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Intelligent Dispatching Method of Short-term Load in Distributed Power System Using Deep Learning

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Abstract

In traditional short-term load dispatching methods for distributed power systems, complex data processing, and low recognition accuracy hinder effective system optimization. To address this issue, an intelligent short-term load dispatching method for distributed power systems based on deep learning was proposed, aiming to improve voltage quality and reduce network losses. The proposed method first collected historical load data from the system, including active power and reactive power, and utilized a long short-term memory neural network (LSTM) for short-term load forecasting. In the forecasting process, the input gate, output gate, and forget gate operations were employed to accurately handle load variations. Based on the forecasting results, a short-term load dispatching model was constructed to minimize network losses, voltage deviations, and power abandonment rates, while incorporating constraints such as power flow, node voltage, and load regulation coefficients. The bee colony Quantum-behaved Particle Swarm Optimization (QPSO) algorithm was used to achieve intelligent load allocation in the distributed power system. Experimental results show that, the proposed method effectively controls voltage fluctuations within ±0.4 p.u. while reducing network losses to below 0.14 MW, significantly improving the overall system performance. The conclusion provides scientific technical supports for the optimization and dispatching of distributed power systems and validates the applicability and effectiveness of intelligent methods in complex power system scenarios.

Keywords: Deep learning, Distributed, Power system, Short-term load, Intelligent dispatching, Constraints

1. Introduction

The continuous development of the global economy and increase in population, as well as the rapid growth in power demand pose unprecedented challenges to the stable operation and efficient dispatch of the power system [1]. Especially today, when distributed energy sources (such as solar energy, wind energy, and other renewable energy sources) are connected in large quantities, the load fluctuation and uncertainty of the power system have increased significantly [2]. Short-term load forecasting is an important component of power system dispatching, and its accuracy is directly related to the stability, economy, and security of the power supply [3]. However, traditional load forecasting methods often rely on time series analysis of historical data or simple statistical models, which cannot accurately capture the nonlinear, dynamic, and random characteristics of power loads, especially during extreme weather and emergencies. Their prediction effect is often greatly compromised when uncertain factors are involved [4]. Therefore, the effective use of big data and artificial intelligence technology to achieve intelligent and accurate prediction and dispatch of short-term load in the power system has become an important practical issue that requires urgent solutions.

Although scholars have conducted considerable research in the field of power load forecasting and intelligent dispatching in recent years and achieved certain results, many shortcomings still exist. On the one hand, traditional load forecasting methods are often based on statistical models or machine learning algorithms. These methods are inadequate when processing large-scale, high-dimensional, and nonlinear power load data, and cannot capture the inherent laws and dynamic characteristics of load changes. On the other hand, most existing intelligent dispatching systems rely on expert rules or heuristic algorithms, which lack sufficient flexibility and adaptive capabilities to cope with emergencies and dispatching requirements under complex working conditions. The wide application of distributed power systems has also introduced stringent requirements for the coordination and real-time performance of intelligent dispatching systems, but the gap in existing systems is still substantial.

To address these problems, a short-term load intelligent dispatching method for distributed power systems based on deep learning is assessed. This method uses long-short-term memory neural network to perform short-term load forecasting of distributed power systems. It combines intelligent dispatching algorithms to formulate optimal dispatching strategies to achieve efficient dispatching of distributed power sources in distributed power systems and to ensure the supply and demand of the power system, achieving balanced and stable operations. This approach is expected to promote further development of distributed power systems, strongly guarantee safe and stable power system operation, and provide a set of scientific, efficient, and intelligent solutions for short-term load forecasting and dispatching of distributed power systems.

2. State of art

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For the scheduling problem of random factors, such as the output fluctuation of renewable energy in the power system, Yamujala et al. investigated a random multi-interval scheduling framework for quantifying the operational flexibility of low-carbon power systems [5]. This framework can quantify the flexibility requirements of power systems at different time scales and spatial distributions and provide a basis for the optimal configuration of flexible resources in these systems. This method considers random factors, such as the output fluctuation of renewable energy in the power system, achieving a scheduling decision that is aligned with the actual situation [6]. However, this framework mainly quantifies and optimizes the operational flexibility of low-carbon power systems. It has certain limitations for optimization of other types of power systems or under different objectives.

For the scheduling problem of load demand in power systems, Krishnan et al. assessed the economic load scheduling method for integrating renewable energy in microgrids [7]. This approach fully utilized wind energy and water resources, realized the effective integration of renewable energy, reduced carbon emissions, and complied with the concept of environmental protection and sustainable development. The wind-driven hydropower generation system can flexibly adjust the energy production according to the wind speed and water wave conditions to satisfy the load requirement of the power system, thereby reducing the operating cost. However, the wind-driven hydropower generation system is greatly affected by environmental factors, such as wind speed, wind direction, water wave height, and frequency. Changes in these factors lead to fluctuations in power generation, affecting the stability of the power system.

In response to various complex power system load forecasting and economic dispatch problems, Kalakova et al. studied a dynamic economic dispatch method for short-term load forecasting using genetic algorithms [8]. The dynamic economic dispatch method adjusts the unit output according to the real-time changes in load over multiple consecutive periods to minimize the operating cost of the entire system and adapt to various complex power system load forecasting and economic dispatch problems. However, inappropriate parameter settings of the genetic algorithm cause the algorithm to fail to achieve an optimal solution or converge inefficiently.

To address the scheduling problem of maintaining the stable operation of microgrids under conditions, such as insufficient energy supply or equipment failure, Ishraque et al. studied the load dispatch strategy optimization method of isolated microgrids connected to renewable energy [9]. Isolated microgrids can fully integrate and utilize renewable energy, such as solar energy and wind energy, and build a green and low-carbon energy structure by optimizing load dispatch strategies. Isolated microgrids use distributed generation and energy storage technology, with the characteristics of multiple backups and redundancy, thereby improving the reliability and stability of power supply [10]. This method can ensure the stable operation of microgrids under conditions, such as insufficient energy supply or equipment failure. The power generation and consumption plans can be arranged more reasonably, unnecessary energy waste can be reduced, and the operating cost can be minimized by optimizing the load scheduling strategy. However, the load scheduling optimization of the isolated microgrid must consider the volatility and uncertainty of renewable energy, as well as the power balance and stability issues within the microgrid [11]. Although the isolated microgrid can operate independently, it may require external support and assistance in the case of insufficient energy supply and equipment failure, increasing the operating risk and uncertainty of the isolated microgrid.

Nourianfar and Abdi used an enhanced multi-objective exchange market algorithm to optimize the use of resources through coordinated scheduling, considering the economic emission scheduling of electric vehicles and wind power [12]. The algorithm takes into account the economy and emissions of electric vehicles and wind power. Schedule optimization reduces the operating cost of the system as well as greenhouse gas emissions, which is conducive to achieving a green and low-carbon energy structure [13]. The algorithm can fully apply the complementarity of electric vehicles and wind power, optimize resource utilization through coordinated scheduling, and improve the operating efficiency of the system [14]. However, the algorithm must consider the charging requirements of electric vehicles, wind power output forecasts, and electricity prices. It is greatly affected by electricity price fluctuations and policy changes in the market environment [15]. The unstable market environment or frequent policy adjustments influence the application effect and stability of the algorithm.

In summary, the research on short-term intelligent dispatching of distributed power systems has made significant progress. Various methods, such as random multi-interval dispatching, economic load dispatching [16], dynamic economic dispatching of short-term load forecasting based on genetic algorithms [17], load allocation of isolated microgrids connected to renewable energy sources [18], and scheduling of enhanced multi-objective exchange market algorithms have been applied in practice. These methods have their advantages, but they also face the following challenges: optimization for other types of power systems or under different objectives; failure to determine the optimal solution or slow convergence; external support and assistance may be required in cases of insufficient energy supply and equipment failure, increasing the operational risk and uncertainty of isolated microgrids; problems that are greatly affected by electricity price fluctuations and policy changes in the market environment still require further exploration.

3. Methodology

3.1 Distributed power system short-term load forecasting based on deep learning

3.1.1 Long short-term memory (LSTM) neural network for distributed power system load forecasting

LSTM neural network is a commonly used approach in deep learning algorithms. It is suitable for predicting short-term loads of distributed power systems with long intervals and delays. The neuron signals of traditional feed forward neural networks can only flow in one direction and independently process the time series of distributed power system loads. The time series information of distributed power system loads can easily be lost during calculations. Compared with traditional neural networks, recurrent neural networks are equipped with memory units, which apply the hidden layer information of the previous moment to the output of the current layer. Recurrent neural networks adopt a chain structure and possess memory characteristics. They are suitable for processing load forecasting problems related to time series. When using LSTM neural networks to predict short-term loads of distributed power systems, the calculation formula of input gate i_t is as follows:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{1}$$

When the LSTM neural network predicts the short-term load of the distributed power system, the calculation formula of the output gate o_t is as follows:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{2}$$

When the LSTM neural network predicts the short-term load of the distributed power system, the calculation formula of the forget gate f_t is as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

In formula (3), W and b represent the weights and biases corresponding to each layer of the network, respectively. h_{t-1} and $t-1$ refer to the incoming information at time E and the input information of the current layer at time t; o denotes the activation function.

According to the values of x_t and h_{t-1}, when the calculation time is t, he candidate state value of the neuron, when the LSTM neural network predicts the short-term load of the distributed power system, is expressed as follows:

$$\hat{S}_t = \tanh(W_s[h_{t-1}, x_t] + b_S) \tag{4}$$

The state value S_{t-1} and the candidate state value $\hat{S}_t$ of the LSTM neural network at the previous moment are determined using the values of f_t and i_t. Their proportion in the state update result S_t is expressed as follows:

$$S_t = f_t \cdot S_{t-1} + i_t\hat{S}_t \tag{5}$$

The short-term load forecasting result of the distributed power system using the LSTM neural network at time t is expressed as follows:

$$h_t = o_t \tanh(S_t) \tag{6}$$

This approach is applied to construct a LSTM neural network for short-term load forecasting in distributed power systems.

3.1.2 Short-Term Load Forecasting of Distributed Power Systems Using Long Short-Term Memory (LSTM) Neural Networks

To address the problem of short-term load forecasting of distributed power systems, time information corresponding to the active power, reactive power, voltage, current, and load data of the corresponding substations of the distributed power system is collected, fully considering the characteristics of distributed power systems. Moreover, short-term load forecasting of the distributed power system is carried out using the constructed LSTM neural network. The short-term load forecasting of distributed power systems mainly includes four components: abnormal data detection, data analysis, feature engineering, and load forecasting. Each element is introduced as follows:

(1) Anomaly Detection in Short-Term Load Forecasting. Input data, such as active power and reactive power, of the distributed power system load forecasting are analyzed, and abnormal data are deleted. According to the outlier data judgment principle of the box plot, the judgment criteria for abnormal data of the distributed power system short-term load forecasting are set as follows:

$$\begin{cases} I = \psi_3 - \psi_1 \\ \xi > \psi_3 + 1.3I \\ \xi < \psi_1 - 1.3I \end{cases} \tag{7}$$

where ψ_1 and ψ_3 represent the first and third quartiles of the LSTM neural network input data, respectively; I and ξ refer to the interquartile range and abnormal data, respectively.

Formula (7) is used to detect whether the data input to the LSTM neural network for short-term load forecasting of distributed power systems contains abnormal data. Moreover, the detected abnormal data are deleted.

(2) Analysis of the data distribution of short-term load of distributed power systems. A power diagram based on the active power of the distributed power system is developed to determine the time nodes of the peak load period of the distributed power system.

(3) Feature engineering. The original data of the distributed power system, which has completed abnormal data detection, are converted into training data for the LSTM neural network. The hidden information in the original input data is extracted to mine the feature information that is important for short-term load forecasting. The time characteristics of the distributed power system load are extracted from the input data to determine the specific time corresponding to the load data, whether it belongs to the working day or the peak load. The input data are encoded using the one-hot vector encoding rule. In the actual application scenario of the distributed power system, the extracted features are fused according to fixed rules. Considering the physical definition of the electrical parameters of the distributed power system [19], the active power, reactive power, voltage, and current data of the power system are fused.

(4) Load forecasting. The feature engineering processing results are used as input of the LSTM neural network constructed in Section 3.1.1, whereas the short-term load forecasting results of the distributed power system are the output. The real-time short-term load forecasting results of the power system are used as the data basis for intelligent dispatching of the short-term load of the distributed power system.

3.2 Distributed power system short-term load intelligent dispatching model

3.2.1 Objective function

Intelligent scheduling of distributed power system short-term loads is carried out using the short-term load forecast results of distributed power systems, fully considering the time-varying characteristics of distributed power sources and short-term loads in distributed power systems. The minimum network loss, voltage deviation, and power abandonment rate are selected as the objective functions of the distributed power system short-term load intelligent scheduling model, and a distributed power system short-term load intelligent scheduling model is constructed. Each component is introduced as follows:

(1) Minimum network loss. The active power loss of the power system line is minimized, and the power purchase cost of the power company to which the distributed power system belongs is reduced, thereby satisfying the load demand of the distributed power system. The useful life of the power system equipment is reduced when the interconnecting switches of the distributed power system are frequently operated [20]. Therefore, when the distributed power system is in operation, the number of operations of the interconnecting switches must be limited. The objective function for minimizing the network loss of the distributed power system within a fixed period is expressed as follows:

$$F_1 = \min\{PC_1 + NC_2\} \tag{8}$$

In formula (8), P and N represent the active load consumed by the power system and the number of times the tie switch is operated, respectively. C_1 and C_2 represent the unit price of active power and the cost required for one tie switch operation, respectively.

(2) Minimum voltage deviation. A fixed period is set, and the objective function for the minimum voltage deviation of the distributed power system is expressed as follows:

$$F_2 = E_1 + E_2 \tag{9}$$

In formula (9), E_1 and E_2 represent the maximum voltage deviation value of all nodes in the distributed power system and the minimum voltage stability value of all branches, respectively; they are expressed as follows:

$$E_1 = \max|U_i - U_i^{'}| \tag{10}$$

where $U_i^{'}$ and U_i indicate the rated voltage and actual voltage amplitude of node i, respectively.

$$E_2 = \max\{4(P_jX_j - Q_jR_j)^2 + (P_jX_j + Q_jR_j)U_j^4\} \tag{11}$$

where P_j and Q_j refer to the active power and reactive power flowing through the power system branch j, respectively. R_j and X_j denote the resistance and reactance values of the power system branch j, respectively. U_j represents the voltage amplitude across branch j.

(3) Minimum power abandonment rate. When the distributed power system is in operation, the maximum power output of the distributed power generation equipment, such as wind power and photovoltaic power, at a fixed time is affected by the size of the solar energy and wind energy in that period. The optimal output power of the distributed power sources is related to the structure of the distributed power system and the load distribution. The minimum power abandonment rate F_3 of the distributed power system is set as another objective function to improve the economic benefits of distributed power sources in the distributed power system and the ability of the distribution network to absorb renewable energy. Under the premise of safe and stable operation of the distributed power system, a lower power abandonment rate indicates higher power transmission and distribution efficiency.

Combining these objective functions, the short-term load intelligent scheduling model of the distributed power system is constructed as follows:

$$F = F_1 + F_2 + F_3 \tag{12}$$

3.2.2 Constraints

To ensure that short-term load intelligent dispatching can effectively satisfy the actual operation requirements of distributed power systems, the following constraints are set for the short-term load intelligent dispatching of distributed power systems:

(1) Flow constraints

$$\begin{aligned} &P_i^a n_i^a + P_i^b n_i^b + P_i^c n_i^c - \lambda P_i^d \\ &= U_i \sum_{j \notin i} U_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \end{aligned} \tag{13}$$

$$\begin{aligned} &Q_i^a n_i^a + Q_i^b n_i^b + Q_i^c n_i^c - \lambda Q_i^d \\ &= U_i \sum_{j \notin i} U_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \end{aligned} \tag{14}$$

where P_i^a and Q_i^a refer to the active power and reactive power of wind power generation equipment i, respectively. P_i^b and Q_i^b represent the active power and reactive power of photovoltaic power generation equipment i, respectively. P_i^c and Q_i^c indicate the active power and reactive power of thermal power generation equipment i, respectively. P_i^d and Q_i^d denote the active load and reactive load of node i, respectively. λ and U_i represent the load regulation coefficient and the voltage of node i, respectively. G_{ij} and B_{ij} indicate the conductance and susceptance of branch j, respectively. θ_{ij} refers to the voltage phase difference between node i and node j.

(2) Node voltage constraints. The node voltage constraints are set as follows:

$$U_{\min} \le U_i \le U_{\max} \tag{15}$$

In formula (15), $U_{\max}$ and $U_{\min}$ represent the upper and lower limits of the node voltage, respectively.

(3) Branch power constraint

$$Q_j \le Q_{j\max} \tag{16}$$

where Q_j and $Q_{j\max}$ indicate the actual power and power upper limit of branch j, respectively.

(4) Load regulation coefficient constraint

$$\lambda_{\min} \le \lambda_i \le \lambda_{\max} \tag{17}$$

where $\lambda_{\max}$ and $\lambda_{\min}$ represent the maximum and minimum values of the load regulation coefficient, respectively.

3.3 Solution of short-term load intelligent dispatch model using swarm QPSO algorithm

The swarm QPSO algorithm is selected to solve the constructed distributed power system load intelligent dispatch model. This method introduces quantum behavior into the particle evolution population of the particle swarm optimization algorithm. Each distributed power system load intelligent dispatch scheme is considered a particle, and the Monte Carlo method is used to express the particle position as follows:

$$x(t) = p_i(t) \pm \frac{2\beta \,|\, m_{best} - x(t-1) \,|}{2} \ln \frac{1}{u} \tag{18}$$

In formula (18), u and t represent the random constants in the interval [0,1] and the number of iterations, respectively. $p_i(t)$ and β indicate the current optimal position of the particle and the contraction factor, respectively.

The particle evolution equation of the QPSO algorithm is expressed as follows:

$$x_i(t+1) = p_i(t) \pm 2\beta \,|\, m_{best}(t) - x_i(t) \,| \cdot \ln \frac{1}{u} \tag{19}$$

$$p_i(t+1) = \omega p_i(t) + (1-\omega) p_g(t) \tag{20}$$

$$m_{best}(t) = \frac{1}{M} \sum_{i=1}^{M} p_i(t) \tag{21}$$

In formulas (19)-(21), ω and M represent the weight and the total number of particles, respectively. $p_g(t)$ and $m_{best}(t)$ refer to the optimal position of the particle after the t iteration and the global optimal position of the particle, respectively.

The swarm search strategy is used to improve the QPSO algorithm and efficiently solve the distributed power system load intelligent dispatching model. The swarm is unaffected by the environment and searches for food locations by smelling the food, such as nectar, with high sensitivity. The swarm search strategy regards the particles representing the distributed power system load intelligent dispatching scheme as swarms in quantum space. It divides the peak groups into leading bees, following peaks, and reconnaissance peaks based on fixed probabilities. The swarm search strategy uses reconnaissance peaks to explore and exploit food sources, avoids falling into local optimality during the swarm search, and enhances the swarm's global search capability. The swarm search strategy sets the particle position x_i as the pollen source, and the pollen source update formula is as follows:

$$x_i(t) = x_i^{\min} + \alpha(x_i^{\max} - x_i^{\min}) \tag{22}$$

where α is a random constant in the interval [0,1], and $x_i^{\max}$ and $x_i^{\min}$ represent the optimal particle value and the worst particle value, respectively.

Adaptive learning factors are used to improve the global search capability of the bee colony QPSO algorithm when solving the distributed power system load intelligent dispatching model. Quantum behavior has the characteristics of parallelism and superposition, which can process a large amount of data in a short time and identify the optimal solution of the distributed power system load intelligent dispatching model. The QPSO algorithm is further improved using the bee colony search strategy, further enhancing the convergence speed of solving the distributed power system load intelligent dispatching model. When the QPSO algorithm solves the distributed power system load intelligent dispatching model, it has a wider search range and the optimal solution obtained is aligned with the actual requirements of the distributed power system application scenario.

4. Experimental results and analysis

The method is applied to a distributed power system of IEEE32 nodes, in which distributed power sources, such as photovoltaic and wind power, are connected to verify the effectiveness of the studied method for intelligent dispatching of short-term loads in distributed power systems. The structural diagram of the distributed power system is shown in Fig. 1.

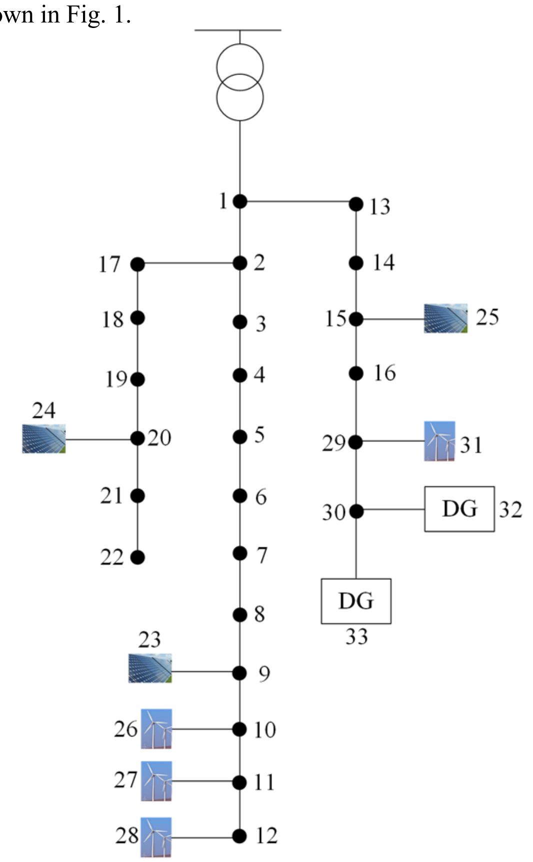

Fig. 1. Structural diagram of the distributed power system

The voltage of the node connected to the upper power grid after normalization is 1∠0°. The parameter settings of the distributed power generation in the distributed power system are shown in Table 1.

Table 1. Distributed Power Source Parameter Settings

Name	Install nodes	Equipment type	Equipment capacity /kVA	Power factor
Distributed power supply	23	Photovoltaic	600	0.92
Distributed power supply	24	Photovoltaic	600	0.92
Distributed power supply	25	Photovoltaic	600	0.92
Distributed power supply	26	Wind power	500	0.92
Distributed power supply	27	Wind power	400	0.92
Distributed power supply	28	Wind power	500	0.92
Distributed power supply	31	Wind power	500	0.92
Distributed power supply	32	Controllable distributed power supply	500	0.92
Distributed power supply	33	Controllable distributed power supply	500	0.92

The proposed method is used to detect whether the input data used for distributed power system load forecasting includes abnormal data. The detection results of abnormal data in different types of input data, such as active power and reactive power, are shown in Fig. 2.

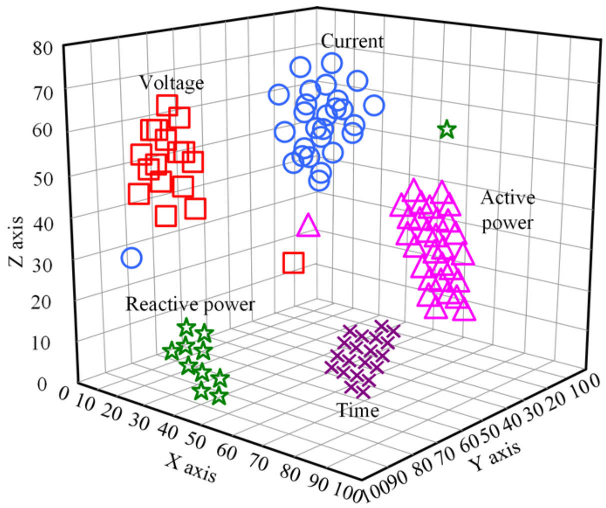

Fig. 2. Abnormal Input Data Detection Results

The experimental results in Fig. 2 are analyzed, suggesting that the proposed method can effectively detect abnormal data from input data of distributed power system load forecasting. These abnormal data show evident outlier characteristics. The outlier data in the input data are set as abnormal data. Then, the abnormal input data of the detected distributed power system load forecasting are deleted to provide high-quality input data for the LSTM neural network to predict the short-term load of the distributed power system.

The proposed method adopts the bee colony search strategy to improve the QPSO algorithm for solving the intelligent dispatching model of the short-term load of the distributed power system. The particle swarm algorithm and the QPSO algorithm are selected for comparison with the proposed method. Moreover, the global search capabilities of different methods when solving the intelligent dispatching model are statistically analyzed. The statistical results are shown in Fig. 3.

"1" in Fig. 3 indicates the optimal pollen source, that is, the optimal solution of the distributed power system short-term load intelligent dispatching model. The experimental results in Fig. 3 illustrate that the proposed method uses the bee colony search strategy to improve the QPSO algorithm, and the search area is significantly larger than those of the two other algorithms. The proposed method can search for the optimal solution of the distributed power system short-term load intelligent dispatching model in a wider range. It can also improve the solution level of the distributed power system short-term load intelligent dispatching model through a higher global search capability.

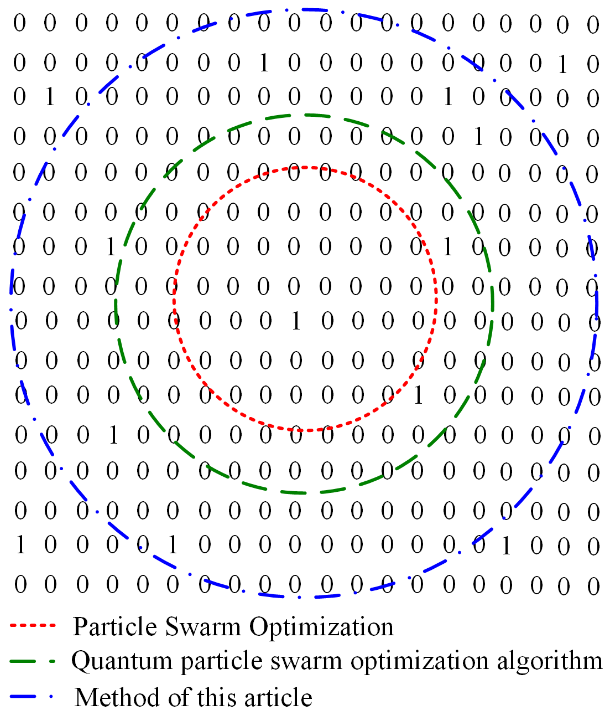

Fig. 3. Comparison of search areas using different methods

The proposed approach uses the LSTM neural network to predict the short-term load changes in the distributed power system. The load forecast results of the distributed power system within 24 hours are shown in Fig. 4.

The experimental results in Fig. 4 suggest that the proposed method can effectively predict the short-term load changes of the distributed power systems. The LSTM neural network shows excellent performance when processing data with long-term dependencies. The load data of the power system exhibit characteristics of a time series, that is, a dependency exists between the load values at different time points. The LSTM neural network can capture the long-term dependency in this time series through its unique gating mechanism, thereby accurately predicting the short-term load of the power system. The LSTM neural network is trained using the preprocessed data and selected features, and the network parameters are adjusted through the back propagation algorithm, which can accurately predict the short-term load of the distributed power system.

The distributed power system is intelligently dispatched using the proposed method, and the output scheme of some units obtained is shown in Table 2.

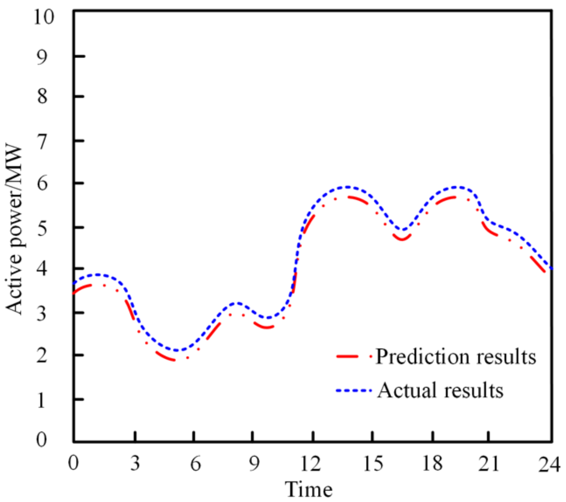

Fig. 4. 24-hour load forecasting results of distributed power system

Table 2. Partial Unit Output Schemes for Distributed Power Systems

Time	Unit 1 /MW	Unit 2 /MW	Unit 3 /MW	Unit 4 /MW	Network loss /MW
8:00-8:59	140	125	158	120.5	15.8
9:00-9:59	140	125	164	130	23.5
10:00-10:59	165	136	138	130	17.5
11:00-11:59	235.1	158	154	130	13.5
12:00-12:59	185.4	176	188.5	115.4	18.5
13:00-13:59	177.5	216	174.5	152.5	34.5
14:00-14:59	205.6	315	166.5	134.5	28.4
15:00-15:59	187.5	241.5	159.1	134.5	16.5
16:00-16:59	168.5	264	150	108.5	21.5
17:00-17:59	155	125	145	95.7	23.5

The experimental results in Table 2 demonstrate that the intelligent dispatching of distributed power systems can be realized by adopting the proposed method in this paper. According to the intelligent dispatching results of distributed power systems by the proposed method, the changes in the transferable load and the load that can be reduced in the distributed power system before and after the intelligent dispatching are statistically analyzed, as shown in Figures 5 and 6, respectively.

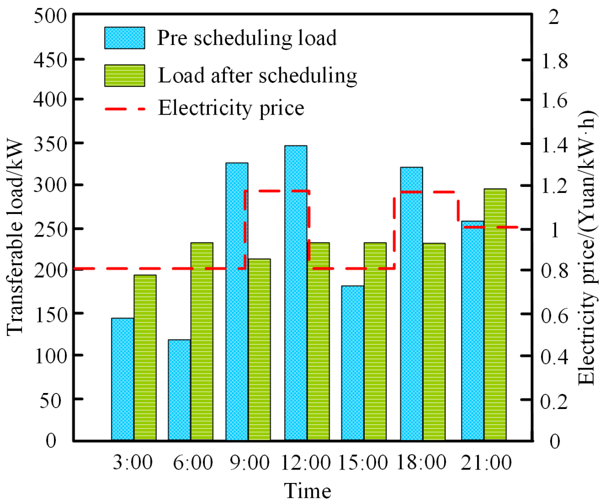

Fig. 5. Transferable load changes

The experimental results in Figures 5 and 6 indicate that after the distributed power system is intelligently dispatched by the proposed method, the transferable load of the power system is more evenly distributed. The proposed method transfers the load from the high electricity price period during peak consumption intervals to the low electricity price period. During high electricity price periods, the reducible load is decreased, whereas that in the low electricity price period is retained. The experimental results show that the proposed method demonstrates the flexibility of the intelligent dispatch for short-term load management in distributed power systems. The intelligent dispatch of controllable loads improves the operating reliability and economic efficiency of the distributed power system.

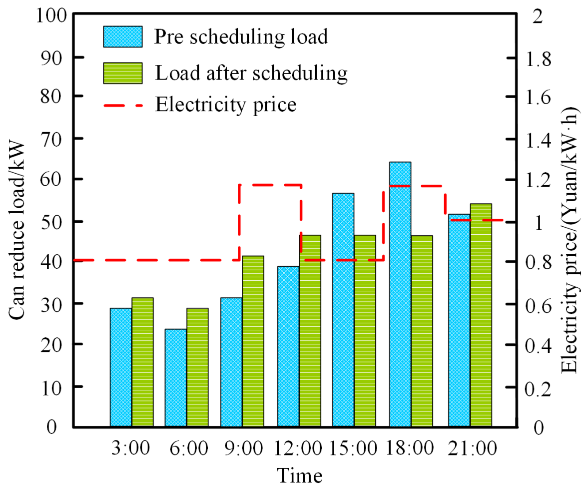

Fig. 6. Reduced load changes

The short-term load of the distributed power system is intelligently dispatched by the proposed method. The daily load change curve of the distributed power system, as compared with the case where the proposed method is not used, is shown in Fig. 7.

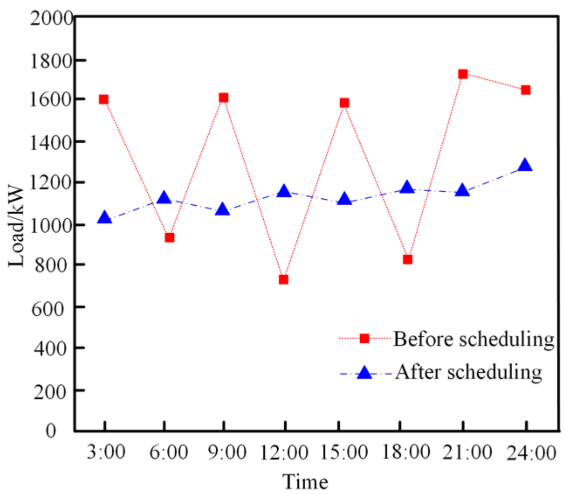

Fig. 7. Daily load variation curve of the distributed power system

The experimental results in Fig. 7 illustrate that the distributed power system is intelligently dispatched by the proposed method, and the daily load fluctuation of the distributed power system is significantly reduced compared with the case where the proposed method is not used. The experimental results in Fig. 7 show that the short-term load of the distributed power system is intelligently dispatched by the proposed method. As a result, the load characteristics of the distributed power system and the power characteristics of new energy efficiently match, flexible adjustment of the load is realized, and the operational stability of the distributed power system is improved.

Statistics show that the network loss, voltage index, and power abandonment rate of the power system changed from November 1 to 3, 2021, and the statistical results are shown in Figures 8, 9, and 10.

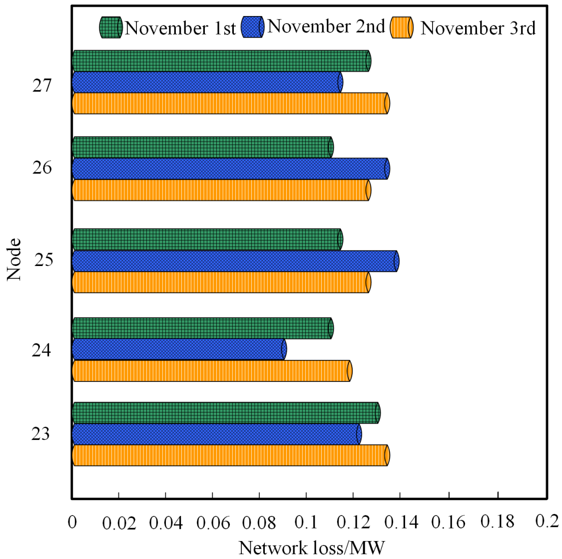

Fig. 8. Changes in grid losses in the distributed power systems

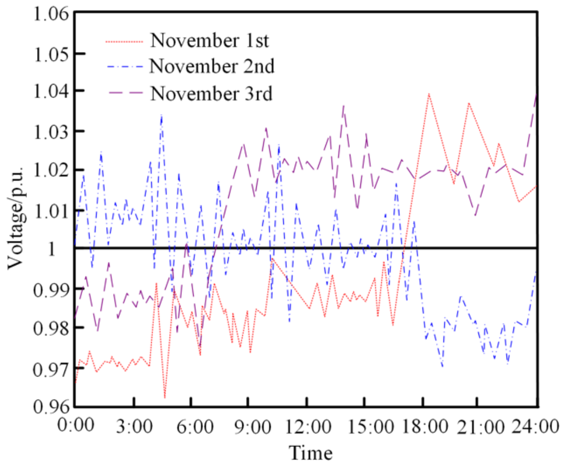

Fig. 9. Voltage variation in the distributed power system

A comprehensive analysis of the experimental results in Figures 8–10 indicates that using the proposed method for intelligent dispatch of the distributed power system, based on the short-term load forecast results, and remarkably optimized the network loss of the system. All network losses are less than 0.14 MW. The proposed method considers the short-term load changes of the distributed power system and effectively reduces the system network loss. The voltage fluctuation of the distributed power system is maintained within ±0.4 p.u. after using the proposed method for intelligent dispatching of the distributed power system. This finding verifies that the method effectively improves the operation quality of the distributed power system. The power curtailment rate is used to measure the gap between the power generated in the system and the actual power used or stored. The level of power curtailment rate directly affects the economic and environmental benefits of the system. The experimental results in Fig. 10 suggest that the proposed method can reduce the power curtailment rate of the distributed power system, which remains less than 3% at different dates. The method improves the accuracy of supply and demand forecasting in distributed power systems, rationally schedules power generation and consumption, and reduces the mismatch between supply and demand. Experimental results verify that this method can realize intelligent dispatching of distributed power systems, improve the voltage quality of distributed power systems, reduce network loss changes during the operation of distributed power systems, and ensure safe and reliable operation of the power system.

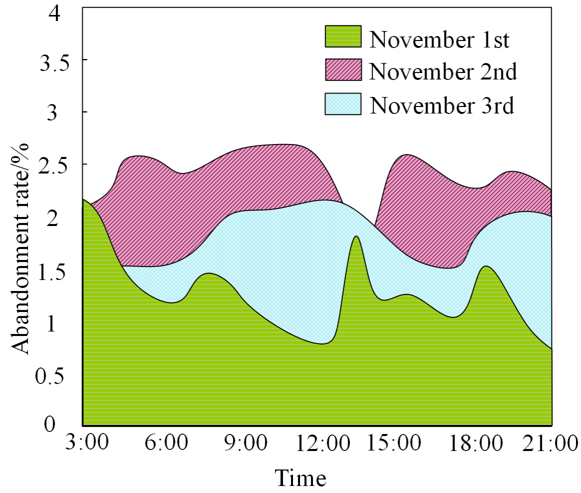

Fig. 10. Abandonment rate of the distributed power system

5. Conclusion

This study proposes an intelligent short-term load dispatching method for distributed power systems based on deep learning. This method utilizes LSTM neural networks for short-term load forecasting and integrates advanced dispatching algorithms to create an optimization model that effectively enhances the operational quality and efficiency of distributed power systems.

(1) This study employs the unique gating mechanism of LSTM neural networks to achieve effective short-term load forecasting for distributed power systems. Experimental results demonstrate that this method accurately captures the dynamic characteristics of load variations, providing a reliable data foundation for intelligent dispatching.

(2) By developing an intelligent dispatching model with objective functions aimed at minimizing network losses, voltage deviations, and electricity curtailment rates, and integrating it with the QPSO algorithm inspired by bee colony behavior, this study accomplishes intelligent short-term load dispatching for distributed power systems. Experimental results show that this method can significantly reduce system network losses while ensuring voltage stability, thereby validating both the model's effectiveness and the algorithm's superiority.

(3) Adopting the method proposed in this study greatly enhances the operational quality and economic benefits of distributed power systems. This approach not only facilitates efficient alignment between load and renewable energy generation characteristics but also improves operational stability and safety through flexible load adjustment strategies.

Despite the study's accomplishments, some limitations remain. For instance, while various constraints were considered during model construction, not all potential complex scenarios were comprehensively covered. Additionally, concerning algorithm implementation, the QPSO algorithm inspired by bee colonies shows good performance, but its parameter settings and convergence characteristics still require further optimization.

Future research will expand the model's applicable scope by considering more constraint conditions in complex scenarios, thereby improving accuracy and practicality. Simultaneously, more advanced optimization algorithms will be explored to further enhance the efficiency and effectiveness of intelligent dispatching. Moreover, attention will focus on the uncertainty issues of renewable energy generation in distributed power systems and how to effectively manage these uncertainties through intelligent dispatching strategies for more reliable and efficient power system operation.

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