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Multiple agents and reinforcement learning for modelling charging loads of electric taxis☆

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HIGHLIGHTS

- A spatial-temporal model of plug-in electric taxi (PET) charging load is proposed.
- A multi-agent framework of PET operation is proposed based on JADE.
- A variety of agent models are built to simulate the players and the environments.
- The multi-step Q(λ) learning is developed to make decisions for the PET agents.
- The shift strategies and electricity pricing mechanisms of PETs are investigated.

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ABSTRACT

The charging load modelling of electric vehicles (EVs) is of great importance for safe and stable operation of power systems. However, it is difficult to use the traditional Monte Carlo method and mathematical optimization methods to establish a detailed and precise charging load model for EVs in both the temporal and spatial scales, especially for plug-in electric taxis (PETs) due to its strong random characteristics and complex operation behaviors. In order to solve this problem, multiple agents and the multi-step $Q(\lambda)$ learning are utilized to model the charging loads of PETs in both the temporal and spatial scales. Firstly, a multi-agent framework is developed based on java agent development framework (JADE), and a variety of agents are built to simulate the operation related players, as well as the operational environment. Then, the multi-step $Q(\lambda)$ learning is developed for PET Agents to make decisions under various situations and its performances are compared with the Q-learning. Simulation results illustrate that the proposed framework is able to dynamically simulate the PET daily operation and to obtain the charging loads of PETs in both the temporal and spatial scales. The multi-step $Q(\lambda)$ learning outperforms Q-learning in terms of convergence rate and reward performance. Moreover, the PET shift strategies and electricity pricing mechanisms are investigated, and the results indicate that the appropriate operation rules of PETs significantly improve the safe and reliable operation of power systems.

1. Introduction

In recent years, in the background of energy resource crisis and environmental degradation, electric vehicles (EVs) are regarded as an effective way to alleviate the current energy crisis and environmental problems with its remarkable characteristics such as high efficiency, energy saving, low noise and zero emission. Consequently, EVs have been widely promoted and applied around the world [1–3]. However, with the increasing penetration of EVs, the charging loads of EVs impose tremendous challenges to the secure and stable operation of power systems [4]. The charging load modelling of EVs can effectively predict the future loads through the historical data, thus it is of significant importance for the operation and planning of power systems [5,6].

Nowadays, a large amount of literature focuses on the research of charging load modelling of EVs, which can be classified into two categories. The first category is Monte Carlo method [7–10]. When this method is utilized to model the charging loads of EVs, the travel patterns of EVs are firstly obtained through analyzing the driving behaviors, then the sampling method is employed to simulate the EV charging processes. Nevertheless, the classical Monte Carlo method only provides the charging loads with time distribution. In order to model the spatial-temporal characteristics of EV charging loads, the trip chain

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[11,12] and origin-destination (OD) analysis [13,14] methods were presented. A trip chain is a scheduling of activities in time and space, generally made by linking home and non-home trips or two or more non-home trips together. In [11], the trip chain models incorporating the information on start time, end time, driving distance, start location and end location of each trip are developed and classified into three categories according to different travel modes. A probability distribution model considering three scenarios based on a trip chain was constructed for weekdays and weekends [12]. The trip chain method is more suitable to model the charging loads for the EVs with strong trip rules, such as private EVs, and it is difficult to describe a series of complex trips for the EVs with strong heterogeneous actions, such as electric taxis. Ref. [14] proposed a spatial-temporal model based on the OD analysis technique to obtain the EV charging loads at each busbar at different time. The second category is the queuing theory modelling method [15,16]. Compared with Monte Carlo method, the queuing theory method solves the problem from the viewpoint of charging stations, and it assumes that the change in the number of EVs arriving at charging stations is a stochastic process. In [15], the M/M/c and the M/M/c/k/Nmax queuing methods were used to build the charging load model of plug-in hybrid EVs at an EV charging station and in a local residential community. In [16], the fluid traffic model and the M/M/s queuing theory were used to establish the charging load model of the EVs in a highway charging station. The queuing theory method may result in great errors due to limited factors taking into account in the charging load model of EVs.

Most of the aforementioned studies focus on the private EVs and electric buses. Few works concentrate on the PET, which is a major kind of EV [17,18]. This is due to the fact that the stochastic characteristics of PET operation are strong and the operation involves two complex networks, the transportation network and the power grid network, and a great number of different players, such as power grid companies, the PET owners and drivers, electric facilities owners and operators [1,19]. It is difficult to build a deterministic and detailed model to describe the charging loads of PETs using traditional methods. Most of the studies of PET charging load model are greatly simplified, which neglect other types of related players and the environment, and fail to provide detailed charging loads of PETs [17,20,21]. In this paper, a multi-agent technology (MAT), which is an advanced emerging technology to deal with the issue of the complex adaptive system, is introduced to simulate multiple players, as well as the environment related to the operation of PETs. Agents are autonomous, proactive and reactive, thus the multi-agent method can be employed to dynamically simulate the daily operation of PETs, including cruising and charging. At present, most of the studies using the MAT mainly focus on the coordination charging for private EVs, while few researches using MAT to build the charging load model of PETs [22,23].

A large number of multi-agent development platforms have springed up recent years, using various communication mechanisms and programming languages, including Java agent development framework (JADE) [24], Swarm [25], NetLogo [26] and Repast [27]. JADE is a common multi-agent development tool, which completely complies with the foundation for intelligent physical agents (FIPA) specifications and adopts pure-to-pure communication way. The multi-agent systems presented in the literature [28–31] focus on the power networks and their frameworks are not expandable since models developed in these literature are suitable for private EVs. In this paper, a multi-agent framework based on JADE for PET operation is firstly proposed. The proposed framework can elaborately simulate the related players, the environment and the interactions between agents and it has advantages in extensibility and flexibility. First of all, the framework also can be applied for other types of EVs to study the charging load modelling, besides the PETs. Secondly, in the framework, a variety of agents are built, such as Time Agent, Map Agent, PET Agent, Power Grid Agent, which are classified into several categories running on different host machines to realize distributed simulation. Thirdly, the framework can be easy to add/delete the agents and revise parameters. For example, in this paper, the power grid is modeled as an agent and is responsible for monitoring the charging loads of PETs and publishing electricity price. In the future, the Power Grid Agent can be subdivided into the Distribution System Operator Agent, Regional Aggregator Agent, Local Aggregator Agent, etc. These subdivided agents can be easily added into the framework by extends and implement methods.

One of the most important problems in multi-agent system simulation is the intelligent learning. Reinforcement learning algorithm (RLA) is a very popular learning algorithm widely used in the field of artificial intelligence, such as AlphaZero. In this paper, RLA is introduced for PET Agents to make decisions whether to find passengers or to charge, as well as to choose the optimal direction to find passengers under various situations. At present, there are many different kinds of RLAs, such as learning automata [32], Sarsa [33], Q-learning [34,35]. Q-learning is widely applied in power systems and achieves good results compared with others [36]. However, there are some problems with the Q-learning algorithm, e.g., the slow convergence of the Q-learning affects the acquisition of optimal strategies [37]. Therefore, this paper develops a multi-step Q(λ) learning, which combines with the multiple agents to dynamically simulate the daily operation of PETs and to obtain the charging loads of PETs both in temporal and spatial scales. The multi-step Q(λ) learning compares with the Q-learning in terms of convergence rate and reward performance. Finally, this paper takes shift strategies and electricity pricing mechanisms as examples to study the impact on PET charging loads and the distribution grid using the proposed framework and method.

In total, this paper proposes a multi-agent framework for PET operation based on JADE. A variety of agent models are elaborately built using MAT in the framework to simulate the operation related players, operational environments and their interactions. The multi-step Q(λ) learning is developed for PET Agents to make decisions under various situations, and it combines the multiple agents to dynamically simulate the daily operation of PETs, including cruising and charging, to obtain the charging loads of PET in both the temporal and spatial scales. Simulation studies are carried out with the data of a city in China and the results demonstrate the effectiveness of the proposed framework and method to obtain the detailed charging loads in both the temporal and spatial scales. The multi-step Q (λ) learning outperforms Q-learning in terms of convergence rate and reward performance. Furthermore, the PET shift strategies and electricity pricing mechanisms are investigated, and the results indicate that the appropriate operation rules of PETs significantly improve the safe and reliable operation of power systems.

The rest of this paper is organized as follows. In Section 2, the multi-agent framework for the PET operation based on JADE is developed and a variety of agent models are built. The multi-step Q(λ) learning algorithm and its behavior decision model are developed in Section 3. The simulation studies and results are shown in Section 4 and Section 5 gives the conclusion to the paper.

2. The multi-agent framework for PET operation based on JADE

2.1. General framework

A multi-agent framework for operation of PETs is developed, which is achieved by JADE and has the advantages in extensibility and flexibility. In this paper, eight kinds of agents are developed in the framework. As the computing capability of a single personal computer (PC) is limited, in order to better manage and analyze the high-frequency information interactions among different types of agents, the eight kinds of agents are classified into five platforms, which run on different host machines to realize distributed simulation. The multi-agent framework for PETs' operation is shown in Fig. 1.

The agents and their functions on each platform are described as follows.

Time Control Platform only contains a Time Agent. It is in charge of