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Research on short-term power load forecasting based on deep reinforcement learning with multiple intelligences

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Abstract

A reliable supply of power systems is critical for industry, commerce, and residential life. Improving the accuracy and reliability of short-term electricity load forecasting plays a crucial role in ensuring the satisfaction of electricity demand and the stable operation of the power system. Therefore, to realize accurate and efficient prediction of short-term power loads, a short-term power load prediction method based on multi-intelligence deep reinforcement learning is proposed to address the complex nonlinear characteristics of load data. In this paper, we analyze the multi-intelligence application architecture in power load forecasting, and analyze the function of each intelligent unit applied to short-term power load forecasting; based on clarifying the interaction relationship of each intelligent unit in short-term power load forecasting, we model short-term power load forecasting as a distributed and partially observable Markov decision-making process, which is suitable for multi-intelligence deep reinforcement learning; based on the MATD3 algorithm, a centralized training-distributed execution framework is used to train multiple intelligences within the model to achieve short-term power load forecasting. The experimental results show that in the August short-term electricity load forecasting using the design method, the obtained MAE value is 35.94 kW, MAPE value is 4.05%, and RMSE value is 32.71 kW. In the short-term power load forecasting evaluation conducted for December, the average absolute error (MAE) value obtained was 36.75 kilowatts, the average absolute percentage error (MAPE) value was 4.51%, and the root mean square error (RMSE) value was 34.82 kilowatts. These evaluation results fully demonstrate that the design method adopted has high prediction accuracy and forecast precision. This method has demonstrated good practical value and broad application prospects in practical applications due to its high-precision prediction performance and strong prediction stability.

Keywords: Multi-intelligent body systems; deep reinforcement learning; Markov decision making; short-term power load forecasting

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1. Introduction

In modern society, electricity plays a crucial role, playing an indispensable role in maintaining the smooth operation of the national economy and improving the quality of life for the people. Accurately estimating the load of the power system is the primary consideration for power generation planning and fuel demand arrangement by the power generation department. It is also the core foundation for the power system dispatch center to ensure the safe and stable operation of the power grid. In addition, it is also an important reference for power planning agencies to coordinate the comprehensive development of the power system. In short, the importance of electricity is self-evident, and load forecasting is a key link in ensuring a balance between electricity supply and demand and promoting the healthy development of the power system [1-2]. With the continuous advancement of intelligent power

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technology, short-term power load forecasting has received widespread attention

Literature [3] is based on multi factor analysis and Long Short Term Memory (LSTM) neural network short-term power load forecasting model. The model first evaluated the correlation between various weather factors and power load using the Spearman coefficient method, and selected weather features that have a significant impact on power load. Subsequently, the sliding window technique was employed to reconstruct the original time series data. Finally, a prediction model was constructed using LSTM. However, it is worth noting that the overall accuracy of the model in load forecasting still needs to be improved; Literature [4] designed a correction function aimed at improving prediction accuracy by applying the Mann Kendall mutation detection algorithm. This function is used as a tool for identifying power system load mutations and conducting short-term power load forecasting. However, the predictive stability of this method still needs to be strengthened; Literature [5] proposes a method that integrates the orthogonal dimensionality reduction and improved gray wolf algorithm for power load prediction method, by combining principal component analysis and preservation projection techniques, utilizing their advantages in maintaining global consistency and local structure of data, it can reduce the complexity of the original high-dimensional data and transform it into a lower dimensional data form. Afterwards, these dimension reduced data are used as inputs for prediction algorithms to achieve accurate short-term power load forecasting goals. However, this method is not applicable when dealing with complex power load forecasting tasks; literature [6], the validity of real-time data of electric power companies based on fuzzy time series, artificial neural networks, and wavelet transforms, and predicts the power dispatch demand in a targeted way to realize the effective prediction of power load after detection, but the method's overall accuracy needs to be improved.

The Multi Agent Double Delay Deep Deterministic Policy Gradient (MATD3) algorithm is a core algorithm in the field of deep reinforcement learning. It is based on the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm to expand and optimize the processing problem of multi-intelligent systems. system processing problem. Based on the deep deterministic policy gradient (DDPG) algorithm, this algorithm effectively addresses the bias and variance issues caused by function approximation in a single agent environment by adopting truncated double-Q learning and delayed strategy updates. In a multi-intelligent body system, each intelligent body needs to consider the behaviors of the other intelligences and the state of the environment to achieve its own optimization goal. Therefore, the MATD3 algorithm adds a mechanism of multi-intelligence body collaboration and communication based on the TD3 algorithm. Power load forecasting involves multiple factors, such as historical load data, meteorological data, economic data, etc.. There are complex interactions and uncertainties among these factors. The multi-intelligentsia collaborative learning of the MATD3 algorithm can effectively deal with such complexity and uncertainty, learn more accurate and effective prediction models through the interaction and collaboration among multiple intelligences, this process relies on historical and real-time data to continuously update and optimize the prediction model, in order to flexibly adapt to the constantly changing power load. Based on this, a short-term power load forecasting method based on deep reinforcement learning with multiple intelligences is proposed.

2. Design of short-term electricity load forecasting methods

2.1. Analysis of multi-intelligent body application architecture in power load forecasting

Multiintelligent body systems are composed of multiple intelligences that can interact, communicate, collaborate, or compete in a shared environment to accomplish tasks or solve problems. Each intelligent body possesses a certain degree of autonomy and intelligence and is able to perceive, make decisions, and perform actions based on environmental information. In the process of short-term power load forecasting, the application of multi-agent relies on the power load forecasting system to achieve, where each intelligent body in the system is responsible for collecting and processing power load-related data, for example, real-time power load data, meteorological data, and historical data are used in short-term power load forecasting tasks, which are achieved through information sharing and collaborative work among intelligent agents [7-9]. The hierarchical structure of a multiintelligent body system is shown in Figure 1:

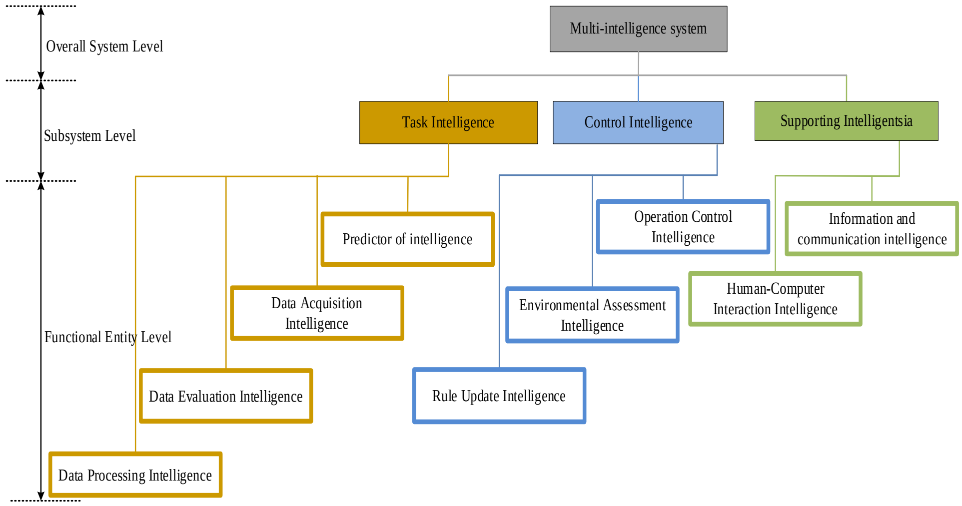


Figure 1. Multi-intelligent body system hierarchy

As shown in Figure 1, the multi-agent system architecture applied in short-term power load forecasting mainly includes the overall system layer, subsystem functional layer, and functional entity layer. In terms of functional entity layer, detailed descriptions have been provided for various intelligent agent units used for short-term power load forecasting. Each intelligent body function is analyzed as follows:

(1) Information communication intelligences that transimit mutual information during the operation of each intelligent body and manage the operation information of each intelligent body.

(2) Human-computer interaction intelligences, which interact and synthesize the call commands entered manually with the call commands generated automatically by the prediction intelligences in a human-computer interaction environment [10-11]. This prediction system mainly synthesizes the call instructions entered manually with the call instructions generated automatically by the predictive intelligent body in the human-computer interaction environment.

(3) The Predictive Intelligence Body, which is composed of the sub-predictive intelligences of different prediction methods, and its specific prediction methods are realized through the calling instructions generated by the interactive intelligence body. It mainly has the function of building a prediction model to fulfill the task of predicting load under the calling instruction.

(4) The environmental assessment intelligent body has the function of calling real-time external environmental factor data in the database and making a fuzzy assessment of the degree of drastic changes in the external environment according to the model of fact and experience.

(5) Rule updating an intelligent body with the function of accepting the signal of updating the prediction rules, updating the inapplicable prediction rules, and passing the updated prediction rules to the prediction rule base for storage.

(6) The operation control intelligent body, in the information transfer process of communication coordination intelligent body, mainly scientific scheduling of the relevant sub-prediction intelligent body in the prediction intelligent body, to realize the synergistic prediction between each sub-prediction intelligent body [12]. Simultaneously, monitor the operational procedures of each subordinate agent to guarantee the seamless functioning of the entire load forecasting system.

(7) Information communication intelligent body, with the function of transmitting mutual information communication during the operation of each intelligent body, and managing the operation information of each intelligent body.

(8) The data acquisition intelligent body has the function of real-time acquisition of data from the external environment that affects load changes in the forecast, and stores them in the database.

(9) Data processing intelligent body, with online real-time collection of all types of related data needed for load forecasting, testing, and proofreading through the data, filtering, correcting, and supplementing the problematic data, and the processed data will be saved in the database.

2.2. Modeling of short-term power load forecasting based on deep reinforcement learning with multiple intelligences

To clearly illustrate the interplay among various intelligent agent units in short-term power load forecasting, a model is constructed based on the multi-intelligent deep reinforcement learning algorithm. Initially, short-term electricity load forecasting is aimed at precisely predicting future electricity demand. [13-15]. It is evident that the goal of short-term power load forecasting is to minimize the discrepancy between the predicted load and the actual load to the fullest extent possible. Consequently, the objective function is established to reduce the prediction error to a minimum:

$$\min \theta = \frac{1}{T}\sum_{t=1}^{T}\left(a_t - a_t''\right)^2 \tag{1}$$

$$a'' = \frac{1}{N}\sum_{b=1}^{T}\lambda_3\left(a_t - \lambda_1\right)^{\lambda_2} \tag{2}$$

In Formula 1-2: θ denotes the value of the objective function, i.e., the mean square error of the prediction error; T denotes the total number of time steps predicted; t denotes a time step; a_t denotes the actual load of the smart body at a particular time step; a_t'' denotes the predicted load of the intelligence at a particular time step; N denotes the total number of intelligences; b denotes an intelligent body; λ_1、λ_2、λ_3 denote the random error term, autoregressive coefficient and moving average coefficient, respectively, that represent the intelligences at a particular time step.

Set the constraints as:

(1) Load balancing constraint: the power system needs to maintain load balancing, i.e., generation should be equal to the load demand plus transmission losses. Therefore, for each time step, the load balance constraint is set as:

$$\sum_{b=1}^{N} G_{b,t} = a_t + \lambda_4 \tag{3}$$

In Formula 3: $G_{b,t}$ denotes the amount of power generation control by the intelligence at a particular time step; λ_4 denotes the transmission loss coefficient.

(2) Power generation resource constraint: the power generation of each intelligent body is limited by its available power generation resources. For example, for renewable energy-based intelligences, their power generation may be affected by weather conditions [16-17], the power generation resource constraint is set as:

$$0 < G_{b,t} \le R_{b,t} \qquad \forall b,t \tag{4}$$

In Formula 4: $R_{b,t}$ denotes the amount of generation resource control available to the smart body at a given time step.

(3) Power system stability constraints: Load changes should be kept within a certain range to avoid severe fluctuations, so it is realized by introducing load change rate constraints:

$$G_{b,t} < \left\| a_{t+1} - a_t \right\| \le \Delta_{\max} \qquad \forall t \tag{5}$$

In Formula 5: $\Delta_{\max}$ denotes the maximum allowable rate of load change.

Given the dynamic variability and unpredictability of the prediction decision-making environment, ensuring prediction accuracy necessitates the adoption of a multi-agent deep reinforcement learning algorithm framework to refine prediction strategies, thereby enhancing the precision and efficiency of forecasts [18-20]. Multi-intelligent deep reinforcement learning constitutes a stochastic game process encompassing elements like the count of intelligences, state space, action space, reward for intelligent agents, and state transition function. It is discernible that the structure of multi-agent deep reinforcement learning algorithms ultimately converges towards the steady state of Markov decision processes [21-23]. Therefore, in this research, short-term power load forecasting is formulated as a distributed partially observable Markov decision process (Dec-POMDP), which aligns well with multi-intelligent deep reinforcement learning (MADRL). Dec-POMDP is represented in the form of a tuple as:

$$\sigma = \left\langle N, s_t, \vec{a}_t, P\left(s_{t+1} \middle| s_t, \vec{a}_t\right), R\left(s_t, \vec{a}_t\right), \kappa_1, \kappa_2 \right\rangle \tag{6}$$

$$s_t = \left(a_{t-1}, a_{t-2}, \ldots, a_{t-n}, \tau_1^t, \tau_2^t\right) \tag{7}$$

$$R\left(s_t, \vec{a}_t\right) = -\left(a_t - a_t''\right)^2 \tag{8}$$

In Formula 6-8: σ denotes the Dec-POMDP tuple; s_t denotes the state space; $\vec{a}_t$ denotes the action space; $P\left(s_{t+1} \middle| s_t, \vec{a}_t\right)$ denotes the state transfer probability function; $R\left(s_t, \vec{a}_t\right)$ denotes the reward function; κ_1、κ_2 denotes the joint observation information set and is the observation probability judgment threshold; n denotes the length of the time window for historical load data; τ_1^t、τ_2^t denotes the weather feature parameter and time feature parameter in the prediction state space.

The basic process of reinforcement learning in a multi-intelligentsia environment based on a Distributed Partially Observable Markov Decision Process (Dec-POMDP) with the corresponding multi-intelligentsia internal structure is shown in Figure 2:

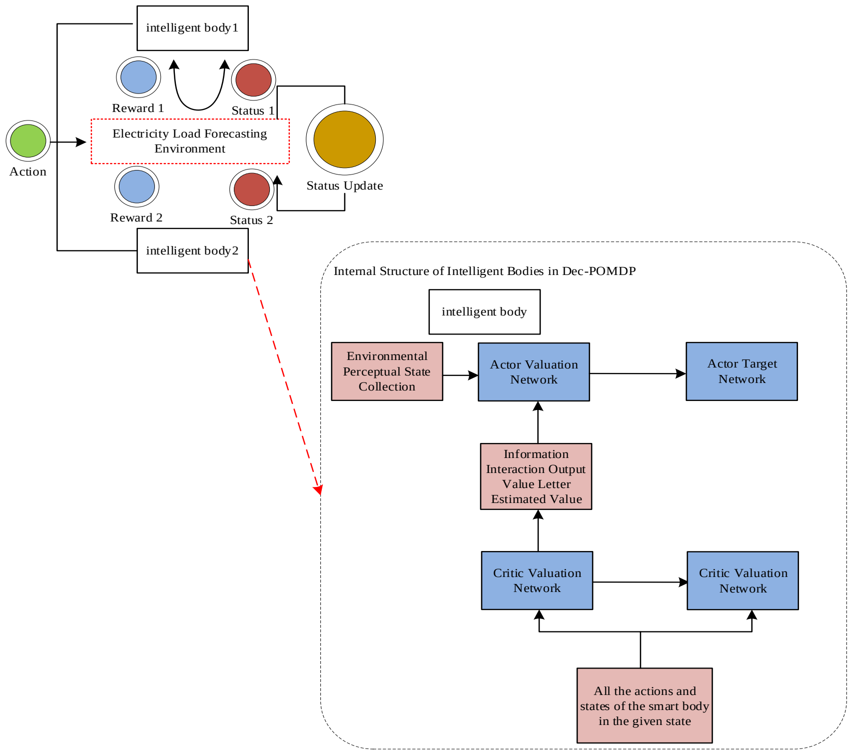


Figure 2. The basic process of deep reinforcement learning and the corresponding multi-intelligence internal structure

As can be seen from Figure 2, the components that make up each intelligent agent include the Actor network and the Critic network, the intelligent body from the environment to perceive the state, the state set of inputs to the intelligent body's strategy network, through the neural network computation to obtain the intelligent body's strategy, and the output of the given state of the intelligent body's all actions. These behaviors will have an impact on the environment, triggering the generation of reward signals in the current state, strategy, and feedback to the intelligent body, after which the environment is transferred to the next state. Each intelligent body evaluates the strategy according to the reward signal obtained, and the process is repeated in a circular manner to obtain a strategy that maximizes the long-term reward.

2.3. Load forecasting implementation based on MATD3 algorithm

Based on the deep reinforcement learning process shown in Figure 2, it can be observed that when applying deep reinforcement learning algorithms in multi-agent environments, there may be an issue of overestimation of value. To address the issue of overestimation in deep reinforcement learning algorithms, the Dec-POMDP prediction model is trained utilizing the MATD3 algorithm. In particular, MATD3 employs a reinforcement learning algorithm with a deterministic policy, distinguished by three key aspects.

Firstly, to mitigate the overestimation issue, the MATD3 algorithm incorporates a dual Q-learning mechanism. This involves introducing two additional Critic networks to assess the Actor network's performance, supplementing the original network of the Multi Agent Deep Deterministic Policy Gradient (MADDPG) algorithm. This is done to prevent the original algorithm's overestimation of the Q value, which can result in policy failure. Secondly, the MATD3 algorithm delays the policy update process [24-25], so that the Critic network is updated slightly more frequently than the Actor network, avoiding the blind iteration of the Actor; third, target policy smoothing processing, the MATD3 algorithm introduces a target policy smoothing regularization strategy to smooth out the target policy. In general, the Critic network is updated twice and the Actor network is updated once; Third, the target policy smoothing process, the MATD3 algorithm introduces the regularization strategy of target policy smoothing to smooth the Q-value, i.e., by adopting the target Q-value computation for the region around the action space $\vec{a}_t$ [26], and adopting the framework of centered training-distributed execution for the multi-intelligence model within the model. framework to train multiple intelligences within the model, and the specific training process is shown in Figure 3:

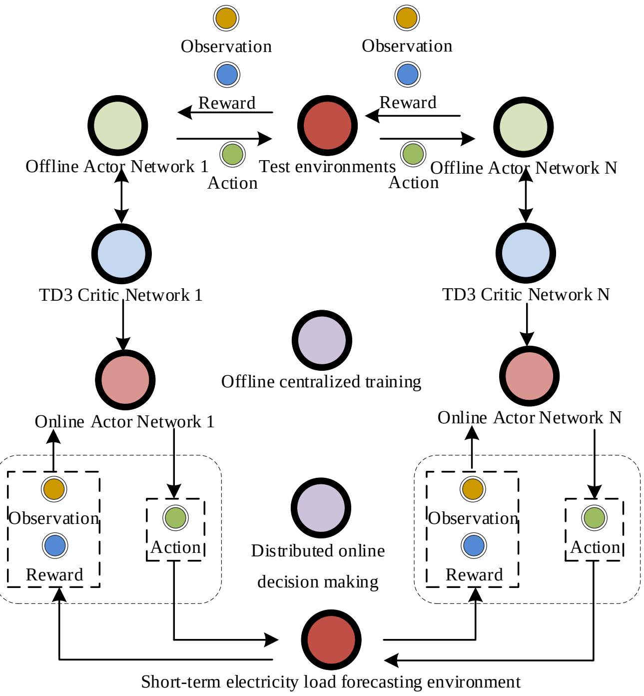


Figure 3. Training process of load forecasting model based on MATD3 algorithm

3. Experimental analyses

3.1. Experimental environment setup

To validate the effectiveness of the design method, this study utilizes a dataset consisting of 53,392 actual short-term power load data points collected from a region in northern China over a three-year period, from January 1, 2019, to January 1, 2022, with a sampling interval of 40 minutes. The power load data is measured in megawatts (MW). The experimental dataset is divided into a training set, a validation set, and a test set in a ratio of 7:1.5:1.5. The training set serves as input to train the proposed model. By evaluating the model's predictions on the validation set, adjustments are made to the model's hyperparameters, the optimal model architecture is chosen, and the model is monitored for signs of overfitting. Subsequently, the trained model is employed to make predictions on the test set. The specific hardware and software configuration of the experimental environment is shown in Table 1:

Table 1. Hardware and software configuration of the experimental environment

Equipment name	Model/Version	Performance parameters
High performance computer	HPE ProLiant DL380 Gen10	2 Intel Xeon Silver 4214 2.2GHz 12-core processors, 128GB DDR4-2666 RAM, 4TB NVMe SSD storage, supports RAID 0/1/5/6/10, dual 1GbE network interfaces
Data acquisition system	National Instruments cDAQ-9185 CompactDAQ Chassis	4-slot USB chassis, hot-swappable module support, built-in 1.33 GHz ARM Cortex-A8 processor for data logging and analysis, -20-50°Coperating temperature range.
Network equipment	Cisco Nexus 9396PX Switch	48 1/10G SFP+ ports, 6 40G QSFP+ ports, VXLAN and EVPN support, advanced QoS and security features
Simulation platform	MATLAB R2020a	——
Deep learning framework	TensorFlow 2.3.0	——
Database management system	MySQL 8.0	——
Visualization tools	Tableau Desktop 2020.3	——

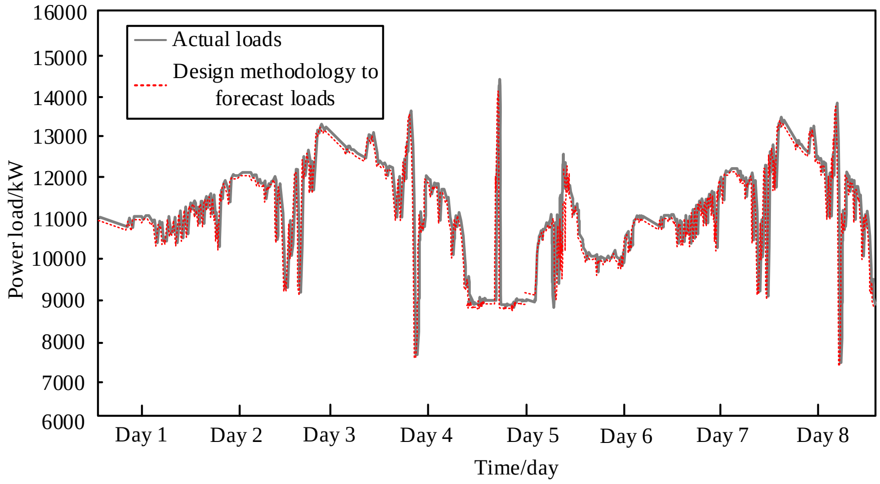
The algorithmic hyperparameters used in the design methodology to construct the predictive model are shown in Table 2:

Table 2. Algorithm hyperparameter settings

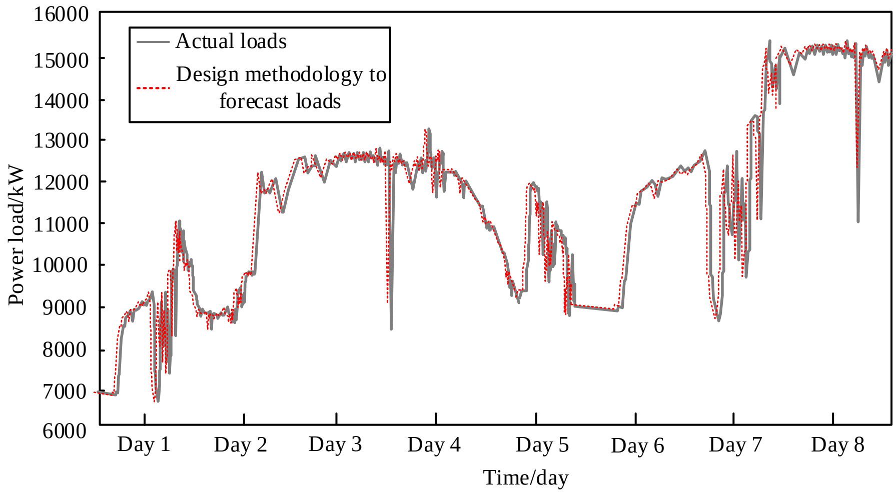
Parameter name	Value
Actor Network learning rate	0.0012
Critic network learning rate	0.0026
Maximum number of training rounds/each	450
Batch size	62
Total training steps	100000
Experience playback pool size	12000
Discount factor	0.98
Soft update factor	0.0013

3.2. Analysis of modeled power load forecasting effects under widely varying operating conditions

To assess the practical effectiveness of the design approach, the power load data of August and December 2021, two representative months with seasonal and temperature variations (difference conditions) in the simulation example data set, the actual load data is selected for validation. In addition, this design method was used to predict the short-term electricity load situation for the second week of August and the second week of December, and the results of the modeled power load prediction under the large difference conditions are shown in Figure 4:



(a)Design Method Short-Term Electricity Load Forecast Results for the Second Week of August



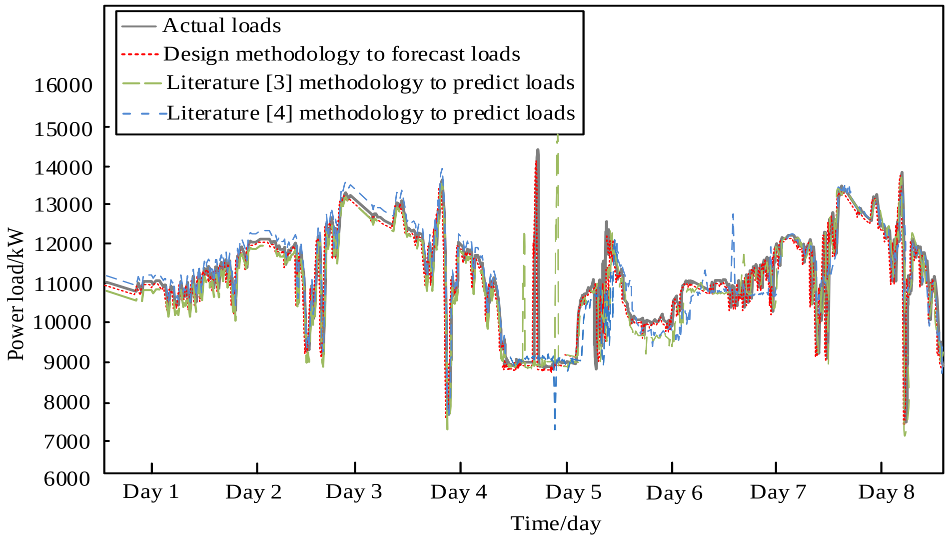
(b)Design Method Short-Term Electricity Load Forecast Results for the Second Week of December

Figure 4. Short-term electric load forecasting results of the model under large differences in operating conditions

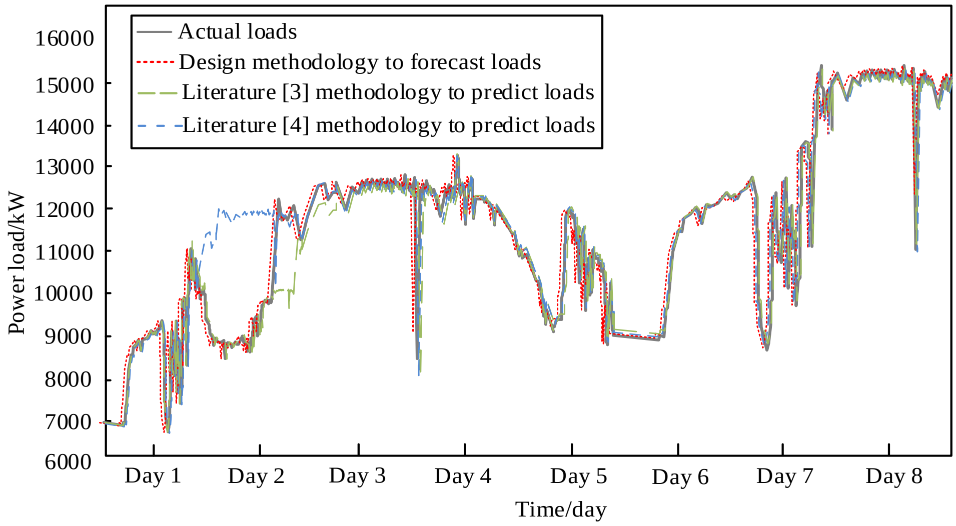
As shown in Figure 4, under significant seasonal variations between August and December, the short-term power load predictions obtained by the design method during the second week align closely with the actual trends in power load changes, with predicted values closely mirroring actual short-term power load fluctuations. This demonstrates that, in the context of short-term power load forecasting, the design method effectively aggregates prediction outputs from various agents to handle complex and dynamic power load data, exhibiting strong generalization capabilities. Consequently, the model maintains high prediction accuracy across different power load change scenarios.

3.3. Comparative analysis of power load forecasting results of different methods under widely varying operating conditions

This further confirms the effectiveness of the design method in practical applications, literature [3] method and literature [4] method are introduced as a comparison method, based on the experimental environment in subsection 3.2 (two weeks of short-term power load prediction environment in August and December), short-term power load prediction, and the results of power load prediction for the different methods under the larger differences in working conditions are shown in Figure 5:



(a)Short-term power load forecast results of different methods in the second week of August



(b)Short-term power load forecast results of different methods in the second week of December

Figure 5. Short-term electric load forecasting results of different methods under widely differing operating conditions

As can be seen from Figure 5, under the different working conditions in August and December with obvious differences in seasonal variations, the short-term power load prediction results obtained using the literature [3] method and the literature [4] method have a certain degree of fit with the actual short-term power load changes on the whole, but there is still a large discrepancy between the predicted and actual power loads in part of the time. Such as literature [3] method in the second week of August, the fourth day, the fifth day of the short-term power load prediction process, the power load aberration, and shows two changes in the peak, and the actual power load changes do not match, literature [4] method in the second week of December, the second day of the short-term power load prediction process, the prediction results show that the distribution of the power load in the period of time around the 11500 kW continuous upward fluctuations, while the actual power load changes around 9000 kW continuous downward fluctuations, the prediction results and the actual results have some differences. The short-term power load prediction results obtained by the design method in the second week of the month are highly compatible with the actual power load changes, and the prediction results are more in line with the actual short-term power load changes. In short-term power load prediction, the design method leverages deep reinforcement learning to automatically learn and adapt to the patterns of power load changes through iterative model parameter optimization. This results in prediction outcomes that closely approximate actual power load variations, achieving high prediction accuracy. Such accuracy ensures a balanced power supply and demand, thereby enhancing resource utilization efficiency.

3.4. Comprehensive performance evaluation analysis of forecasting methods

$$MAE=\frac{1}{O}\sum_{j=1}^{O}\left|v_j-\tilde{v}_j\right| \tag{9}$$

$$RMSE=\sqrt{\frac{1}{O}\sum_{j=1}^{O}\left(v_j-\tilde{v}_j\right)^2} \tag{10}$$

$$MAPE=\frac{1}{O}\sum_{j=1}^{O}\frac{\left|v_j-\tilde{v}_j\right|}{v_j}\times 100\% \tag{11}$$

In Formula 9-11: O denotes the total amount of data; j denotes the data index; v_j 、 $\tilde{v}_j$ denotes actual versus predicted values.

Based on the experimental environment in subsection 3.3, the method of literature [3] and the method of literature [4] are introduced as the comparison methods, and the prediction method evaluation indexes, evaluate and analyze the prediction accuracy and stability of different methods using indicators such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE and RMSE provide measures of prediction error in absolute terms, offering direct insights into prediction accuracy. Specifically, a high RMSE value indicates a significant discrepancy between predicted and actual values, suggesting instability in the prediction method and significant variations in predictions across different time points. Conversely, MAPE offers a relative measure that facilitates comparisons of prediction issues across different scales or units. The results of the metric evaluation of different forecasting methods are shown in Table 3:

Table 3. Evaluation results of accuracy and stability indicators of different prediction methods

Testing Cycle	Testing Methods	MAE/kW	MAPE%	RMSE/kW
Second week of August	Design Methods	35.94	4.05	32.71
	Literature [3] method	39.72	5.53	36.33
	Literature [4] method	44.03	6.08	39.17
Second week of December	Design Methods	36.75	4.51	34.82
	Literature [3] method	41.65	5.97	40.36
	Literature [4] method	48.95	6.14	47.12

Table 3 reveals that for short-term power load prediction in August, the design method yields an MAE of 35.94 kW, a MAPE of 4.05%, and an RMSE of 32.71 kW. Similarly, in December, the corresponding values are 36.75 kW for MAE, 4.51% for MAPE, and 34.82 kW for RMSE. These results suggest that the design method demonstrates high prediction accuracy, robust prediction stability, and a superior practical application effect.

4. Concluding remarks

The multi-agent deep reinforcement learning-based approach for short-term power load forecasting introduced in this research efficiently achieves precise, effective, and stable predictions. The study delves into the hierarchical structure of a multi-intelligent system and models short-term power load prediction using a multi-intelligent deep reinforcement learning algorithm. A prediction model is trained with the MATD3 algorithm for short-term power load forecasting. Experimental findings indicate that this method can automatically learn and adapt to power load variations through continuous iteration and optimization of model parameters using deep reinforcement learning. Consequently, the predictions closely align with actual power load changes, achieving high accuracy. This ensures a balanced power supply and demand and enhances resource utilization efficiency. In conclusion, the method presented in this paper addresses the timing, seasonality, and contingency challenges faced by power system load forecasting. It offers flexibility to adapt to various power system needs and provides a more dependable tool for short-term power load forecasting.

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