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Load Forecasting of Distribution Network in High Load Density Area by Integrating on Improved BiLSTM and DRL Models

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Abstract. The load of power grids in high load density areas fluctuates violently, and traditional prediction models are difficult to capture dynamic changes, resulting in insufficient prediction accuracy and scheduling efficiency. This paper constructs a joint optimization model that integrates the improved bidirectional long short-term memory network (BiLSTM) and deep reinforcement learning (DRL), taking advantage of bidirectional learning and dynamic optimization to improve load forecasting accuracy and dynamic scheduling capabilities. Multi-source heterogeneous load data is integrated through data cleaning and standardization and normalization technology to enhance the consistency of input data. For the BiLSTM model, the optimized network structurethe and attention mechanism is introduced to improve the ability to capture key features of historical loads, and multi-layer perceptrons are combind to enhance nonlinear feature extraction. The dynamic feedback mechanism of DRL is further used to adjust the load scheduling strategy in real-time to achieve collaborative iteration of prediction and optimization. The experimental results show that the improved model has superior performance in short-term to long-term load forecasting, with a mean absolute error (MAE) of 0.05-0.12, a mean square error (MSE) of 0.005-0.025, and a determination coefficient (R^2) of 0.97-0.99, which is more accurate than the traditional model. In the 100% high load scenario, the scheduling time is reduced by 6 minutes after joint training, and the energy loss rate is reduced by 1.4%, significantly optimizing the operation efficiency of the power grid. This study provides a high-precision, low-latency solution for the intelligent scheduling of power grids in high-load density areas.

Key words. Distribution network, Load forecasting, High load density area, Bidirectional long short-term memory, Deep reinforcement learning

1. Introduction

Grid loads in high-load density areas are highly volatile, and demand is irregular and unpredictable. These areas are accompanied by dense urban activities and diversified electricity demand, and load changes are frequent and rapid [1,2]. Power dispatching requires high-precision load forecasting and real-time optimization of grid load distribution to cope with changing demand patterns, which brings great challenges to grid dispatching [3,4]. Combined with the new methods of deep learning and reinforcement learning, the potential mode in the historical load data can be fully explored, and the load dispatching scheme can be optimized in real-time to enhance the power grid's operation efficiency and stability.

The power system in high-load density areas faces many challenges, and traditional load forecasting models cannot effectively cope with the demand volatility in such areas. Previous methods are capable of short-term load forecasting, but for highly volatile regional power grids, the accuracy and stability of the forecast results are still insufficient [5,6]. These models rely too much on historical load data for prediction and are unable to capture complex dynamic changes [7,8]. Under the influence of sudden demand fluctuations and local events during peak hours, the models cannot adapt to these changes in real-time. The nonlinear characteristics of the high load density region and the interweaving of many factors bring great challenges to the existing algorithms [9,10]. Statistical analysis models based on time series [11,12] and simple neural network models [13,14] can provide a certain reference for load forecasting, but they are not good enough in the face of the nonlinear characteristics unique to high load density areas. These old methods fail to fully utilize the complex feature extraction capabilities of deep learning and have obvious bottlenecks in the accuracy and efficiency of processing large-scale, multi-dimensional historical load data [15,16]. These methods are also relatively weak in their ability to respond to emergencies and real-time adjustments and are unable to make timely optimization adjustments when grid load demand changes rapidly.

Regarding load optimization, some models attempt to cope with demand fluctuations through scheduling optimization, but the optimization algorithms generally have problems such as slow convergence speed and high computational complexity [17,18]. Traditional optimization methods lack the ability to adapt to dynamic changes in the power grid and cannot make effective scheduling decisions in a short period of time, which affects the operating efficiency and safety of the power grid [19,20]. Previous load forecasting and optimization methods are also difficult to provide accurate solutions in high load density areas, and more advanced algorithms are needed to improve their accuracy.

This paper studies and constructs a new method for load forecasting and optimization of high-load density regional power grids that integrates improved BiLSTM and DRL to address the shortcomings of existing models in dynamic scheduling and accurate prediction. The study combines the time series prediction capability of BiLSTM with the adaptive scheduling capability of reinforcement learning, uses reinforcement learning algorithms to optimize load forecasting results in real-time, simulates the feedback mechanism in power grid operation, and optimizes load distribution and scheduling strategies. The fusion method focuses on improving the accuracy of load forecasting and how to adjust the grid load in a real-time and dynamic environment, so that the forecast results can quickly adapt to complex changes in power demand. In terms of model improvement and innovation, the BiLSTM structure is improved, and the optimized network structure and the attention mechanism is added to more effectively obtain important information in historical load data and improve the modeling ability of nonlinear load changes. The experimental results prove that the improved model has superior performance in short-term to long-term load forecasting. In high load scenarios, after 6 minutes of joint training scheduling time, the energy loss rate increases by 1.4%, improving the accuracy of load forecasting and solving key problems in complex scheduling and real-time optimization of power grids in high load density areas. This provides a new solution for intelligent scheduling and optimization of power systems.

2. Related Work

On the problem of load prediction optimization, some studies have used the LSTM (Long Short-Term Memory) [21,22] model to predict power load and achieved good results [23,24]. Liu T proposed a short-term photovoltaic power prediction method that combined genetic algorithm (GA) and LSTM, which optimized data through wavelet denoising and GA's LSTM network optimization. This method reduced about 98.43% and 98.97% in MAE and Root Mean Square Error (RMSE), respectively, significantly improving the prediction accuracy [25]. Rui H proposed a short-term power load parallel forecasting method that combined variational mode decomposition (VMD) and LSTM. VMD was used to decompose load data, and LSTM was used to predict each component. The forecast result was then corrected by combining external factors. This method effectively reduced the daily load forecast error by 2.18% [26]. LSTM can better handle the long-term dependency problem in time series data, but it still has certain limitations when facing nonlinear and diversified load fluctuations. Some studies have introduced reinforcement learning algorithms [27,28] and tried to apply them to power grid load optimization [29,30]. Zhang Y proposed a model-free optimization algorithm for power distribution systems using multi-agent DRL, which transformed the problems in the distribution network into an intelligent deep Q network framework, avoiding the need to solve the optimization model under time-varying operating conditions. This method performed well in voltage regulation and power loss reduction [31]. These studies have made some progress, but their models are relatively complex and have poor adaptability to real-time scheduling. Current research has not yet been able to simultaneously address the dual challenges of load forecasting accuracy and optimized scheduling, which has not been effectively studied in high-load density areas.

On the problem of power load prediction accuracy and scheduling optimization, some scholars have used the BiLSTM algorithm to optimize the power grid load forecasting accuracy, successfully improving the load forecasting performance and the stability of the power grid to a certain extent [32,33]. Li F proposed a multi-energy load prediction method based on BiLSTM and parallel feature extraction network. The residual network, convolutional block attention module, and BiLSTM were combined to obtain spatial and temporal features, and linear superposition was used to obtain accurate prediction results. The prediction error of this method was reduced by more than 20% [34]. Some scholars have combined BiLSTM with DRL, trying to use bidirectional learning and dynamic optimization to improve the prediction effects, and have achieved good optimization results. Liu P proposed a multi-type data fusion framework based on DRL, combined with BiLSTM extraction of stock data, technical indicators, and K-chart features, excellent performance in Chinese stock market and S & P 500 index data, achieving higher profit and Sharpe ratio [35]. These methods have improved the prediction effect to some extent, but few studies have applied it to the research of power grid load prediction. These studies are only optimized for specific problems and are not suitable for the actual needs of high load density areas, and the adaptability and versatility of the model are limited. Therefore, combining BiLSTM and DRL and performing joint optimization in multiple scenarios organically are still an urgent problem to be solved. In this paper, a new method for regional load forecasting combining BiLSTM and DRL is studied and constructed, which improves the structure of BiLSTM, optimizes the network structure, and adds attention mechanism to more effectively obtain important information from historical load data. The reward mechanism in the DRL algorithm is dynamically adjusted, and the optimal scheduling scheme is learned.

Table 1. Methods comparison.

Method Category	Advantages	Applicable Scenarios
Basic LSTM	Captures long-term dependencies; suitable for sequential data.	Mid-/short-term load forecasting
LSTM+GA	Combines prediction with global optimization; enhances scheduling stability.	Simple multi-objective optimization scenarios
VMD-LSTM	Decomposes non-stationary signals; improves modeling of high-frequency fluctuations.	Non-stationary, noisy load forecasting
BiLSTM	Bidirectional learning	High-variability load forecasting
DRL Optimization Models	Dynamically adjusts scheduling strategies; adapts to real-time demand fluctuations.	Real-time scheduling and demand response
Improved BiLSTM+DRL	Combines bidirectional learning, attention, and DRL; joint training improves prediction-scheduling synergy.	High-load-density areas with complex fluctuations

3. Method

Figure 1 shows the load forecasting and optimization process for power grids in high-load density areas. Load data is collected from multiple power systems; data cleaning is performed; noise and outliers are removed, and data is processed using standardization and normalization techniques. Data from different sources can be input into subsequent models at a unified scale. An improved BiLSTM model is constructed, with an added attention mechanism and optimized network structure to enhance the model's memory capacity and nonlinear feature extraction capabilities. A reinforcement learning model is used for dynamic optimization to adjust grid load scheduling based on prediction results. The BiLSTM and DRL models are jointly trained; different optimization strategies are compared, and the optimal strategy is selected to improve the load forecasting accuracy and optimization stability, so as to achieve accurate prediction and dispatch optimization of power grid load. This process simply shows the training and optimization process of the entire model, which helps to understand how the various modules work together.

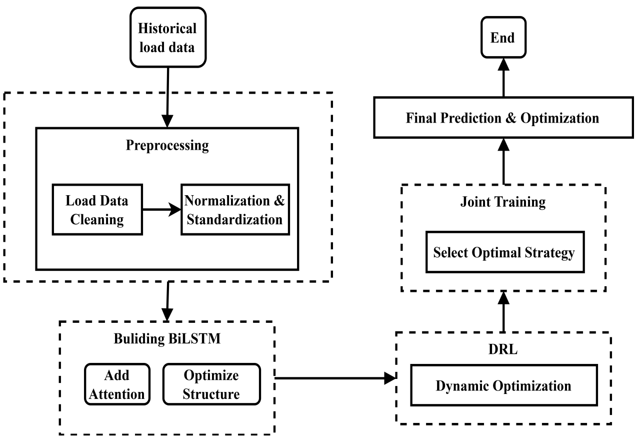

Figure 1. Load forecasting and optimization process for power grids in high-load density areas

A. Load Data Collection and Preprocessing

This paper collects the historical load data of multiple power systems (real-time load, peak, valley value, seasonal change, etc.) in high load density area. The data type is power load data. Noise and outliers are removed, and data standardization and normalization techniques are used to transform historical load data into a consistent scale for subsequent training and validation of the model. BiLSTM is implemented through the following steps. 1) Structural optimization: the hidden layer is increased to 3 layers, and the number of units is expanded (128); the ReLU activation function is used to alleviate the disappearance of the gradient and improve the long-term dependency processing capability. 2) Attention mechanism: the formula for calculating the weight at each moment is introduced to dynamically focus on the key period and enhance the sensitivity to load fluctuations. 3) Feature enhancement: one-dimensional convolution is combined to extract local remporal features and strengthen the multilayer perceptron (MLP). The attention mechanism optimizes memory ability by weighting historical information, and convolution and MLP cooperate to improve the extraction effect of complex features.

1) Data Collection and Cleaning

Electric load data in high load density areas is very important for studying load forecasting and optimization algorithms. Data collection focuses on representative data sources covering multiple time periods to make the data comprehensive and high-quality. The selected data covers but is not limited to daily load, weekly load, seasonal load fluctuations, etc. These data represent the load changes of the power grid at different time scales. During the data collection phase, cross-seasonal and cross-regional data is obtained from different power systems, covering peak load, valley load, and load fluctuation. The data comes from the power supply bureau, recorded by the monitoring system or smart meter inside the power system, and exported through the data interface. Multiple power systems have differences in time granularity and load density. These data can reflect the performance of the power grid under various environmental conditions and provide sufficient information for subsequent model training. Table 2 shows the power load data collection. Power system A collects 13,357 daily load data, and each record corresponds to a day's load statistics. Power system B collects 5,217 weekly load fluctuation data, and each record corresponds to the weekly load statistics. Power system C collects 2,119 seasonal load difference data, and each record corresponds to a quarterly load statistics.

Table 2. Power load data collection.

Data Source	Time Granularity	Data Type	Feature Description	Data Volume
Power System A	Daily Load	Real-time Load	Peak, Valley, Average	13,357 entries
Power System B	Weekly Load	Real-time Load	Weekly Load Fluctuation	5,217 entries
Power System C	Quarterly Load	Seasonal Variation	Winter/Summer Load Difference	2,119 entries

The data collected in the actual power system is susceptible to noise and outlier influence, and the data quality is not high, which affects the accuracy of load forecasting. Data cleaning is an essential step in this case. The detection of outliers can effectively identify data points that deviate from the normal distribution. The mean and standard deviation of the data are calculated. Each data point is considered an outlier if it meets the following conditions:

$$|x_i - \mu| > 3\sigma \quad (1)$$

If the deviation of the absolute value of a data point x_i from the mean μ exceeds 3 times the standard deviation σ, it is determined as an outlier. Outliers are data points that are sudden changes or deviate too much from the rest of the data. Removing these data points can reduce their impact on the model and improve the accuracy of the data set. The remaining data is further eliminated using IQR (Interquartile Range). The IQR method calculates the upper and lower quartiles Q_1 and Q_3 of the data and defines the normal range of the data as:

$$Q_1 - 1.5\times \text{IQR} \text{ to } Q_3 + 1.5\times \text{IQR} \quad (2)$$

IQR is the interquartile distance, and Q_3 and Q_1 represent the third and first quartiles. Data outside this range is considered extreme outliers and needs to be removed. The cleaning operation of these data ensures the quality and consistency of the data set, which helps to train the subsequent model efficiently; the statistics of load data cleaning are shown in Table 2.

In the case of noise in the data, simply removing data points is not enough. The moving average method is used to smooth the data and reduce the impact of short-term fluctuations. The data at each moment is averaged using the data in its adjacent window. The window size is w, and the calculation method is:

$$y_i = \frac{1}{w}\sum_{j=i-\frac{w}{2}}^{i+\frac{w}{2}} x_j \quad (3)$$

For each data point x_j, the average of its $\frac{w}{2}$ neighbors is taken as the smoothed value y_i. The moving average method can average adjacent data, effectively reduce short-term random fluctuations, make the data more stable, and facilitate subsequent model training and load forecasting. Removing noise also reduces the risk of overfitting and improves the adaptability of the model. Table 3 is the statistics of load data cleaning.

Table 3. Statistics of load data cleaning.

Time Granularity	Outlier Proportion (%)	Outlier Distribution Features	Extreme Value Proportion (%)	Cleaned Data Proportion (%)
Daily Load	5.2	Outliers during peak load, significant fluctuations during nighttime	1.9	92.9
Weekly Load	2.1	System errors during low load periods	0.7	97.2
Quarterly Load	4.5	Outliers due to seasonal changes, extreme weather conditions	3	92.5

Table 3 shows the data cleaning statistics and outlier distribution characteristics at different time granularities. The time granularity is divided into daily, weekly, and quarterly load data, reflecting the load fluctuation characteristics at different time scales. The outlier ratio refers to the proportion of outliers in the original data. The daily load anomaly reaches 5.2%, indicating that abnormal fluctuations are prone to occur during peak hours due to sudden demand or measurement errors; the quarterly load anomaly (4.5%) is mostly caused by extreme weather or seasonal differences. The extreme value ratio further distinguishes the proportion of extreme outliers. The cleaned data ratio shows the proportion of valid data retained after cleaning, indicating that after removing noise and outliers, high-quality data is still retained for model training. The outlier distribution characteristics of different time granularities are significantly different: daily load anomalies are concentrated in peak hours, while quarterly load anomalies are strongly correlated with seasonal changes. The data cleaning method combines the 3σ rule, IQR , and moving average method to remove short-term random noise and retain long-term trend information.

2) *Data Standardization and Normalization*

The power load data in high load density areas comes from different power systems. There are large differences in data magnitude and range. Directly inputting it into the model can lead to poor training results. Z-score is used; the mean of each feature is transformed to 0; the standard deviation is adjusted to 1. This process gives all data the same dimension and the influence between different features. The Z-score normalization formula is as follows:

$$x' = \frac{x-\mu}{\sigma} \quad (4)$$

x represents the original load data; μ is the mean of the feature; σ is the standard deviation of the feature, and x' is the standardized data. The standardized data has a similar value range at the same scale to avoid training deviations caused by differences in data magnitude. The standardized data facilitates effective learning using models such as neural networks, improving stability and training efficiency.

Considering that the model has high requirements for the distribution of input data, the Min-Max normalization method is used to further process the data. The normalization method compresses the data into a fixed interval and eliminates the numerical differences between features. The normalization formula is:

$$x' = \frac{x-x_{\min}}{x_{\max}-x_{\min}} \quad (5)$$

$x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature, respectively, and x' is the normalized data. This method can scale the load data to a uniform range, reduce the dimensional differences between the load data, and avoid the situation where large numerical features dominate the model learning process. In many deep learning-based optimization algorithms, normalized data can accelerate the convergence process and improve training efficiency.

Standardization and normalization eliminate the scale differences between features and retain the trend information in the time series data of load data. Standardization and normalization effectively reduce the deviation between different features, so that each feature has a certain balance in model training. Normalized data is more conducive to the training of models such as neural networks, avoiding the influence of some feature values on the learning effect of the model due to being too large or too small.

B. *Improved BiLSTM Model*

Adding attention mechanism and optimizing network structure to the traditional BiLSTM model improves the model's ability to remember historical load data and extract nonlinear features. The improvement helps to accurately obtain complex time series patterns in load data. The study improves BiLSTM through the following steps. 1) Structural optimization: the hidden layer are added, and the number of units is expanded; the Rectified Linear Unit (ReLU) activation function is used to alleviate the gradient vanishing and improve long-term dependency processing capabilities. 2) Attention mechanism: a formula for calculating the weight at each moment is introduced to dynamically focus on key periods and enhance the sensitivity to load fluctuations. 3) Feature enhancement: one-dimensional convolution is combined to extract local remporal features and superimposing the MLP layers. The attention mechanism optimizes memory capacity by weighting historical information, and convolution and MLP work together to improve the extraction of complex features.

1) *Network Structure Optimization and Memory Improvement*

On the basis of the conventional BiLSTM structure, multiple key structure optimizations are added to improve the memory of historical load data and the ability to extract complex time series patterns. The network structure is hierarchically adjusted to increase the number and units of hidden layers and enhance the model's memory when dealing with long-term dependencies. The single hidden layer of the traditional BiLSTM model is difficult to obtain complex patterns in high-dimensional data. After adding more hidden units and hierarchical structures, it can more effectively learn the long-term temporal dependencies in the data. The input is the preprocessed standardized time series data, and the output is the load predicted value. The model employs an activation function to prevent the gradient from vanishing, and the Adam optimizer accelerates the convergence. The number of hidden units in each layer is h, and the output of each layer in the network can be expressed as:

$$h_t = f\left(W_h \cdot \left[h_{t-1}, x_t\right] + b_h\right) \quad (6)$$

W_h is the weight matrix of the current layer; b_h is the bias term; h_{t-1} is the hidden layer state at the previous moment; x_t is the current input data; f is the activation function. The addition of multiple hidden layers effectively improves the model's ability to process deep information of time series data, allowing the potential long-term dependencies in historical load data to be more fully utilized.

By adding the convolution operation of the LSTM unit, the data at each moment can be transmitted in time series through the recurrent neural network, and local convolution can be used to extract features. This improvement enhances the ability to extract the load data.

The introduction of the convolution operation improves the performance of the original BiLSTM structure in processing high-frequency fluctuations, short-term mutations, and other features. The output is:

$$z_t = \sum_{k=0}^{K} w_k \cdot x_{t-k} \quad (7)$$

w_k is the weight of the convolution kernel, and x_{t-k} is the data of the current time step and the previous time steps. This processing method allows the network to extract time series features, retain local changes in the time series, and reduce the risk of losing key information.

2) *Attention Mechanism and Enhanced Nonlinear Feature Extraction Capabilities*

The study deliberately adds an attention mechanism to improve the ability to extract complex nonlinear features, allowing the model to automatically focus on important moments and data areas that affect load changes. When processing long time series, the traditional BiLSTM model averages or weights all input time series information, ignoring the potential key moments and important patterns. The addition of the attention mechanism allows the model to assign different weights to the input at each moment during the training process, highlighting the key periods of load change. This is achieved by calculating the importance weight of the input at each moment at each time step and weighting it using the following formula:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=0}^{T} \exp(e_k)} \quad (8)$$

e_t is the weight score calculated based on the input features and hidden layer state; T is the total length of the time series data; α_t is the attention weight of the data at that moment. The weighted input data can be used to calculate the network output at the next moment, allowing the model to focus on the most influential load fluctuation period and improve the model's ability to obtain time series patterns.

Combined with the MLP module, the output of each time step is further nonlinearly mapped to improve the expressive ability when processing complex time series data. The multilayer perceptron adds a nonlinear activation function to enable the model to learn more complex feature patterns. The output of the network is y_t, which can be calculated using the following formula:

$$y_t = \sigma\left(W_o \cdot \mathrm{ReLU}\left(W_i \cdot h_t + b_i\right) + b_o\right) \quad (9)$$

W_o and W_i are weight matrices; b_o and b_i are bias terms; the ReLU (Rectified Linear Unit) activation function is used to improve the nonlinear mapping ability of the network. This structure enables the network to better adapt to the complex nonlinear characteristics presented in the power load data, and uses back propagation to optimize the feature extraction process, making the load prediction results more accurate.

Table 4. Comparison of improved BiLSTM structure configuration.

Configuration	Traditional BiLSTM Model	Improved BiLSTM Model	Description
Number of Layers	2 layers	3 layers	The improved model adds layers to capture more complex temporal features.
Units per Layer	64 units	128 units	Increased units improve model capacity and feature extraction ability.
Activation Function	Tanh	ReLU	ReLU prevents vanishing gradients and enhances non-linear mapping capability.
Optimization Algorithm	SGD	Adam	Adam optimizer improves training efficiency and stability.
Attention Mechanism	None	Yes	Attention mechanism focuses on important moments, improving prediction accuracy.
Convolution Operation	None	1D Convolution	1D convolution helps extract local features, improving response to short-term fluctuations.
Time Step Input	Fixed time steps	Dynamic time steps	Dynamic adjustment of time steps adapts to variations in load data.

Table 4 shows the comparison of the improved BiLSTM structure configuration. The traditional BiLSTM parameters listed in the table are typical default configurations of BiLSTM models in the deep learning domain and are commonly found in earlier studies or standard implementations. The traditional BiLSTM uses fewer layers and units, 2 layers and 64 units, which is suitable for simpler time series data processing; the activation function is Tanh, which is prone to gradient disappearance problems in long sequence training. The optimization algorithm uses SGD (Stochastic Gradient Descent), which has a slow update speed and results in low convergence efficiency. The structure does not introduce an attention mechanism and is unable to focus on important information when processing long time series data, which limits the prediction accuracy. The improved BiLSTM adds a third hidden layer and 128 units to the traditional model to improve the ability to process complex time series data. The ReLU activation function solves the gradient vanishing problem, enabling the network to better learn nonlinear relationships. The optimization algorithm uses Adam, which greatly improves training efficiency and convergence stability; the introduced attention mechanism helps the model dynamically focus on the input at critical moments and improves sensitivity to timing changes. The added one-dimensional convolution layer extracts local timing features, improves the ability to respond to short-term fluctuations, and further improves the accuracy of load forecasting.

Improvements in nonlinear feature extraction have enhanced the network's ability to learn short-term mutations and long-term trends. They have also greatly enhanced the network's ability to mine potential complex patterns in multi-dimensional load data, allowing the power load forecasting model to have a certain degree of accuracy and stability in high load density areas. The added attention mechanism and nonlinear feature extraction method can more effectively identify the key factors affecting grid load fluctuations, provide more accurate prediction results, and provide a theoretical basis for grid scheduling and optimization. Figure 2 shows the structure of the improved BiLSTM model, covering the bidirectional LSTM layer, the attention mechanism layer, and the multi-layer perceptron layer. The processed historical load data of the high-load density area is input into the bidirectional LSTM layer, which consists of forward and reverse LSTMs to extract features from past and future time series information and obtain the global dependencies of the load data. The attention mechanism dynamically adjusts the importance of the input data according to the weights of different time steps, effectively highlighting the key moments of load changes. The adjusted data enters the multi-layer perceptron layer, uses nonlinear activation functions to extract deeper features, and outputs load forecasting results based on the processed information. The optimization of the entire structure aims to improve the model's ability to identify complex load fluctuations, and to more accurately predict power grid loads in high load density areas.

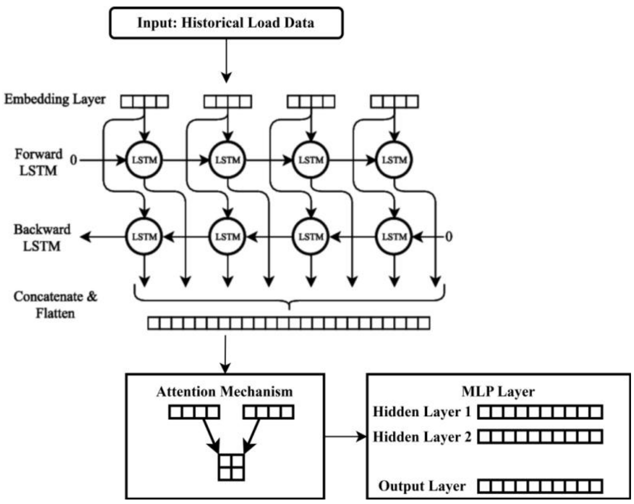

Figure 2. Improved BiLSTM model structure

C. Dynamic Reinforcement Learning Optimization

The DRL algorithm is introduced to dynamically optimize the load forecast results, simulate the feedback signals in the environment, adjust the grid load scheduling plan in real-time, and solve the demand fluctuation problem of the grid in high load density areas.

1) Dynamic Optimization Process and Real-Time Feedback Mechanism

In the load forecasting of power systems, a dynamic optimization mechanism of DRL is introduced to solve the problem of demand fluctuation in high load density areas. The DRL mechanism can adjust the power grid load dispatching plan in real-time according to the load forecasting results, effectively coping with the fluctuation of power demand. DRL constructs a state-action space, making the load dispatch of the power grid an optimization process. Each dispatch adjustment can affect the future state of the power grid and be corrected according to the real-time feedback signal.

The state space of power grid dispatch is composed of multiple factors, covering the current load demand of the power grid, available energy, system load distribution, etc. According to these states, a dispatch strategy is selected, that is, a set of appropriate control actions is selected to achieve the optimal distribution of load. Each dispatch adjustment of the power grid can return a reward signal as an evaluation indicator of the adjustment. The reward signal needs to consider the accuracy of the prediction and the feasibility of the scheduling scheme, and the reward calculation is:

$$r_t = \gamma r_{t-1} + \mathrm{Reward}\left(a_t, s_t\right) \quad (10)$$

r_t represents the reward at the current moment; γ is the discount factor; r_{t-1} is the reward at the previous moment; $\mathrm{Reward}\left(a_t, s_t\right)$ is the immediate reward calculated based on the current action and state. By continuously optimizing the reward function, the model can continuously improve the dispatching strategy and gradually achieve the stable operation of the power grid load and the effective control of demand fluctuations.

The intelligent agent uses the optimization method of the Q -learning algorithm to learn the state-action value. Each time the agent selects an action, it adjusts its strategy based on the current state and action feedback, gradually approaching the optimal load scheduling solution. The core formula for updating the Q value is:

$$Q\left(s_t, a_t\right) = Q\left(s_t, a_t\right) + \alpha\left[r_t + \gamma \max_{a'} Q\left(s_{t+1}, a'\right) - Q\left(s_t, a_t\right)\right] \quad (11)$$

$Q(s_t, a_t)$ represents the state-action value of selecting action a_t under state s_t, and α is the learning rate. γ is the discount factor; r_t is the reward at the current moment; a' is all possible actions at the next moment. By continuously updating the Q value, the agent can gradually learn the strategy that makes the power grid load scheduling plan optimal.

2) Dynamic Adjustment and Long-Term Optimization Goals

The load forecasting and optimization of power grids in high load density areas not only face the problem of short-term demand fluctuations, but also the requirement of long-term stability. The dynamic reinforcement learning algorithm simulates the feedback signal of the long-term system and adjusts the load dispatching strategy of the power grid, which can not only solve short-term fluctuations but also maintain long-term stability and efficiency. The study adopts a strategy of maximizing long-term rewards, so that the model can ensure real-time adjustment and consider the long-term optimization of power grid operation.

The model adopts a reward mechanism based on long-term discounts. Each decision not only plays a role in the short-term system load balance, but also has a positive impact on future load demand fluctuations. In actual operation, an iterative update strategy is used to maximize the long-term expected rewards of all state-action pairs, which is expressed using the following optimization objectives:

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{T_m} \gamma^t r_t\right] \quad (12)$$

$J(\pi)$ represents the long-term reward expectation of the optimization strategy π, and γ is the discount factor. By repeatedly optimizing this objective function, the model can gradually form a load scheduling strategy that is both adaptable to short-term load changes and has long-term stability.

Dynamic reinforcement learning also enables dynamic tuning at different time scales. In the face of sudden load fluctuations, the algorithm can quickly adjust the load scheduling strategy to respond to changes in instantaneous demand with minimal energy loss and system fluctuations. By introducing a reinforcement learning algorithm with environmental adaptation function, the system can adjust the dispatching plan in real-time and predict future load demand under different load demands and environmental conditions, effectively solving the problem of demand fluctuations in high load density areas.

Power grid load dispatching not only relies on demand forecasting at the current moment, but also combines the time series mode of historical data to ensure the rationality and efficiency of power grid load dispatching plans. The introduction of dynamic reinforcement learning can dynamically adjust strategies based on feedback signals. By using long-term strategy optimization, the power grid can cope with sudden demand fluctuations and maintain efficient and stable operation.

D. Joint Model Training and Optimization Strategy

BiLSTM and DRL are jointly trained, and by comparing different optimization strategies, the optimal strategy is selected to achieve the coordinated improvement of load forecasting and optimization. The model is updated through multiple rounds of iterations to improve the accuracy of load forecasting and the stability of optimization.

1) Joint Training Strategy and Collaborative Optimization Process

The prediction and optimization of high load density areas need to combine the advantages of dual models and combine the two core modules. The training is designed to be multiple rounds of iterations, and the accuracy of load forecasting and scheduling schemes are alternately optimized in each round of training. The goal of training is to minimize the load forecast error and ensure that the forecast results can be optimized during the scheduling process to achieve the synergistic improvement of load forecasting and optimization strategies.

The joint training strategy requires the mutual influence and adjustment of the two sub-models during the optimization process. In the training of the load forecasting model, the current predicted load results are used as input to adjust the grid dispatching and achieve the synchronous update of load forecasting and optimization objectives. A joint loss function is used to evaluate the performance of the two models. The loss function is the traditional load forecasting error term, taking into account the system operation cost and energy loss caused by dispatch optimization. The optimization objective is:

$$L_{\text{total}} = \lambda_1 L_{\text{forecast}} + \lambda_2 L_{\text{optimize}} \quad (13)$$

L_{forecast} is the loss function of load forecasting, and L_{optimize} is the loss function of scheduling optimization, reflecting the energy loss and time delay in scheduling. λ_1 and λ_2 are weight coefficients used to balance the impact of forecast error and optimization cost. By iteratively adjusting these parameters, load forecasting and optimization strategies can be synergistically improved to achieve accurate prediction and stable optimization of power grid load.

Each round of iteration uses the back propagation algorithm to update the model parameters. The load forecasting part can affect the scheduling optimization strategy, and the feedback signal of scheduling optimization can reversely affect the learning process of the load forecasting model. This two-way information flow allows the two to complement each other, gradually improving the accuracy of power grid load forecasting and the effectiveness of scheduling, and achieving the synergistic effect of load forecasting and scheduling optimization.

2) Multi-Round Iterative Update and Optimization Stability

The iterative update mechanism of the joint training model in multiple training rounds improves the stability of prediction performance and scheduling optimization. Each round of iteration can not only optimize the prediction performance, but also dynamically adjust the power grid load dispatching strategy according to the current prediction error. The high matching degree between the prediction results and the actual power grid demand is required, so as to avoid the problem of overfitting or poor adaptability caused by a single model.

A gradual optimization strategy is used in multiple iterations, with the weight of the loss function dynamically adjusted in each round of update. When the load forecasting model has a large prediction error, the weight of its loss function is increased to force more accurate prediction training; when the prediction accuracy is close to the target, the weight of the scheduling optimization is appropriately increased to improve the accuracy of the optimization solution. The strategy can be implemented using the following formula:

$$\begin{cases} \lambda_1^{(t+1)} = \lambda_1^{(t)} \cdot \left(1-\eta_{\text{forecast}}\right) \\ \lambda_2^{(t+1)} = \lambda_2^{(t)} \cdot \left(1-\eta_{\text{optimize}}\right) \end{cases} \tag{14}$$

$\lambda_1^{(t)}$ and $\lambda_2^{(t)}$ represent the weight coefficients in the t iteration, and η_{forecast} and η_{optimize} are adjustment coefficients, controlling the balance between prediction accuracy and scheduling optimization. The model gradually adjusts these coefficients in multiple rounds of training to strengthen the interaction between load prediction accuracy and scheduling strategy.

With the increase in training rounds, the joint model can gradually converge to a stable state. In this state, the load forecasting accuracy and optimization stability reach the best balance point, that is, the forecast results can reflect the actual load fluctuations of the power grid, and the dispatching strategy can efficiently allocate power grid resources according to the forecast results to reduce energy waste and load overload. The comparison and selection of multiple optimization strategies can quickly adapt to different load demand changes and power grid load fluctuations in actual applications.

The multi-round iterative update mechanism makes the entire model highly adaptable in complex power grid environments. Each update can gradually improve the prediction error and dispatch decision through the feedback of historical data. The trained model finally shows a higher prediction accuracy and optimization effect in dealing with power demand fluctuations in high-load density areas, improving the overall performance of power grid load prediction and optimization.

4. Method Effect Evaluation

A. Prediction Accuracy Evaluation

The study uses three indicators: MSE, MAE, and determination coefficient R^2. MSE is used to measure the sum of squares of the differences between predicted values and actual values, reflecting the overall magnitude of the error; MAE calculates the mean absolute value of the difference between predicted values and actual values, reflecting the average level of error and more intuitively showing the deviation of the model. The R^2 value is the ability to explain the variability of data. The BiLSTM+DRL model in this paper and the traditional BiLSTM, LSTM+GA (Genetic Algorithm), and VMD-LSTM (Variational Mode Decomposition-Long Short-Term Memory) models all use the same historical load data set for training and prediction. The error of the results can be quantified using the above indicators to compare the performance of different models in terms of prediction accuracy and verify the advantages of the model in complex time series load forecasting tasks. Table 5 configures the parameters of each model. LSTM and BiLSTM themselves do not contain attentional mechanisms, and the model presented here uses BiLSTM in combination with attentional mechanisms.

Table 5. Model parameter configuration.

Model	Layers	Units per Layer	Activation Function	Optimizer	Learning Rate Range
BiLSTM	2	64	Tanh	SGD	0.01~0.02
LSTM+GA	2	64	Tanh	GA + Adam	0.003~0.008
VMD+LSTM	2	64	Tanh	Adam	0.004~0.006
BiLSTM+DRL (Proposed)	3	128	ReLU	Adam	0.0005~0.002

Table 5 shows the core configuration parameters of the four load forecasting models, including the number of layers, the number of units per layer, the activation function, the optimizer, and the learning rate range. The typical configurations of BiLSTM, LSTM+GA, and VMD+LSTM all adopt a two-layer structure; the number of units is 64; the activation function uses Tanh; the optimizers are SGD, GA+Adam, and Adam, respectively. The proposed BiLSTM+DRL adopts a three-layer BiLSTM structure; the number of units is increased to 128; the ReLU activation function is introduced. The optimizer is Adam, which has stronger feature extraction capabilities. It is worth noting that LSTM and BiLSTM themselves do not contain an attention mechanism. The model proposed in this paper uses BiLSTM combined with an attention mechanism. The data intuitively reflects the structural characteristics of different models and provides a basis for model comparison and optimization.

Figure 3 shows the comparison of MAE and MSE of different load forecasting models in different time intervals. It can be seen that the BiLSTM+DRL model proposed in this paper shows better prediction accuracy than other models in all time intervals. In short-term and long-term predictions, the MAE range is 0.05-0.12, and the MSE range is 0.005-0.025. Both MAE and MSE are low, indicating that the model can more accurately obtain short-term and long-term fluctuations in load data. As the prediction time increases, the errors of all models converge slightly, and the BiLSTM+DRL model maintains good performance, showing its strong generalization ability and adaptability. The traditional BiLSTM model has a higher MAE when the prediction time increases, which shows that it has limited ability to obtain long-term time series patterns. The prediction accuracy of the LSTM+GA model and the VMD-LSTM model is also lower than that of the BiLSTM+DRL model, and their performance in long-term prediction is also insufficient. The data results show that in high load density areas, load changes have a strong time series correlation. The improved BiLSTM model introduces a dynamic optimization mechanism of reinforcement learning, which can more effectively adjust the grid load dispatch and improve the overall prediction accuracy. The advantage of BiLSTM+DRL is that it combines the two-way learning ability of historical data and the real-time feedback adjustment ability of load demand fluctuations, adapting to complex grid load fluctuation patterns.

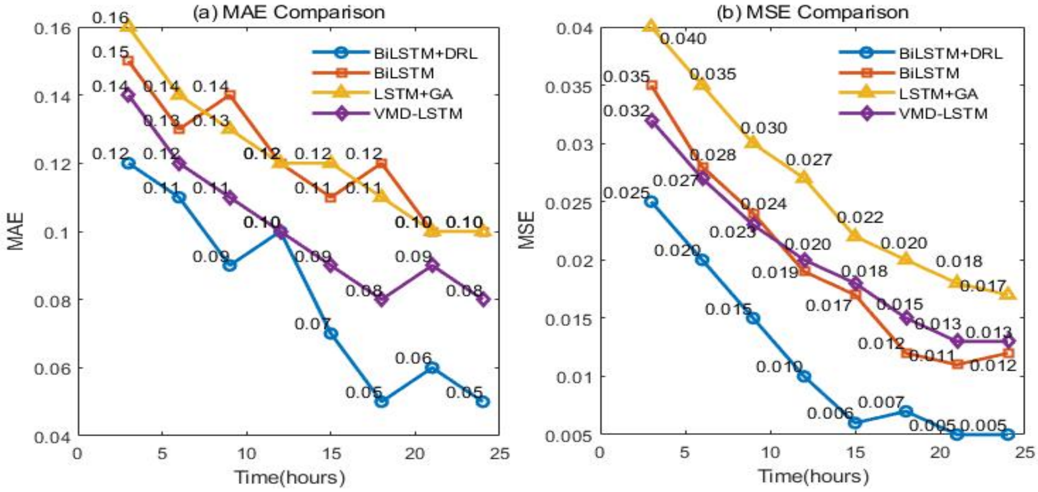

Figure 3. Comparison of load forecasting errors

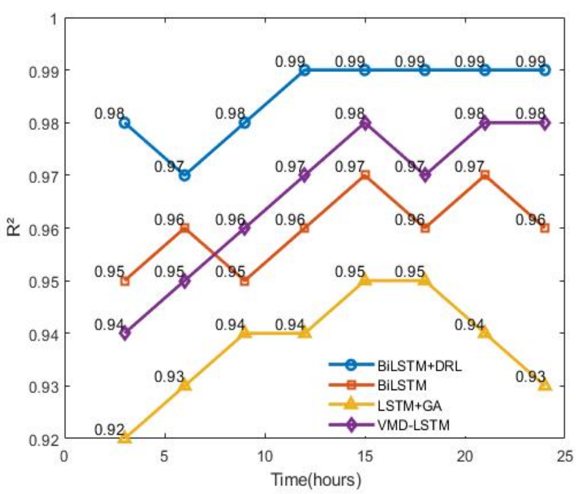

Figure 4. Comparison of determination coefficients

Figure 4 shows the comparison of the determination coefficient values of different models in load forecasting over time. BiLSTM+DRL shows the highest R^2 value in all time periods, which is stable between 0.97 and 0.99. This shows that the model has excellent fitting ability in load forecasting and can accurately obtain the time series relationship in load data. The R^2 value of the BiLSTM model is between 0.95 and 0.97. Although it can fit the data well, it performs slightly worse in the prediction of longer time intervals. The R^2 value of LSTM+GA is slightly lower and fluctuates more, mainly because the model fails to effectively handle complex load time series patterns, and the prediction accuracy is affected to a certain extent. The overall performance of the VMD-LSTM model is between BiLSTM and BiLSTM+DRL. It has better time series learning ability, but it still has certain shortcomings in complex load fluctuations. These data reflect the differences in adaptability and accuracy of different models in load forecasting. The advantages of BiLSTM+DRL are particularly obvious. It can provide more accurate and stable forecasting results in the changing power load demand, which is of great significance to the optimal dispatch of the power system.

B. Optimization Effect

Figure 5 shows the load forecasting and optimization scheduling effect. In the reward change diagram, the reward signal shows a fluctuating trend, which reflects the environmental feedback adjustment in the dynamic optimization process. The cumulative value of the reward is constantly changing, indicating that the system is constantly adjusting its strategy based on real-time feedback to achieve the optimization goal. This fluctuation reflects that at different time points, the optimization degree of load dispatch strategy is different, adapting to the needs of grid demand fluctuation and environmental changes. The load dispatch and actual demand comparison chart shows the difference between predicted load and actual demand. The actual demand curve shows periodic fluctuations. Affected by seasonal changes, weather conditions, and other factors, the predicted load shows a relatively stable trend. The difference between the two is mainly due to the fact that the forecast model fails to fully capture the short-term fluctuations in demand. In the case of high load or sudden demand, the actual demand exceeds the predicted value, which requires the load dispatch system to make appropriate adjustments in actual applications. However, overall, the forecast model can be very close to the actual demand, reflecting the optimization effect. The energy loss comparison chart reflects the difference in energy loss between the dispatch strategies before and after optimization. The optimized energy loss curve is significantly lower than the actual dispatch curve. Under the action of the optimization algorithm, the grid dispatch plan has been improved, and energy waste has been reduced. The system dynamically adjusts the dispatching strategy according to load demand and energy supply, successfully reducing unnecessary energy losses and improving the overall operation efficiency of the power grid. These data changes show that the introduced DRL optimization algorithm can effectively alleviate the energy loss problem in the power grid in high-load density areas and improve the dispatching efficiency of the power grid.

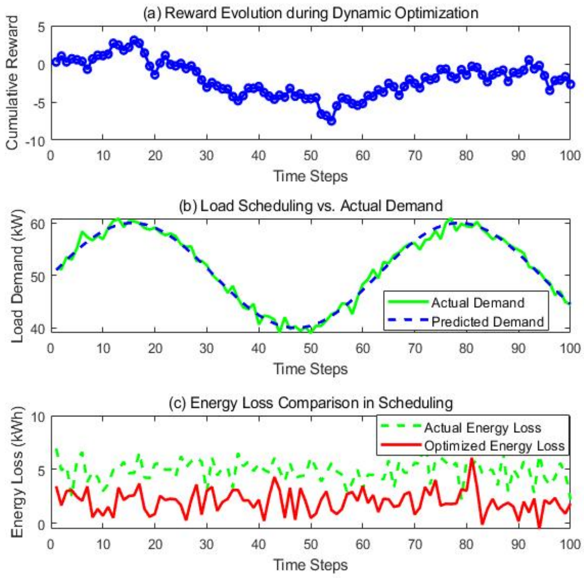

Figure 5. Load forecasting and optimization scheduling effect

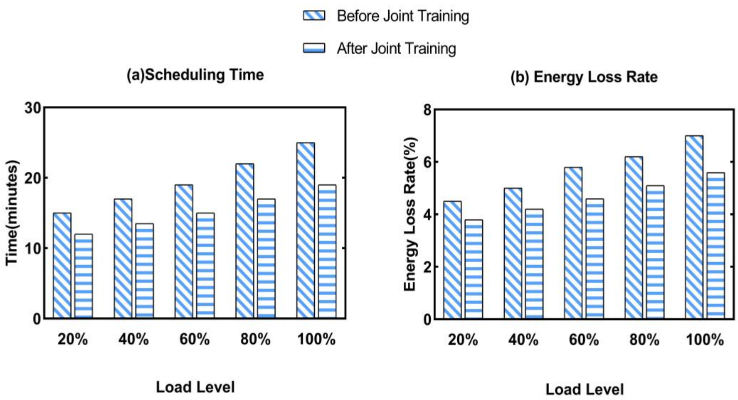

Figure 6. Comparison of scheduling time and energy loss rate

Figure 6 compares the dispatch time and power loss rate of different load levels before and after the joint training of the proposed model. Joint training significantly improves scheduling time and energy loss rate. In the comparison of dispatch time, as the load level increases, the dispatch time shows an upward trend in both cases, and the dispatch time after joint training is greatly reduced at each load level. Joint training enables the power grid system to respond to load fluctuations more quickly, optimizes dispatch decisions, and reduces unnecessary time consumption. The dispatch time for 20% low load is reduced by 3 minutes, and the dispatch time for 100% high load is reduced by 6 minutes, showing that the dispatch efficiency of joint training in handling high load has been significantly improved. The comparison of energy loss rate shows that the energy loss rate after joint training has been reduced at all load levels, and the performance is more prominent in the high load area. The energy loss rate under 100% high load decreases by 1.4%, which shows that the load forecasting and scheduling strategy optimized by joint training can allocate resources more accurately under high load conditions, avoiding over-scheduling and energy waste. Joint training improves scheduling accuracy and decision-making efficiency, reduces scheduling time, and effectively reduces energy loss, thereby improving the operating efficiency and energy utilization rate of the power grid system.

C. Computational Efficiency Evaluation

The prediction time of each model can be compared to evaluate the computational efficiency of the improved model when processing load data of different scales. This indicator helps to determine the feasibility of the model in practical applications.

The bar chart in Figure 7 shows the prediction time of each model under different data volumes. When the data volume increases from 1,000 to 5,000, the prediction time of all models increases. The prediction time of the BiLSTM+DRL model is always lower than that of other traditional models. As the data scale increases, the computing resources and processing time required by the model also increase. When processing large-scale data, traditional models have efficiency bottlenecks. The optimized structure and joint training strategy of the BiLSTM+DRL model enable it to effectively improve computing efficiency and reduce prediction time when processing complex time series data. In addition, DRL uses dynamic optimization and strategy iteration to enable load forecasting to gradually converge during the training process, further reducing computing time. When the amount of data increases, the prediction time of LSTM+GA and VMD-LSTM increases significantly, reflecting that these two traditional methods have the problem of excessive computational overhead when processing large amounts of data. Although BiLSTM performs well, its computational efficiency is still not as good as the BiLSTM+DRL model.

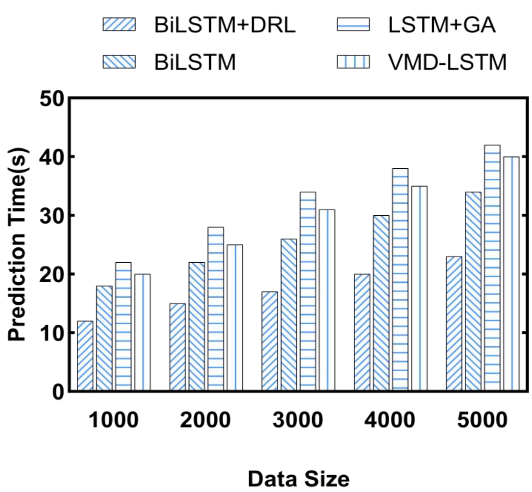

Figure 7. Comparison of prediction time under different data volumes

5. Conclusions

This study constructs a load forecasting optimization model for high-load density regional distribution networks based on improved BiLSTM and DRL, and improves load forecasting accuracy and grid dispatching efficiency through joint training. Regarding load forecasting, the improved BiLSTM model introduces an attention mechanism and optimizes the network structure, which improves the ability to remember historical load data and extract nonlinear features, and can more accurately obtain complex time series patterns in load data. Regarding dispatch optimization, the DRL algorithm uses a real-time feedback mechanism to dynamically optimize the forecast results, effectively solving the demand fluctuation problem of high-load density regional power grids and improving the stability and real-time performance of grid load dispatching. The experimental results show that compared with the traditional BiLSTM, LSTM+GA, and VMD-LSTM models, the proposed BiLSTM+DRL model has a mean absolute error (MAE) of 0.05-0.12, a mean square error (MSE) of 0.005-0.025, and a determination coefficient (R^2) of 0.97-0.99. In the 100% high load scenario, the scheduling time is reduced by 6 minutes after joint training, and the energy loss rate is reduced by 1.4%, showing obvious advantages in load forecasting accuracy and scheduling optimization effect. The prediction time is significantly lower than other models under large data volume. After joint training, the power loss rate is effectively reduced, and the scheduling time is also greatly shortened. The improved model improves the prediction accuracy, optimizes the power grid scheduling efficiency and power utilization, and has strong practical application value. Future research can further optimize the feedback mechanism of the DRL algorithm, explore more efficient multi-objective optimization methods, and further improve the performance of power grid load forecasting and optimization.

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Consent to Publish

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Author Contribution

Yuanfang Zeng: Edited and refined the manuscript with a focus on critical intellectual contributions.

Yongyuan Wang, Mingke Li: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

Junshu Su, Min Zhang: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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