging time prediction, which requires more assumptions and rules, reinforcement learning will fully consider the impact of current decisions on the future, i.e., to maximize the expected cumulative payoff, interact directly with the dynamically changing complex environment, and train using historical data with real-time data to obtain the overall optimal policy.

However, the following problems occur when reinforcement learning is used to make recommendations for charging stations: consider L charging stations where the state space size is S S1 S2 SL and the action space size is A A1 A2 AL , meaning that the space size is exponential. The charging environment in a city with many charging stations has a wide state and action space, which is not good for the stability of network training. Zhou et al. [12] described the charging station recommendation problem as a single-agent action-value function learning task using an improved DQN (Deep Q-Networks) algorithm that takes into account information about surrounding charging stations when estimating the value function, utilizes graph convolutional neural networks for training, and reduces the state information input dimension. Nevertheless, in addition to the state and action high-dimensional problem, another major issue of directly learning a centralized agent system is the high latency associated with obtaining the overall state data and handing it off to the agents for computation, which is not suitable for large-scale charging scenarios that request for real-time recommendations.

In large-scale environments, multi-agent reinforcement learning (MARL) can reduce latency [13,14]. In [15], a distributed training method with performance comparable to centralized training was developed to address the central server congestion problem by sharing parameters only with the neighboring agents during the training process. Wu et al. [16] designed a distributed computing architecture to reduce the network latency in the Nash actor-critic algorithm-based traffic signal control. Chu et al. [17] added a long and short-term memory network to the network structure of the value function, using historical data and the current state as input, to improve the stability of training.Zhang et al. [18] treated each charging station as an independent agent and considers EV charging recommendation as a multi-objective optimization task. Each autonomous agent has a constant-level action space, which can be expanded to include settings with greater complexity, in this way. However, for the case of multiple requests in a short period time, the independent recommendation strategy of each charging station is still essentially a centralized sequential decision, which is difficult to process in parallel, i.e., it cannot take into account the actions taken by other charging requests in the same state at the same time, prolonging the wait time for EVs in the case of multiple requests in a short period of time.

In this paper, a distributed multi-agent reinforcement learning model is designed. The overall goal is to minimize the overall driving time and queuing time at charging stations in a day. Present a distributed multi-agent reinforcement learning framework, to request per minute charging electric cars as the agent, on the one hand, can take into account the future behavior of the agent, on the other hand, can coordinate cooperation between multiple agents in order to reduce decision time delay, using distributed decision-making method, each agent chooses according to their local observations charging stations. Mean field theory is employed concurrently to address the problem of the variable number of agents.

2. Charging Environment

The first part of this section describes the procedure from charging request through charging completion. The fundamental components of multi-agent reinforcement learning for charging environments are described in the second part.

2.1 Charging Process

In continuous time, the moments when the vehicle sends a charging request and the state of the charging station is bound to change are called "charging important time points", and the whole charging process is described by these moments. As shown in Fig. 1: At the moment T0, the user has a charging demand and sends a charging request to the platform to go to a recommended charging station or chooses a charging station according to his habits. At the moment of T2, two possible events will happen: (1) the electric car leaves without charging due to the long queue time; (2) in the second case: there are free charging piles, and the electric car starts charging and leaves at the moment of T3.

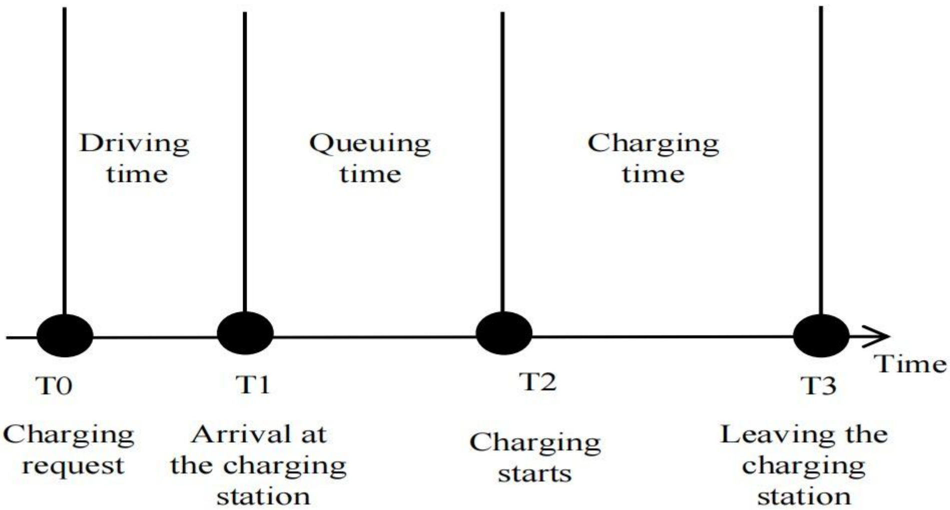

Figure 1. Charging process of electric vehicle

2.2 MARL Model for Charging Environments

Reward: After the driver arrives at the recommended charging station, if $time\_cost$ is less than 1 hour and leaves after the EV charging is completed, the EV charging is successful, otherwise, the charging fails. The maximum reward setting is 60 minutes. The reward function is defined as:

$$reward\_cwt = \begin{cases} \frac{(-time\_\cos t + 60)}{60}, & \text{success} \\ 0, & \text{failure} \end{cases}$$

3. Multi-agent Reinforcement Learning Framework based on Mean Field Theory

3.1 Centralized Training Decentralized Execution Framework

The Centralized training decentralized Execution (CTDE) framework [19,20] uses information from other agents during training .It utilizes only the local states observed by itself when executing actions, which significantly reduces the state space. The framework has the advantage of distributed execution and is easy to deploy to practical applications. During the training process, CDTE can coordinate the communication and cooperation among agents using more comprehensive state information, actions of other agents ,and future information, and thus learn the action-value function effectively. When using the policy network to select actions, each agent uses only its observed local environment state without global information. This decentralized execution method can reduce real-time recommendation latency and improve recommendation efficiency.

3.2 Distributed Decision Making

The time interval between two adjacent charging requests is short during the whole charging process in a day, and this phenomenon increases significantly during peak charging periods. Most of the previous studies are based on a first-request-first-service strategy [21,22] and do not consider the important impact of decision order in the execution of intensive actions.

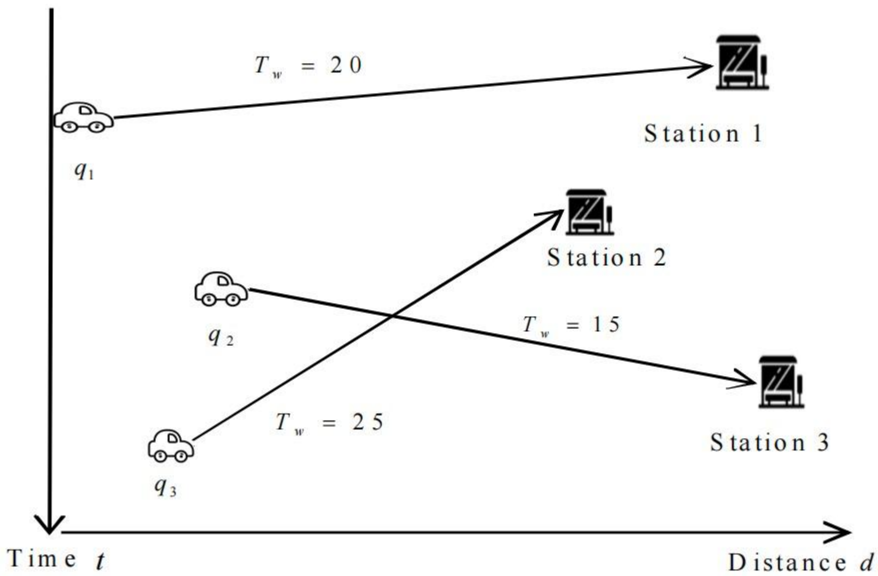

Figure 2. Recommendation results based on first-request-first-serve decision

Therefore, to improve the recommendation speed and reduce the overall time, a plurality of charging request vehicles in the Δt truck is used as agents. Because the number of charging requests is different and the action space is different in different states, each agent shares the same action-state value function network and policy network. At the same time, the mean field multi-agent reinforcement learning algorithm [23] is used to approximate the expected reward of each agent by averaging the action value of other agents.

In a multi-agent system, the agents make decisions simultaneously for multiple requests within Δt , i.e., the problem to be solved is the allocation of resources to achieve the shortest overall time task.

3.3 Recommendation of Charging Stations with Mean Field Approximation

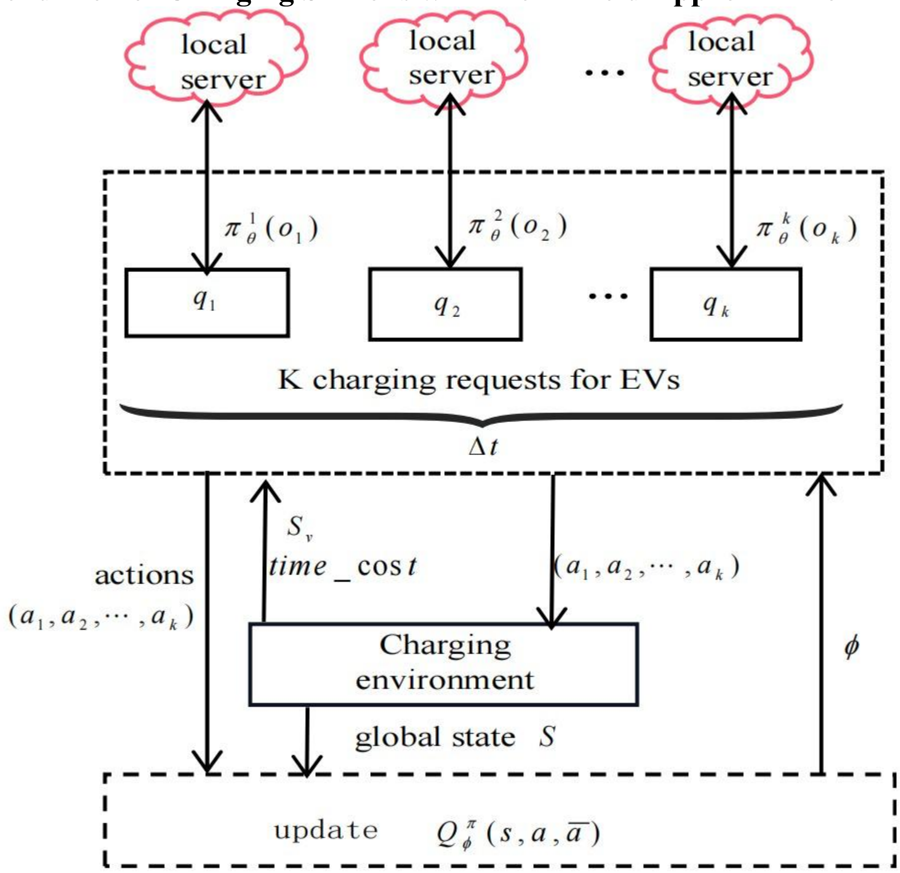

Figure 3. Distributed multi-agent reinforcement learning framework

This section presents a charging station recommendation algorithm using mean field theory (CSMF). Each agent's action-value function Q uses the global state, action, and average action values of other agents. Fig. 3 is a distributed multi-agent reinforcement learning framework. When making recommendations for electric vehicles, there is no need for unified calculation by the central server, only real-time data of electric vehicles are needed to calculate the recommendation results.

$$L(\phi) = \mathrm{E}_{(s,a,\bar{a},r,s')\sim D}[y - Q_\phi^\pi(s,a,\bar{a})]^2$$

$$\approx \frac{1}{N}\sum[y - Q_\phi^\pi(s,a,\bar{a})]^2 .$$

$$y = time\_\cos t + \gamma Q_{\phi'}^{\pi'}(s',a',\bar{a}')\Big|_{a'=\pi'(o')}$$

During the policy parameter learning process, each agent is trained based on its observed local state, without information from other agents. The strategy update uses the stochastic gradient descent method:

$$\nabla_\theta J(\theta) = \mathrm{E}[\nabla_\theta \pi(o)\nabla_a Q_\phi^\pi(s,a,\bar{a})\big|a=\pi_\theta(o)]$$
$$\approx \frac{1}{N}\sum[\nabla_\theta \pi(o)\nabla_a Q_\phi^\pi(s,a,\bar{a})\big|a=\pi_\theta(o)]$$

Table 1. Algorithm 1: CSMF

Initialize parameters $\phi, \phi', \theta, \theta'$, replay buffer D, episode $Ep=0$
Input the parameters τ used to update the target function Q with the target function π, Δt
For each episode:
Initialize state s
For each agent $agent_i$, sample action $a_i = \pi_\theta(o_i)$, get the actions of all agents $\mathbf{a}$
Compute the mean action $\bar{\boldsymbol{a}} = [\bar{a}_1, \bar{a}_2, \ , \bar{a}_m]$ by Eq. (4)
After each agent selects a charging station, it is rewarded with $\mathbf{r}=[r_1, r_2, \ , r_m]$; State transition, get the next state s'.
Store $(s, \mathbf{a}, \bar{\mathbf{a}}, \mathbf{r}, s')$ in D
Take the next state as the new state: $s \leftarrow s'$
Update the critic network by minimizing the loss Eq. (2)
Update the actor network using stochastic gradients Eq. (5)
Update the parameters of the target critic networks:
$\phi' = (1-\tau)\phi' + \tau\phi$, $\theta' = (1-\tau)\theta' + \tau\theta$

4. Experiment

4.1 Data Description

The number of charging stations is fixed at 10, and the area of 100 km^2 is divided into 100 grids of 1 km^2. A grid unit is occupied by each charging station. The number of charging requests every minute for each grid is determined by the Poisson distribution, and the time of day is divided into 1440 minutes. The training set for the electric vehicle charging suggestion simulator developed in this study consists of 30 days of operation, and the testing set consists of 10 days of operation.

4.2 Evaluation Metrics

Take into account q as a collection of charging requests that follow our advice and are successfully charged; qnum is the quantity of q , and M is the collection of requests. The waiting time for each request is Wt(q) . The average waiting time for all charging requests is measured in minutes to determine the overall waiting time for charging.

$$Mwt = \frac{\sum_{q\in M} Wt(q)}{q_{num}}$$

4.3 Algorithm

In CSMF, a mean field multi-agent reinforcement learning algorithm based on the actor-critic framework, the Q network builds a five-layer fully connected network using the ReLU activation function. The policy network uses a three-layer fully connected network and the output layer uses the SoftMax activation function. Meanwhile, with the increase of t , the number of agents and the future charging environment information change more. This demonstrates the CSMF algorithm's robustness in relieving charging congestion scenarios.

$$T_{rate}(t) = \frac{\underset{\Delta t}{Max}(hour\_mwt_t) - \underset{\Delta t}{Min}(hour\_mwt_t)}{\underset{\Delta t}{Max}(hour\_mwt_t)}$$

Table 2. The $hour\_mwt$ of CSMF at different Δt

Period of time	$\Delta t = 1$	$\Delta t = 5$	$\Delta t = 10$	$T_{rate}(\%)$
6:00-8:00	**3.65**	4.76	6.47	43.6
8:00-10:00	**4.82**	7.74	12.66	61.9
10:00-12:00	**6.03**	9.59	16.92	64.4
12:00-14:00	**38.53**	39.73	41.39	**6.9**
16:00-18:00	**4.31**	6.74	9.64	55.3

The Q-function network consists of a four-layer fully connected network with a hidden layer of dimension 256, using the ReLU activation function. The policy function network uses a three-layer fully connected network with a tanh activation function for the output layer. To extend the MADDPG to a large-scale charging environment, the critic network is shared among all the agents.

While CSMA utilizes distributed decision making to make suggestions simultaneously, Nearest, DQN, and MADDPG all use sequential decision making to make recommendations for each charging request.

Fig. 4 shows the process of the training phase: each algorithm interacts with the charging environment during the training process. The number of available charging posts at the charging station changes during this process with the actions selected by the agents. $Tmwt$ denotes Mwt in a day. Nearest is similar to Mwt for DQN. Among the reinforcement learning algorithms, the single agent DQN algorithm based on centralized learning performs the worst. The single agent DQN algorithm based on centralized learning performs the worst among reinforcement learning algorithms. The multi-agent reinforcement learning algorithm based on centralized training MADDPG and CSMA not only uses the current state but also adds the future data of the charging station; as a result, it performs better overall than DQN and has a shorter average waiting time. The CSMA algorithm performs the best since it simultaneously considers the actions of other charge requests.

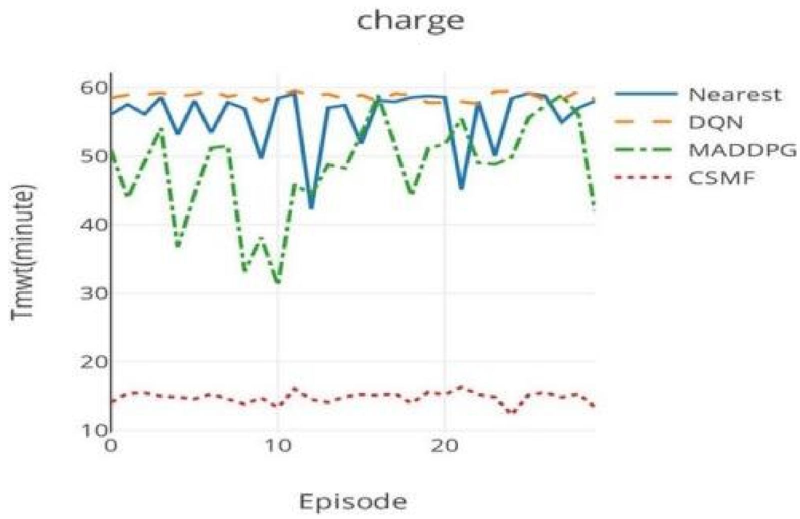

Figure 4. Tmwt during training for all algorithms

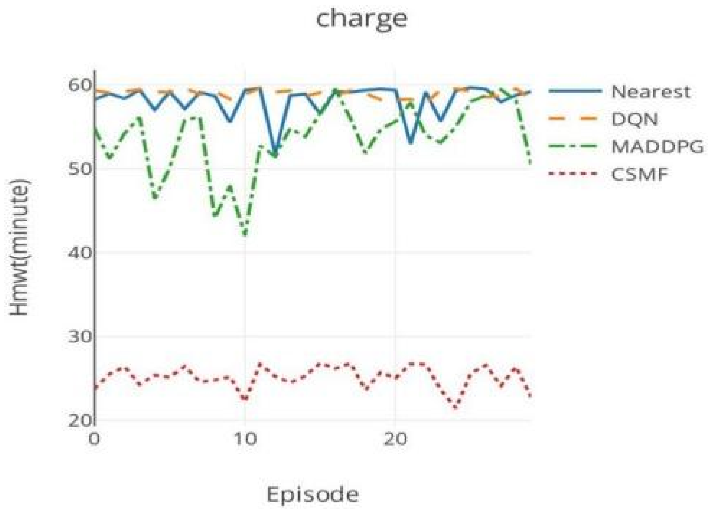

Figure 5. Hmwt during training for all algorithms

Table 3 shows the average waiting time for each charging request during the test phase. In order to compare the performance of the three algorithms, the environment is initialized with the same random seed, and the results are shown in Table 3. Multi-agent reinforcement learning algorithm achieves better results than Nearest and DQN. The *Tmwt* and *Hmwt* of the CSMA algorithm are reduced by
71.8 and 54.8 percent, respectively, when compared to MADDPG, showing that distributed decision making can significantly enhance the recommendation effect.

Table 3. Overall performance of each algorithm

Performance	*Tmwt* (minute)	*Hmwt* (minute)
Nearest	53.56	57.76
DQN	59.96	59.98
MADDPG	53.28	57.00
CSMF	15.05	25.76

5. Related Works

5.1 The Training Framework of Reinforcement Learning

There are now a number of popular agent training frameworks. A fully centralized training framework is the first. For instance, the CommNet suggested in [26] employed a central controller to manage all of the agents' actions. The controller is made up of a multi-layer neural network, which inputs the state of every agent, outputs every agent's action, and facilitates agent communication. A policy network and a Q network control all agents in the Bidirectionally-Coordinated Net (BiCNet) that Peng et al. [27] suggested. The second is a fully decentralized framework. Mnih et al. [28] designed a completely asynchronous parallel agent training method to speed up the training speed and applied it to Sarsa, Q-learning, and Actor-Critic single-agent reinforcement learning algorithms. Wen et al.

[29] proposed a decentralized multi-agent reinforcement learning framework in which each agent finds its own best response according to the opponent's strategy. Tian et al. [30] used Kullback-

Leibler (KL) divergence to model the opponent to improve the training performance of multi-agent. The third is an effective framework for decentralized execution and centralized training. This framework is more suited for multi-agent reinforcement learning tasks with a large state space and a non-stationary environment when compared to the other two frameworks. Based on this, certain studies have improved more successfully. Foerster et al. [31] proposed a counterfactual multi-agent (COMA). In order to reduce the noise in calculating the gradient, the CTDE framework is used to train to take into account the impact of the behavior of each agent on the global reward. To arrive at the best strategy for decentralized execution, Mahajan et al. [32] developed a novel action exploration method based on CTDE. In [33], a more all-encompassing method of value function decomposition is put out that may be applied to a wider variety of tasks.

5.2 Charging Station Recommendation

A significant portion of the associated research on the recommendation of charging stations is based on the algorithm in the recommendation system and utilizes the charging station attributes for driver preference recommendations. For example, in some studies [2,6], a collaborative filtering algorithm is used to calculate user preferences, and Wang et al. [3] used the factorization machine method. In [4], the recommended criterion with the shortest distance is adopted. The other part is based on the recommendation with the shortest waiting time. Related studies have taken into account the behavior of other electric vehicles [1,5,7]. In the large-scale and ever-changing actual charging environment, the effect of the reinforcement learning method is better [12,18].

6. Conclusion

In order to reduce the total amount of charging waiting time each day, we investigate the problem of recommending charging stations in this research. By using the finished training policy network to find recommended charging stations in a simulated charging environment, the superiority of the CSMF algorithm is demonstrated. The CSMF algorithm is much less in $Tmwt$ and $Hmwt$ than Nearest, DQN, and MADDPG. Personalized recommendations for charging stations will be made in the next work while taking user preferences into account.

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