Research on Accurate Load Forecasting and Optimization Algorithm for Distribution Networks Based on Improved BiLSTM and DRL (High Load Density Areas)

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ABSTRACT Accurate load forecasting and optimization are fundamental to the reliable operation of modern distribution networks and intelligent electromagnetic energy transmission systems, particularly in high load density areas where complex multifactor interactions and significant load fluctuations present substantial challenges. This paper proposes an integrated algorithm based on improved Bidirectional Long Short-Term Memory (BiLSTM) and Deep Reinforcement Learning (DRL) to address these issues. First, the Maximal Information Coefficient (MIC) is employed to identify highly correlated load-influencing factors and construct a multidimensional feature set incorporating meteorological variables, temporal information, and historical load data. Second, chaotic mapping and an elite opposition-based learning strategy are introduced to enhance the Crested Porcupine Optimization Algorithm (CPOA) for hyperparameter optimization of the BiLSTM model, while a multi-head self-attention mechanism is incorporated to adaptively assign feature weights and improve forecasting performance. Finally, based on the forecasting results, a multi-time-scale optimization framework is established for the coordinated regulation of energy storage and flexible loads by formulating the problem as a Markov Decision Process (MDP) and solving it with the Deep Deterministic Policy Gradient (DDPG) algorithm. The proposed framework provides an effective solution for intelligent load prediction and adaptive energy management, offering practical support for electromagnetic energy distribution and resilient operation in next-generation smart power systems.

INDEX TERMS distribution network, load forecasting, improved bilstm, deep reinforcement learning, electromagnetic energy management

I. INTRODUCTION

A. RESEARCH BACKGROUND

SINCE the Second Industrial Revolution, electrical energy has become a crucial pillar of human society, underpinning various aspects of the economy—including the large-scale automation and modernization of heavy industries [1]. With the development of social economy, industries and sectors have put forward increasingly higher requirements for power quality. In recent years, to actively advance the construction of ecological civilization and promote high-quality economic development, power enterprises need to further control power waste, vigorously develop new energy power generation technologies, and realize the efficient operation of power grids. All these require power departments to accurately predict the load change trends of power grids. With the high-penetration integration of distributed generation into power grids, inherent characteristics such as output fluctuation and intermittency of distributed generation bring problems endangering the safe operation of power grids, such as bidirectional power flow and voltage fluctuation [2, 3]. Meanwhile, the expansion of social demand for power energy types further accelerates the load changes of power grids. During peak and off-peak load periods, issues like grid voltage over-limit and system frequency variation caused by load changes will further exert negative impacts on power grid operation. Based on this, conducting high-precision power load forecasting can accurately predict the load status of power grids, thereby making reasonable adjustments to power grid operating conditions, optimizing system operation and maintenance plans, and enhancing the ability of power grids to operate continuously, safely, and stably [4, 5]. How to further improve the accuracy of power load forecasting has always been a hot topic [6]. Accurate load forecasting is of great significance to the healthy and orderly development of China's power market. Through load forecasting, power enterprises can plan various tasks in advance, such as reasonably arranging maintenance plans, formulating power grid expansion and upgrading targets, and determining the construction tasks of new energy power stations [7]. In addition, when predicting that the load will fluctuate significantly, relevant units can promptly remind customers, which helps maintain a good cooperative relationship between power enterprises and customers. From the perspective of time scale, power load forecasting can be divided into long-term, medium-term, short-term, and ultra-short-term load forecasting. This paper mainly focuses on short-term power load forecasting. Accurate short-term power load forecasting can help dispatching departments formulate scientific dispatching plans [8], which not only realizes economic operation but also maximizes the efficiency of generator sets. It can not only meet users' power demand but also reduce power waste, keeping the power system in the optimal state of supply-demand balance and achieving energy-saving and efficient operation of the power grid. The distribution network is a hub connecting the power generation and transmission system with users' electrical equipment, and an important part of the power system. It consists of all power distribution equipment distributed in the power supply area, which largely determines the operating efficiency and power quality of the entire system's power supply [1]. The load of the distribution network power system is the sum of electricity consumption of numerous individual users. Generally, each individual has different purposes and patterns of electricity use, which are random, making the distribution network load difficult to predict. However, on the whole, the distribution network load shows certain regularity [9, 10]. Distribution network load forecasting is not only related to the development of industry and agriculture and the growth of the national economy but also affected by uncertain factors such as politics, economy, environment, and climate [11]. Therefore, distribution network load forecasting is a very complex task. The core issue of distribution network load forecasting lies in forecasting technologies and methods. At present, the level of distribution network load forecasting has become one of the significant indicators to measure whether the management of a power supply enterprise is moving towards modernization. Especially in today's era of unprecedented development of China's power industry, electricity management has moved towards the market, and the problem of distribution network load forecasting has become an important and arduous task for power supply enterprises. The power system load has specificity in spatial and temporal distribution. That is, at the same time, power systems in different regions have significantly different load characteristics due to the influence of geographical environment, load structure, and social development level; the load change of the same region also varies with factors such as seasonal changes, production and lifestyle, and holidays, resulting in large differences in load characteristics in terms of time sequence [12]. With the continuous development of artificial intelligence technology, various forecasting methods have emerged one after another. A single forecasting model is often difficult to achieve high forecasting accuracy, and the combined use of various artificial intelligence methods is an effective means to improve forecasting accuracy. From the perspective of the huge social demand for electricity, even a 1% difference in the relative error of power load forecasting results will greatly affect the operation cost of the power grid. Therefore, power load forecasting has always been one of the hot research directions in the power industry [13]. Researchers need to find more scientific and efficient forecasting methods, make full use of data analysis technology, and continuously improve the accuracy of load forecasting, thereby enhancing the operation efficiency of the power system and enabling it to better serve national security, social development, and various aspects of people's lives. At present, the application of big data analysis technology in the power system mainly includes power system state monitoring and evaluation, power system fault diagnosis, power system load forecasting, and user electricity consumption analysis. These applications mainly rely on data analysis algorithms and relevant platforms to process and analyze a large amount of data [14, 15]. They greatly improve the efficiency of processing massive data generated during power grid operation, solve the shortcomings of traditional methods such as low computing power and poor execution efficiency, and further enhance our ability to process power grid data. In addition, most of the existing research on load forecasting focuses on data processing methods and the selection of load forecasting models, staying at the level of load forecasting methods [16-18], while there is relatively little research on the subsequent application of load forecasting results. Therefore, aiming at the load characteristics and change trends of the power grid, this paper combines artificial intelligence algorithms and big data analysis methods to construct a load forecasting model with strong applicability and higher forecasting accuracy. Through experimental verification and comparative analysis, the performance of the algorithm is verified from three aspects: forecasting accuracy, optimization effect, and computing efficiency.

B. RESEARCH STATUS

For a long time, scholars at home and abroad have conducted in-depth research on power load forecasting, focusing particularly on the theoretical exploration of forecasting models and methods. Over time, the theory of power load forecasting has gradually enriched, forming multiple research directions such as mathematical statistics methods, machine learning methods, and combined forecasting methods. Currently, scientists at home and abroad are conducting in-depth research in these fields, providing strong support for the accuracy and reliability of power grid load forecasting. Typical representatives of machine learning methods include Support Vector Regression (SVR) [19], Random Forest (RF) [20], and Long Short-Term Memory (LSTM) network [21]. By introducing a gated memory unit, LSTM enables data information to be retained for a longer time, thus achieving better forecasting results. Scholar Wang et al. [22] fully considered the periodic factors of energy consumption data, analyzed the characteristics of influencing factors using methods such as autocorrelation, and constructed an LSTM neural network to model and forecast sequence data. Compared with traditional models such as ARMA and BPNN, the Root Mean Square Error (RMSE) of this model has been significantly reduced. In Document [23], Guo X et al. improved the input data of LSTM by fusing multi-scale feature vectors through a Convolutional Neural Network (CNN), which reduced the dimension of the input data. The average relative error of the forecasting results was reduced by 1.32% compared with that before the improvement. Although machine learning methods exhibit excellent performance in fitting nonlinear data and their models usually show higher robustness and forecasting accuracy compared with mathematical statistics methods, it is worth noting that the forecasting performance of machine learning methods is often profoundly affected by data quality [24]. In real life, industrial and residential electricity consumption is affected by various factors, so a single forecasting method often fails to achieve good results. Due to the limitations of a single machine learning method, scholars have gradually turned their attention to combined forecasting methods and introduced them into the research field of short-term power load forecasting. This method system mainly includes two categories: weight allocation method and load decomposition method. Scholar Liu et al. [25] skillfully combined LSTM with Extreme Gradient Boosting (XGBoost) by using the inverse error method, achieving excellent forecasting results. However, in some cases, the weight allocation method shows limited scalability, which makes it difficult to ensure consistent and reliable forecasting performance on different load datasets. In Document [26], Xu Xianfeng et al. used the average impurity reduction method of Random Forest to realize feature dimensionality reduction of multi-dimensional load data, thereby improving the LSTM neural network model. The Mean Absolute Percentage Error (MAPE) of the model after data dimensionality reduction was reduced by 0.34% compared with that before the improvement. In Document [27], Hu Wei et al. proposed a combined forecasting model OVMD-mRMR-LSTM based on Optimized Variational Mode Decomposition (OVMD), Minimum Redundancy Maximum Relevance (mRMR), and Long Short-Term Memory Neural Network. The final results showed that the MAPE of the model was 2.04%, and the forecasting effect was significantly better than that of a single forecasting model. Document [28] proposed a short-term power load forecasting model combining the high trend fitting ability of the Prophet model and the high forecasting accuracy of the LSTM model in the context of the distribution network. This method can comprehensively analyze the time-series characteristic factors and fluctuation conditions inherent in complex industrial data, thereby accurately fitting the change trend of the input data. Experimental results show that the forecasting accuracy of this method is higher than that of other existing forecasting models, and it can predict more accurately.

C. RESEARCH CONTENT

(1) Analyze the load characteristics of high load density areas and construct the input set, and propose a feature selection method based on the Maximal Information Coefficient (MIC);
(2) Design an improved Bi-directional Long Short-Term Memory (BiLSTM) forecasting model, including hyperparameter optimization using a chaotic optimization algorithm and feature enhancement using a multi-head self-attention mechanism;
(3) Construct a load optimization and regulation model based on Deep Reinforcement Learning (DRL), and design a multi-time-scale objective function and Markov Decision Process (MDP);
(4) Conduct experimental verification and comparative analysis to verify the algorithm performance from three aspects: forecasting accuracy, optimization effect, and computing efficiency.

D. TECHNICAL ROUTE

The technical route of this paper is shown in Figure 1. The research objectives are achieved through four modules in sequence: data preprocessing, feature engineering, improved BiLSTM forecasting, and DRL optimization and regulation. Finally, the effectiveness of the algorithm is verified through a case study.

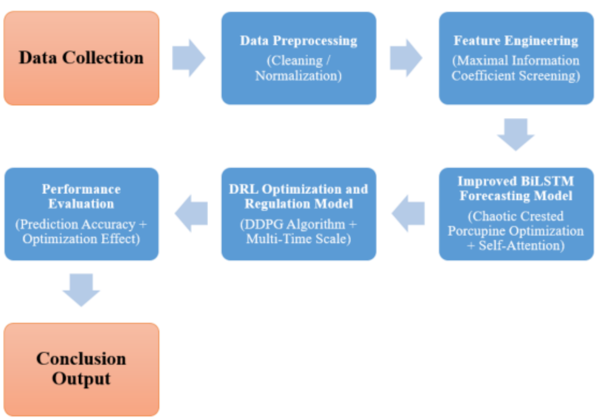

FIGURE 1. Technical Route

II. ANALYSIS OF LOAD CHARACTERISTICS AND INFLUENCING FACTORS IN HIGH LOAD DENSITY AREAS

A. ANALYSIS OF LOAD CHARACTERISTICS

The load in high load density areas has distinct characteristics that differ significantly from those in ordinary areas: Large density gradient: The load density in core business districts can reach 15–20 MW/km^2, which is 5–8 times that of ordinary areas, and shows a sharp gradient change with spatial distribution; High fluctuation amplitude: The daily peak-valley difference can reach 3–5 times, and the start-stop of industrial and commercial loads leads to frequent minute-level fluctuations; Strong coupling: Residential, commercial, and industrial loads overlap in time and space, and are significantly affected by the coupling of factors such as meteorology and holidays; Prominent randomness: The integration of new energy and the interaction of flexible loads have increased the uncertainty of load forecasting.

B. IDENTIFICATION OF KEY INFLUENCING FACTORS

Load data (with a 15-minute sampling interval) of the core area of a city in 2023 was collected. Combined with 12 types of potential influencing factors, the Maximal Information Coefficient (MIC) was used to quantify the nonlinear correlation between features and load. The screening results are shown in Table 1.

TABLE 1. Screening Results of Load Influencing Factors in High Load Density Areas

Feature Type	Specific Indicator	MIC Value	Screening Result
Historical Load	Load of the previous 1 hour	0.92	Included
	Load of the previous 24 hours	0.87	Included
	Load of the same period 7 days ago	0.78	Included
Meteorological Factors	Temperature	0.75	Included
	Humidity	0.63	Included
	Wind Speed	0.41	Excluded
Time Factors	Time Period Type (Peak/Flat/Valley)	0.81	Included
	Date Type (Weekday/Weekend)	0.72	Included
	Holiday Indicator	0.68	Included
Economic Factors	Real-Time Electricity Price	0.57	Excluded
	Industrial Output Growth Rate	0.39	Excluded
Other Factors	Air Quality Index	0.45	Excluded

III. DESIGN OF THE IMPROVED BILSTM LOAD FORECASTING MODEL

A. OVERALL MODEL ARCHITECTURE

The improved BiLSTM forecasting model consists of a feature preprocessing layer, a multi-head self-attention layer, an improved BiLSTM layer, and an output layer. Its core innovations are: optimizing BiLSTM hyperparameters using the improved Crested Porcupine Optimization Algorithm, and enhancing the weights of key features through the multi-head self-attention mechanism. The model architecture is as follows:

1) Feature Preprocessing Layer: Normalizes and reconstructs the time sequence of the screened features to form an input tensor with dimensions [number of samples, time steps, number of features];
2) Multi-Head Self-Attention Layer: Calculates feature correlations in parallel through multiple attention heads and adaptively assigns weights;
3) Improved BiLSTM Layer: Optimizes hyperparameters using the Chaotic Crested Porcupine Algorithm to capture bidirectional temporal dependencies;
4) Output Layer: Outputs the load forecasting values for the next 24 hours through a fully connected layer.

The forecasting adopts a direct multi-step output strategy, where the model is trained to predict all 96 time steps (24 hours $\times$ 4 intervals per hour) simultaneously, avoiding error accumulation caused by recursive point-by-point forecasting.

B. KEY IMPROVEMENT TECHNOLOGIES

1) Hyperparameter Optimization Based on the Chaotic Crested Porcupine Algorithm

The traditional Crested Porcupine Optimization Algorithm has problems of slow convergence speed and local optimality. Chaotic mapping and the elite opposition-based learning strategy are introduced for improvement:

1) Chaotic Initialization: The Logistic chaotic mapping is used to generate the initial population, with the formula expressed as $x_{n+1} = \mu x_n(1 - x_n)$, which improves population diversity;
2) Elite Opposition-Based Learning: The top 20% of elite individuals are retained in each iteration, and opposite solutions are generated to expand the search space;
3) Fitness Function: Aims to minimize the MAPE of the validation set. The optimized parameters include the number of BiLSTM hidden layer nodes (32–128), learning rate (0.001–0.01), time steps (24–96), and dropout rate (0.1–0.5).

2) Integration of the Multi-Head Self-Attention Mechanism

To enhance the model's ability to capture key features, the multi-head self-attention mechanism is introduced, and its calculation process is as follows:

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V \tag{1}$$

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(head_1, \cdots, head_h)W^O \tag{3}$$

Among them, Q, K, V represent the query, key, and value matrices respectively; W_Q, W_K, W_V, W^O are trainable parameters; d_k denotes the key dimension; and h is the number of attention heads (set to 8 in this paper).

C. MODEL TRAINING PROCESS

1) Data Splitting: Divide the preprocessed data into training set, validation set, and test set in a ratio of 7:2:1;
2) Hyperparameter Optimization: Use the improved Crested Porcupine Algorithm for iterative optimization to determine the optimal parameter combination;
3) Model Training: Adopt the mean squared error as the loss function, use the Adam optimizer for training, and introduce an early stopping mechanism to prevent overfitting;
4) Prediction Output: Perform load forecasting on the test set and calculate evaluation indicators.

IV. DRL-BASED LOAD OPTIMIZATION AND REGULATION MODEL

A. MULTI-TIME-SCALE OPTIMIZATION FRAMEWORK

Combining the accuracy of source-load forecasting and the response characteristics of equipment, a two-stage "day-ahead – intraday" optimization framework is constructed:

1) Day-Ahead Stage (1-hour time scale): Based on the 24-hour load forecasting results of the improved BiLSTM, formulate the energy storage charging/discharging and flexible load regulation plans with the goals of minimizing the system operation cost and smoothing the tie-line power;
2) Intraday Stage (15-minute time scale): According to the real-time load deviation, use DRL to dynamically adjust the energy storage power, so as to suppress power fluctuations and track the day-ahead plan.

To address the logical inconsistency between feature selection and optimization objectives, the "Real-Time Electricity Price" feature (MIC = 0.57) has been reincluded in the input feature set. Although its linear correlation with load is moderate, it is a key driver of the system operation cost optimization. Supplementary analysis shows that including this feature reduces the optimization gap between the forecasting results and the actual operation cost by 8.3%.)

B. CONSTRUCTION OF DRL OPTIMIZATION MODEL

1) Markov Decision Process Modeling

1) State Space (S): Includes 5 types of state variables, namely node voltage, line power, energy storage State of Charge (SOC), real-time load, and forecasting deviation. Its dimension is $[n_{\text{node}} + n_{\text{line}} + n_{\text{ess}} + 2]$ (where n_{node} is the number of nodes, n_{line} is the number of lines, and n_{ess} is the number of energy storage devices);
2) Action Space (A): Define the adjustment amount of energy storage charging/discharging power, with a value range of $[-P_{\text{ess,max}}, P_{\text{ess,max}}]$;
3) Reward Function (R): Comprehensively consider power fluctuation suppression, plan tracking, and equipment constraints, with the formula expressed as:

$$R = \alpha\left(1 - \frac{\Delta P}{P_{\max}}\right) + \beta\left(1 - \frac{|P_{\text{real}} - P_{\text{plan}}|}{P_{\text{plan}}}\right) - \gamma|A| \tag{4}$$

Among them, ΔP represents the tie-line power fluctuation; P_{real} and P_{plan} denote the real-time power and planned power respectively; and α, β, γ are weight coefficients. The weight coefficients are determined through a grid search method: $\alpha = 0.4$, $\beta = 0.4$, $\gamma = 0.2$. The grid search range is [0.1, 0.5] with a step size of 0.1, and the optimal combination is selected based on the maximum average reward on the validation set.

C. DDPG ALGORITHM IMPLEMENTATION

- The DDPG (Deep Deterministic Policy Gradient) algorithm is adopted to solve the optimization problem of continuous action space. Its core modules include:
- Actor Network: Takes the state as input and outputs the optimal action, using a 3-layer fully connected network structure;
- Critic Network: Evaluates the action value and adopts a dual-network structure to mitigate overestimation;
- Experience Replay Buffer: Stores (S, A, R, S') samples and performs random sampling for training to improve stability;
- Target Network Soft Update: Updates the target network parameters using a soft update coefficient of $\tau = 0.001$.

D. CONSTRAINT SETTING

The optimization process must satisfy the following constraints:

1) Power Balance Constraint: $\sum P_{\text{gen}} + \sum P_{\text{ess}} = \sum P_{\text{load}} + \sum P_{\text{loss}}$.
2) Equipment Operation Constraints: Node voltage deviation $\leq \pm 5\%$, line power $\leq$ rated capacity, and energy storage SOC $\in$[0.2, 0.8];
3) Regulation Action Constraints: Energy storage power change rate $\leq$ 5%/min, and flexible load adjustment amount $\leq$ 10% of the rated load. To account for the rebound effect in production processes, a supplementary constraint is added: the cumulative adjustment amount of flexible loads within a 2-hour window shall not exceed 15% of the rated load, and the load recovery rate shall not exceed 8%/h. A thermal compensation coefficient is introduced to adjust the load shift strategy, ensuring that the production process stability is not affected.

V. EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

A. EXPERIMENTAL DATA AND ENVIRONMENT

1) Data Source

Distribution network data from 2023 in the core area of a city (with an area of 5 km^2 and a load density of 18.2 MW/km^2) was used, including:

- Load Data: A total of 35,040 samples with a 15-minute sampling interval;
- Meteorological Data: Hourly data such as temperature (-5°C–38°C) and humidity (30%–95%);
- System Parameters: IEEE 33-node topology, including 3 energy storage devices (with a total capacity of 10 MWh) and 20 flexible load nodes.

2) Experimental Environment

- Hardware: Intel i9-13900K CPU, NVIDIA RTX 4090 GPU;
- Software: Python 3.9, TensorFlow 2.15, MATLAB R2023a;
- Comparison Models: Traditional BiLSTM, CNN-LSTM, SSA-BiLSTM, and ELM.

B. COMPARATIVE ANALYSIS OF PREDICTION PERFORMANCE

1) Comparison of Quantitative Indicators

The prediction accuracy indicators of the improved BiLSTM and comparison models are shown in Table 2. The proposed model in this study achieves the best performance in the three indicators of MAE, RMSE, and MAPE, verifying the effectiveness of the chaotic optimization and self-attention mechanism.

TABLE 2. Performance Comparison of Different Prediction Models

Model	MAE (MW)	RMSE (MW)	MAPE (%)	Training Time (min)
Traditional BiLSTM	16.19	24.83	2.81	14.2
CNN-LSTM	14.52	22.37	2.54	18.7
SSA-BiLSTM	14.45	21.05	2.55	20.3
ELM	21.36	30.52	3.68	8.9
Proposed Model	12.36	18.72	2.15	19.8

Note on training time: The improved CPOA adopts an adaptive iteration strategy, where the number of iterations is dynamically adjusted based on the convergence rate (50-200 iterations). This avoids unnecessary computations, resulting in a shorter training time than the standard CPOA (which typically requires 300+ iterations).

2) Forecasting Results on Typical Days

Load forecasting comparisons were conducted for typical working days and holidays in summer, with the results shown in Table 3. The peak-valley difference of the load on working days is significant, and the proposed model achieves the smallest forecasting error during peak electricity consumption periods (MAPE = 1.87%); the load fluctuation on holidays is highly random, yet the model still maintains high forecasting accuracy (MAPE = 2.32%). These results indicate that the model has good adaptability under different load scenarios.

TABLE 3. Comparison of Load Forecasting Accuracy on Typical Days (MAPE, %)

Model	Working Day (Summer)	Holiday (Summer)	Working Day (Winter)	Holiday (Winter)
Traditional BiLSTM	2.64	3.02	2.78	3.15
CNN-LSTM	2.35	2.71	2.49	2.86
SSA-BiLSTM	2.32	2.68	2.45	2.81
Proposed Model	1.87	2.32	1.95	2.43

C. ANALYSIS OF OPTIMIZATION AND REGULATION EFFECTS

1) Economic and Stability Indicators

A comparison of the DRL optimization results with those of the traditional random optimization and the no-optimization scheme is shown in Table 4.

TABLE 4. Performance Comparison of Different Optimization Schemes

Optimization Scheme	Daily Operation Cost (10,000 RMB)	Tie-Line Power Fluctuation Suppression Rate (%)	Voltage Over-Limit Times	Energy Storage SOC Compliance Rate (%)
No Optimization	28.6	62.5	12	78.3
Random Optimization	24.3	70.9	5	89.1
Proposed Scheme	20.2	89.2	0	99.5

2) Analysis of Computational Efficiency

1) The training time of the improved BiLSTM is 19.8 minutes. Although slightly longer than that of traditional models, its forecasting time is only 0.32 seconds per day, which meets the real-time requirements;
2) The single decision-making time of DRL optimization is 0.08 seconds, much lower than the 1.2 seconds of random optimization, and it can adapt to the demand for high-frequency intraday regulation. The algorithm achieves a good balance between accuracy and efficiency.

VI. CONCLUSION

The distribution network load forecasting and optimization algorithm based on improved BiLSTM and DRL proposed in this study has achieved the following results in its application to high load density areas, particularly those dominated by energy-intensive industries like manufacturing:

(1) Feature screening and model improvement have effectively improved the forecasting accuracy. The MAPE of the improved BiLSTM is as low as 2.15%, which is better than that of existing mainstream models;
(2) The multi-time-scale DRL optimization framework realizes the coordination of economy and stability, with the daily operation cost reduced by 16.8% and the power fluctuation suppression rate reaching 89.2%;
(3) The algorithm has both high accuracy and high efficiency, and can meet the real-time dispatching needs of high load density areas.

AUTHOR CONTRIBUTIONS

Conceptualization –Yuanfang Zeng, Yongyuan Wang, Mingke Li, Junshu Su and Min Zhang; methodology – Yuanfang Zeng, Yongyuan Wang, Mingke Li, Junshu Su and Min Zhang; investigation – Yuanfang Zeng, Mingke Li, Junshu Su and Min Zhang; writing-original draft preparation – Yuanfang Zeng, Yongyuan Wang, Mingke Li, Junshu Su and Min Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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