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Research article

An intelligent scheduling control method for smart grid based on deep learning

Zhanying Tong[1,*], Yingying Zhou[1] and Ke Xu[2]

[1] School of Electrical Engineering and Automation, Henan Institute of Technology, Xinxiang, 453003, China
[2] Engineering Technology Education Center, Henan Institute of Technology, Xinxiang, 453003, China

* **Correspondence:** Email: tongzy@hait.edu.cn.

Abstract: Nowadays, data analysis is been the most important means to realize power scheduling in smart grids. However, the sharp increase in business data of grids has posed great challenges for this purpose. To deal with such issue, this paper utilizes deep learning to discover hidden rules from massive large-scale big data and particle swarm optimization (PSO) algorithm for generation of control decision. Therefore, an intelligent scheduling control method for smart grid based on deep learning is proposed in this paper. By modeling the historical data of the power company, the long short-term memory algorithm can effectively extract the effective features and realize the prediction of the coal consumption of the unit under certain conditions. At the same time, a kind of intelligent power scheduling algorithm is designed by using PSO, so as to save energy and reduce emissions as much as possible while fulfilling the real-time power generation task. Experiments on a real-world smart grid dataset show that the proposal can achieve a relatively good performance with respect to intelligent scheduling.

Keywords: intelligent computing; scheduling control; smart grid; deep learning; PSO optimization

1. Introduction

With the continuous progress of the times, the Microgrid has gradually evolved into a complex independent system. The main characteristic of its operation is that it can be coupled with various energy devices to form a diversified system, so as to achieve the optimal operation efficiency and obtain benefits [1]. Connecting distributed devices to the energy Internet in the form of Microgrid can greatly reduce problems such as excessive load, difficulty in control and low efficiency caused by large-scale access to the power supply. Therefore, integrating different energy systems into a Microgrid and optimizing its energy scheduling strategy have become a hot topic for current scholars [2]. Nowadays, digitalization and intellectualization have penetrated into all aspects of people's lives, and smart grids have emerged, as the times require. The security of the power system is an important part of national security. Therefore, a unified power grid and a unified dispatching communication mode are required [3]. The power system in China is above 500 kV, which is a unified power grid. The power used in cities is 500 kV, and the voltage level is gradually reduced by power transformation. Whether the whole power grid has a good communication mode to ensure the reasonable operation of the power grid is the problem that the smart grid needs to consider at present [4]. The power grid dispatching control system is the nerve center of the whole power grid system [5]. It controls a series of important indicators, such as power flow control, power balance, voltage balance and frequency control, and is the front line of the power grid security [6]. In case of natural disasters such as typhoons and mountain torrents, the power grid will inevitably be affected, and problems will occur [7]. At this time, the power grid dispatching control system can assume all responsibilities to ensure the safe and stable operation of the power grid [8]. Now, with the gradual expansion of the power system, the dispatching level of the power system has also changed [9].

At present, the data of provincial dispatching, network dispatching and national dispatching are collected level by level, sent from provincial dispatching to network dispatching and then sent from network dispatching to national dispatching, forming the real-time data of the whole network [10]. The main purpose of level-by-level collection is to realize the analysis of the whole network [11]. The theory of the Microgrid is also in full swing, generally from the modeling process and algorithm strategy. From the point of view of the model, it is mostly analyzed from the use efficiency of its distributed energy and the economic benefits of the Microgrid, such as the optimization of distributed power generation, the optimization of energy storage system and load and the economic benefits of the Microgrid [12]. Specifically, from the perspective of a distributed energy system, [13] uses energy storage power technology to stabilize the power of the power grid. [14] and [15] use other energy systems to adjust the load. However, there are still some defects in the actual operation of the dispatching control system, such as the need for sufficient energy support to convert energy into electric energy. Furthermore, it needs higher quality of electrical equipment [16]. However, there is a shortage of energy in our country. At this time, if the dispatching control system of smart grid wants to give full play to its role, it must consider the use of new energy [17]. At present, people's demand for power use is growing, and the energy issue has become the focus of consideration. In addition, there are many factors that cause power grid failure, especially in bad natural weather. This uncertain factor causes power grid failure, which has a certain impact on the operation of the smart grid dispatching control system [18]. Moreover, if the short-circuit current is not controlled in time during the operation, it has an impact on the dispatching; and at the same time, it will greatly increase the management cost of the power grid dispatching. In addition, the quantitative evaluation of the power grid operation performance is not enough, and the multi-objective adjustment control cannot be realized.

In the power market, the price of electricity also plays an important role. The dispatcher realizes various goals by controlling the price of electricity and adopts different price mechanisms for different Microgrid models. By analyzing and predicting the electricity price, the electricity price is controlled at a lower level when the load is high, which meets the demand of the user. The time of use electricity price can be used to formulate the electricity price strategy according to the time period. [19] studied the influence on the load curve of changing the electricity price, so as to achieve the effects of peak shaving and valley filling. In recent years, the electric energy trading between Microgrids has also received special attention. [20] describes the scenario of electric energy trading among multiple Microgrids and analyzes its economic benefits. There must be cooperation or competition in transactions between multiple Microgrids. By analyzing its Nash equilibrium and using game theory to model, [21] achieves the goal of mutual benefit and a win-win situation. In terms of design algorithm, optimal scheduling is an important branch. Generally, the power quality is guaranteed under the premise of meeting the load demand by controlling the scheduling strategy. The algorithm used is usually particle swarm optimization [22] or simulated annealing algorithm. For complex wind power systems, it is also important to predict the wind power value through a data-driven method. [23] also uses a mixed integer linear programming algorithm to calculate the wind power consumption. For the optimization of the Microgrid system after the wind and solar energy prediction, [24] uses the kernel function limit learning machine to establish a model for load prediction and shows good prediction performance, and it studies the factors that may affect the error through correlation analysis. In terms of energy management, [25] establishes a stochastic planning and dispatching model by satisfying the principle of optimal comprehensive benefits, and it optimizes the model with particle swarm optimization algorithm, so as to minimize the expected value of Microgrid operation cost. However, with the increase of control accuracy and precision required by the Microgrid, traditional algorithms have difficulty meeting this demand. People urgently need more accurate and effective algorithms to control the scheduling strategies [26,27].

With the rapid development of China's economy, the demand for electricity is increasing. The power load itself is affected by many factors and policies, such as date, weather, climate, market and other factors. These factors greatly increase the difficulty of accurate power load forecasting [28-30]. With the rise of machine learning, many scholars have also applied machine learning to Microgrid control, training using large sets of wind and light data with neural networks to obtain predicted wind and light data [31]. At the same time, with the deepening of reinforcement learning, some scholars have applied reinforcement learning to the field of energy dispatching: using reinforcement learning to stabilize the fluctuation of renewable energy in a Microgrid [32]. The power trading model of the Microgrid is iterated through reinforcement learning to obtain the optimal scheme in [33]. [34] uses reinforcement learning to control the energy storage device for the load; [35] uses deep reinforcement learning to accurately control various devices of an automobile, reducing the cost of fuel consumption. As shown above, applying machine learning to Microgrids has become a hot research topic. At present, the ability of machine learning to solve problems largely depends on the quality of the extracted features. However, deep learning technology can obtain high-quality features without manual extraction, so the long short-term memory network (LSTM) is a technology of deep learning, which can establish a model well. In view of the good robustness and positive heuristic of particle swarm optimization (PSO), this paper designs a load allocation algorithm based on PSO. The main contributions are summarized as follows: (1) The time-series model of power data is established. Compared with the traditional model, the time series model can better reveal the internal relationship of the data. (2) The convolution neural network (CNN) in the long and short memory network model can extract the feature information of the original load related data and reduce the complexity of the information input into the prediction model to extract the data features. (3) An intelligent power dispatching algorithm is designed using particle swarm optimization (PSO), which can save energy and reduce emissions as much as possible while completing real-time power generation tasks.

2. Architecture research of smart grid framework and problem description

2.1. Architecture design of smart grid

As the support of the whole power grid, the network dispatching control system has great importance for the power system. With the increasing demand for power, the requirements for the security and stability of the power system are also higher and higher. At present, the power grid dispatching control system can realize integrated coordination control and form an integrated intelligent dispatching system. For example, the new energy power prediction system in power grid dispatching can predict the short-term and ultra-short-term on grid power generation of wind power plants and photovoltaic power plants. Compared with manual prediction, the new energy power prediction system has established an accurate prediction model based on the historical data of power generation, combined with more detailed and accurate numerical weather forecast information, Under normal circumstances, the prediction accuracy in the next 24 hours is more than 85%, and the prediction accuracy in the next 4 hours is more than 90%, which is convenient for the grid dispatching and operation personnel to make the power generation plan in advance, more reasonably dispatch the grid and reduce the impact of the randomness and volatility of new energy generation on the grid operation. The power grid dispatching control system is the decision-maker and commander of the power grid operation. It is an indispensable part of the power grid. Recently, the R&D and construction of a smart grid dispatching control system has been gradually carried out in the power industry. The basic structure mainly includes dispatching management, monitoring and early warning and dispatching plan. In terms of monitoring and early warning, it mainly monitors and evaluates the operation of the power system, and it can give early warning in case of failure. The dispatching management is mainly aimed at the daily management and resource maintenance of the dispatching organization. On the scheduling plan, the plan formulation and distribution are realized according to different scheduling mode requirements. Smart micro-grid refers to a small power generation and distribution system composed of distributed power supply, energy storage device, energy conversion device, load, monitoring and protection device, etc. It realizes the flexible and efficient application of distributed power supply through the use of advanced Internet and information technology, and it has certain energy management functions. Therefore, the Architecture of a Smart grid is designed as shown in Figure 1.

As is shown in Figure 1, a household microgrid system consists of a distributed generation unit, energy storage unit, smart meter, residential load and electric vehicle. Considering the natural complementarity of wind energy and solar energy in time and space, the distributed generation unit composed of wind turbine and photovoltaic array can effectively reduce the capacity configuration of the energy storage battery. The energy storage unit can suppress the random fluctuation of distributed generation and improve the power quality. The household loads include water heaters and hair dryers, and there are certain differences in each household. Electric vehicles are parked together for unified regulation. Electric vehicles can not only be used as vehicles, but they also help as energy storage units to solve the intermittent problem of distributed generation and reduce the configuration cost of energy storage units. The smart meter in the system has a two-way metering function and a two-way data communication function, which is one of the key factors to realize the energy and information interaction between the microgrid system and the energy Internet. The energy control center is the core module of the household type microgrid system. It networks the components in the system, reduces the total operating cost and improves the load characteristics through the operation control of these components to achieve the purpose of energy optimization management. The main functions of the energy control center are divided into two aspects: One is to receive the electricity price information of the distribution network and collect the output information of the distributed power supply, the unified load of each household, the power demand information of electric vehicles and the energy storage status. The second is to release real-time control information for the unified load, electric vehicle and energy storage unit in the system.

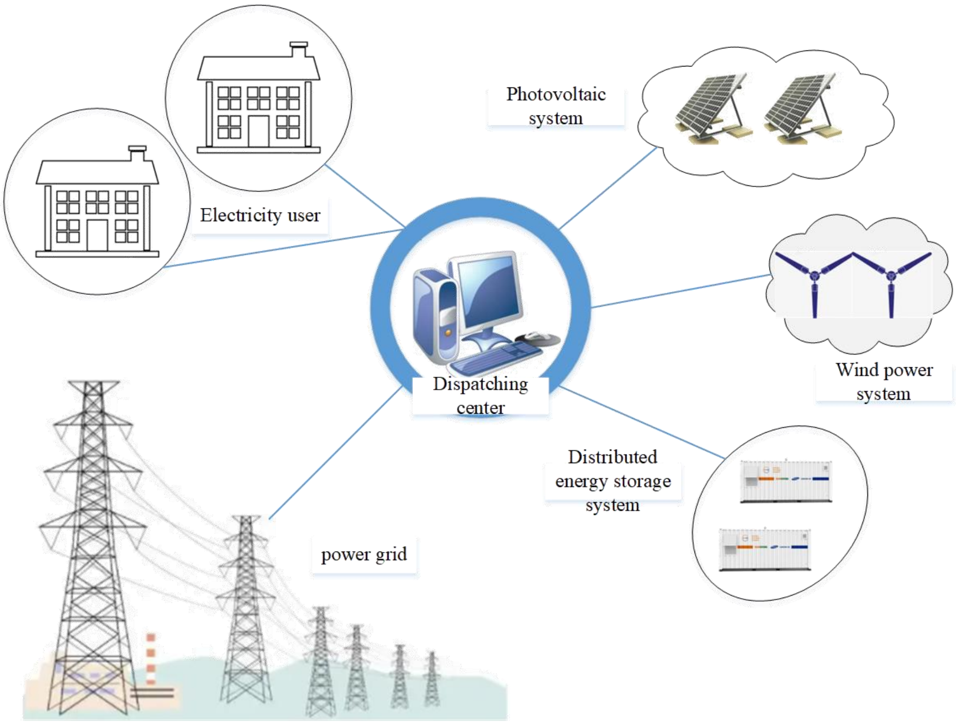

Figure 1. The structure design of microgrid system.

2.2. Description of intelligent power dispatching problem

In this section, the energy regulation of the microgrid system is carried out by dynamic optimization. The specific implementation process is shown in Figure 2.

(1) Input/update demand information: When the new decision-making cycle begins, the energy control center receives the power demand information of residential electric appliances and electric vehicles through the Advanced Metering Infrastructure (AMI), including the minimum operating power, maximum operating power, operating time and minimum energy consumption of each residential electric appliance, as well as the network access time, off network time State of charge (SOC), off grid SOC and rated power of charge and discharge. After optimized dispatching, the system energy control center updates energy consumption of residents' load and SOC information of electric vehicles through AMI. (2) Renewable energy prediction: According to the existing research conclusions on the output power of wind and solar renewable energy, the wind and light output in the future is predicted with the wind and solar output in the current period as the starting value. (3) Finite

time domain optimization: According to the power demand information of household electrical appliances and electric vehicles, the prediction information of wind and light output and the energy storage status and the developed new internal real-time electricity price mechanism, the optimal power consumption scheme of controllable electrical appliances, electric vehicles and energy storage systems of each household is formulated. (4) Real time regulation: In the current period, each controllable electric appliance, electric vehicle and energy storage system performs specific power consumption, idle or discharge operations according to the power consumption scheme and transmits regulation information through AMI. The energy management strategy based on the new real-time electricity price and Model Predictive Control (MPC) algorithm gives play to the auxiliary service potential of the active load, which can minimize the adverse impact caused by the uncertainty of distributed wind and light output prediction in the optimization process, significantly reduce the total cost of the microgrid system and effectively improve the net load characteristics.

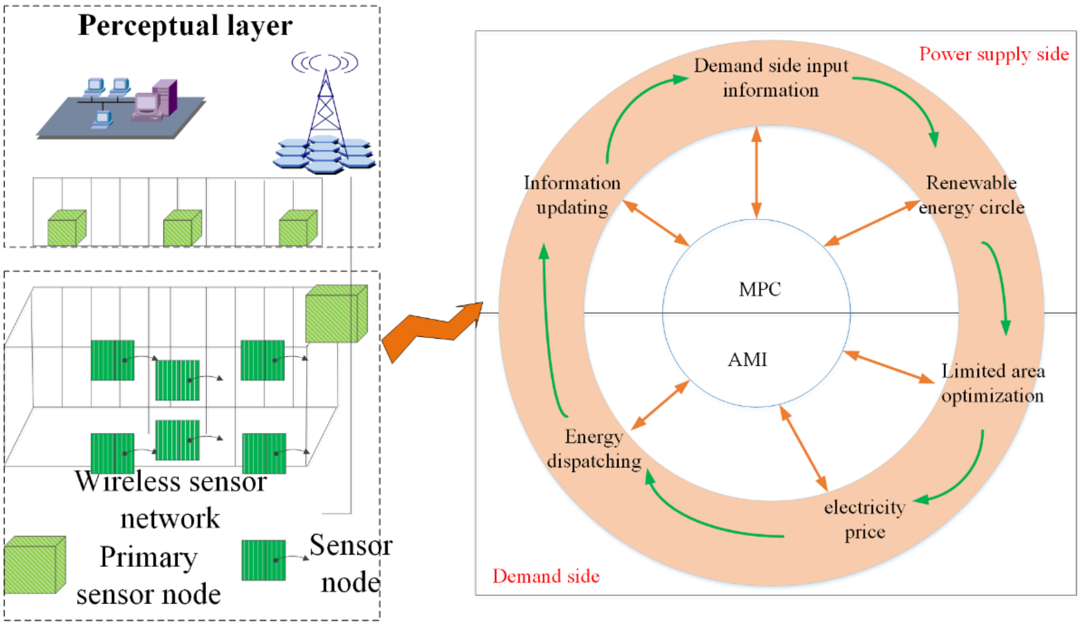

Figure 2. Implementation process of basic dynamic energy regulation of microgrid system.

3. Dispatching control method for smart grid based on machine learning

The algorithm framework is mainly divided into three parts: One is the dimension reduction method of power grid big data. First, there is collection of the operation data of the microgrid through the combination of wireless sensor network and cloud platform to provide the basis for data mining [36]. Second, on the basis of the LSTM regression model [37], the system conducts modeling through historical data, obtains the regression relationship between the data load of each sensor of the unit and the coal consumption of the generator and predicts the coal consumption in a certain time. Third, after obtaining the regression model and the real-time load distribution system based on PSO, according to the current real-time data of each unit, it obtains the load distribution scheme with the lowest overall coal consumption under the completion of power generation tasks and other constraints. The dispatching system framework is shown in Figure 3.

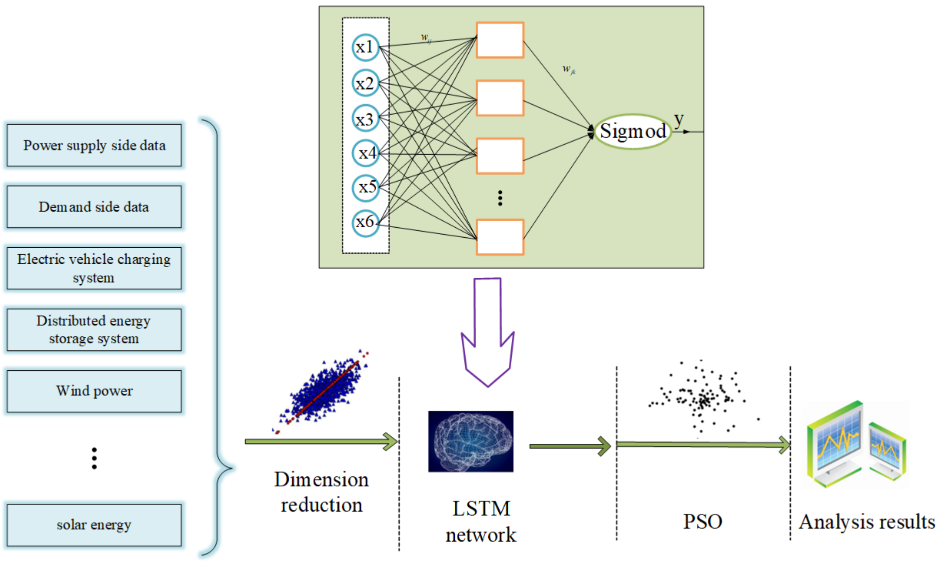

Figure 3. The structure of the algorithm.

3.1. Research on dimension reduction algorithm of Laplace feature mapping data

The high-dimensional sample data (d dimension) collected from the smart grid is actually in a manifold, and the manifold structure retains the geometric features of the original data, while l is the intrinsic dimension of the sample data. As an effective dimensionality reduction method of machine learning big data, Laplace feature mapping is a nonlinear dimensionality reduction method to construct the relationships between data from a local perspective, the idea of which is to calculate and find out the points that are related to each other and can retain the useful information of the high dimensional data.

In Laplacian algorithm, *I* and *j* should retain the similarity relationship in the target low-dimensional subspace after the dimension reduction and be as close as possible. Therefore, Laplacian eigenmaps are

$$min \sum_{ij} W_{ij} \|y - y_i\| \quad (1)$$

where D is a diagonal matrix, and the formula (s) can be expressed as follows:

$$min\, tr(Y^T LY), s.t. Y^T DY = l \quad (2)$$

where the matrix is the Laplace matrix. The constraints ensure non-zero eigenvalues (including multiple roots) of the following generalized eigenvalue problem:

$$Ly = \delta Dy \quad (3)$$

Laplace feature mapping establishes a domain map. Data points will be a cloud node in the domain map, and the connection relationship between each nodes is determined. The effect of this process can be generally expressed as

$$M^D \overset{LE}{\Rightarrow} M^L \quad (4)$$

where $M^D$and M^L, respectively, represent the original features in the d-dimensional space and the mapping features in the L-dimensional space.

3.2. LSTM deep learning regression model

The artificial neural network algorithm has the advantages of generalization and strong learning ability. Now, this algorithm has been widely used in the field of power load forecasting and has achieved good results. They often use data directly through neural networks to achieve power grid scheduling. This paper mainly uses LSTM network to extract features from power data and then combines the traditional PSO algorithm to achieve power dispatching. This method can better improve the efficiency of the algorithm and improve the accuracy of the algorithm. In ordinary deep neural networks, the nodes of each layer are connectionless. If the current state of the problem is related to the previous state, it is easy to cause poor processing results. The recurrent neural network (RNN) can solve this problem by adding recursive edges to the hidden layer neurons, so that the neural network has memory. The structure of a recurrent neural network is shown in Figure 4. RNN is equivalent to a multi-layer deep neural network (DNN) developed according to time series. Due to the large number of layers, the gradient may disappear.

Compared with RNN, the LSTM network structure contains candidate states of memory function for memory and transmission of effective information. In addition, the LSTM structure also includes a forgetting gate, an input gate and an output gate. The three gate control signals are as follows:

$$f_t = \sigma\left(W_f\ [h_{t-1}, x_t] + b_f\right) \tag{5}$$

$$i_t = \sigma(W_C\ [h_{t-1}, x_t] + b_C) \tag{6}$$

$$\tilde{C}_t = tanh(W_C\ [h_{t-1}, x_t] + b_C) \tag{7}$$

$$\tilde{C}_t = tanh(W_C\ [h_{t-1}, x_t] + b_C) \tag{8}$$

$$o_t = \sigma(W_o\ [h_{t-1}, x_t] + b_o) \tag{9}$$

$$h(t) = o_t * tanh(C_t) \tag{10}$$

3.3. Energy optimal dispatching strategy of microgrid

When the microgrid is in the isolated grid operation mode, the objective of its optimal dispatching is to achieve the lowest power generation cost and the lowest pollution gas emission under the constraints of meeting the operation constraints of each distributed unit and the thermal power load demand. When the microgrid is in the grid connection mode, in addition to considering various constraints under the isolated grid operation, the two-way flow of power flow and mutual purchase of electric energy between the microgrid and the large grid should also be considered. The objective function of the energy management optimization dispatching of the microgrid system can be expressed as

$$min\, Z_{cost} = \lambda_1 C_g + \lambda_2 C_e \tag{11}$$

where Z_{cost} is the objective function of total operation cost of the microgrid, C_g is system power generation cost, C_e is penalty cost of pollutant gas emission, and λ_1 and λ_2 are weight proportion of power generation cost and pollution gas emission penalty cost.

In this paper, the bacterial foraging algorithm is used to improve the PSO algorithm, which is prone to "premature convergence" and needs to deal with many constraints in the micro grid energy management optimization scheduling problem. The speed and position updating formulas of the improved PSO are

$$v_{ij} = wv_{ij} + c_1(pbest_{ij} - p_{ij}) + c_2(gbest_{ij} - g_{ij}) + c_2(frw_{ij} - p_{ij}) \tag{12}$$

$$C(i) = \frac{\sum_{k=1}^{\xi}|Error_{i,k}|+1}{\sqrt{Iteration}} \tag{13}$$

where j is the dimension of the i-th particle; N is the total dimension of the particle; $frw_{ij}$is the j-th coordinate of the i-th particle foraging random step position; p_{ij} and g_{ij} are the dimensional coordinates of the position and velocity of the i-th particle, respectively; $pbest_{ij}$ and $gbest_{ij}$ are the j-th coordinate of the individual optimal solution of the i-th particle and the j-th coordinate of the global optimal solution, respectively; $C(i)$ is the random step size of foraging.

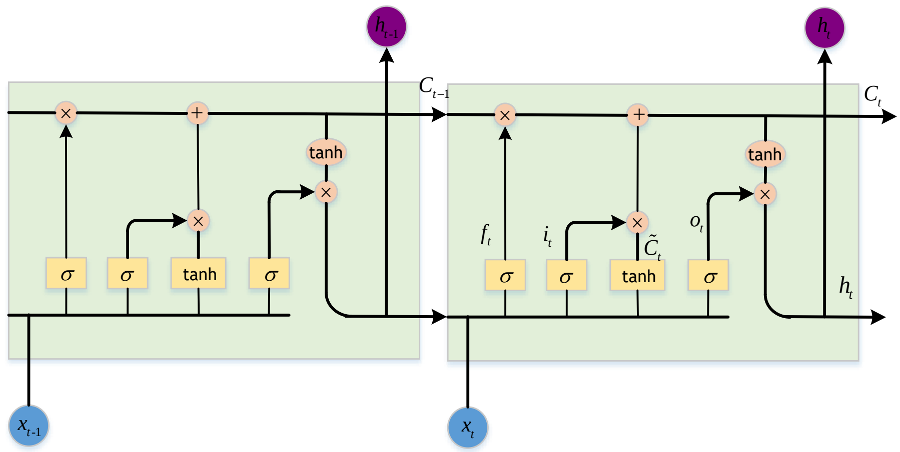

Figure 4. The simple structure LSTM.

Therefore, it is necessary to deal with each constraint condition before calculation. The equality constraints considered in this paper include node power flow constraints and power balance constraints. The inequality constraints considered mainly include rotation reserve constraints, distributed unit output constraints, node voltage constraints and interaction capacity constraints with large power grids. The flow of the improved particle swarm optimization algorithm for energy optimization scheduling of microgrid in this paper is shown in Figure 5. As is shown in Figure 5, the main process of the PSO algorithm is as follows: First, the particle swarm optimization algorithm is composed of a group of particles moving in the search space, which is affected by its own best past position pbest and the best past position gbest of the whole group or its nearest neighbor. Then, calculate and update the latest position of particles by formulas (12) and (13). Finally, from the velocity update formula, we can see that if the algorithm needs to converge quickly, we need to increase the acceleration constant. However, doing so may lead to "precocity" of the algorithm. If the inertia weight is increased, it can increase the "enthusiasm" of particles to detect new positions, avoiding falling into local optimization prematurely, but also reduce the convergence speed of the algorithm. For some improved algorithms, a random term will be added to the last term of the speed update formula to balance the convergence rate and avoid "premature" convergence. According to the characteristics of the location update formula, particle swarm optimization is more suitable for solving continuous optimization problems.

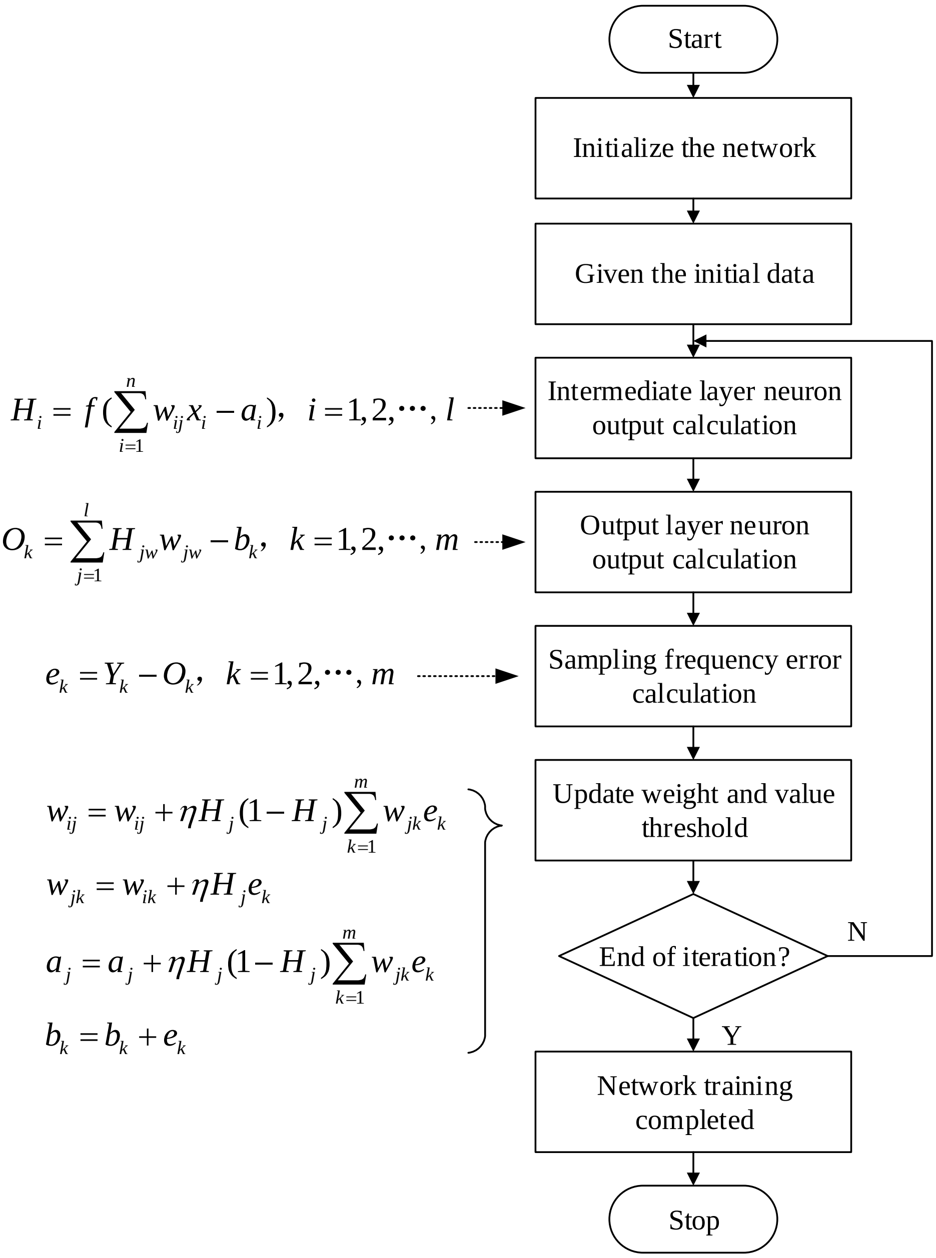

Figure 5. The flowchart of PSO for energy optimization scheduling of microgrid.

4. Simulation results and performance analysis

4.1. Data sources and data processing

The historical data of two units of Xuancheng Power Plant in Anhui Province were collected. For the #1 unit, the selected data were from August 10, 2020, to August 10, 2020, with a total of 43 measuring points The data of the #2 unit from June 1, 2020, to July 1, 2020, were selected. There were 46 measuring points in the test. Since the time interval for each sensor to acquire data is different, the test needs to understand the current stable state of the system, so the original data is processed to obtain the average data of each sensor within 1 min. The Laplacian eigenmaps grid big data dimension reduction algorithm was encoded in the Java language and tested in the Hadoop platform. Hadoop is a distributed system infrastructure. It adopts master/slave mode. One master node manages one or more slave nodes in a unified manner. Hadoop version 2.2.0 system was used in the experiment. The performance of Laplacian eigenmaps algorithm was analyzed by using two types of data, which are from a smart grid in Southwest China.

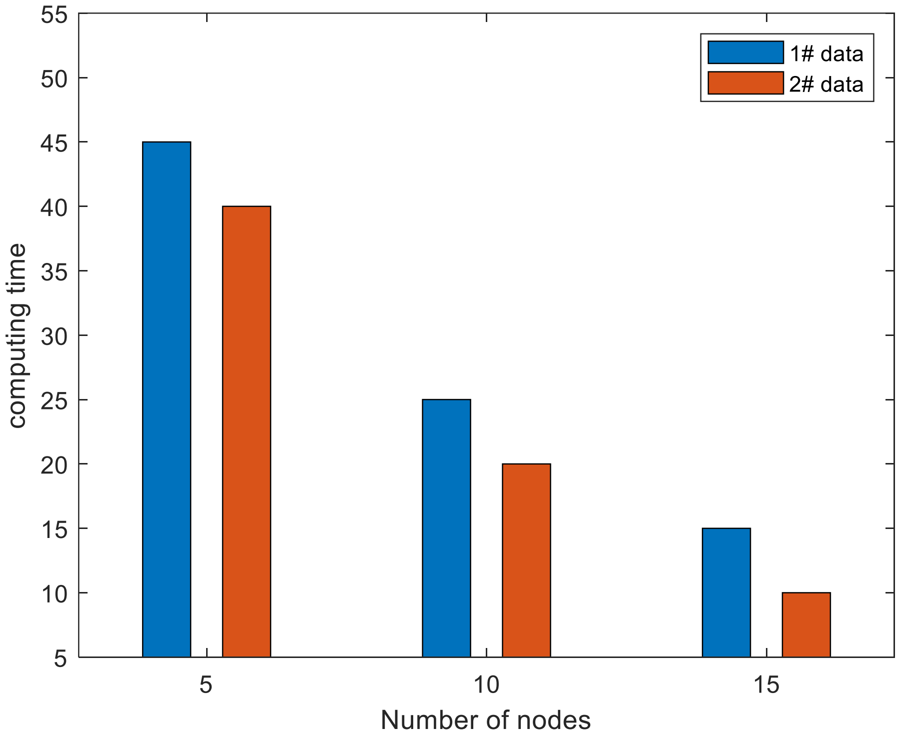

Figure 6. Data dimension reduction performance verification.

The fault detection data of transformer is denoted as data1, and the prediction of intelligent substation is denoted as data2. The data set capacity of data 1 and data 2 is 15GB. The condition attributes of these two kinds of data sets are reduced to compare the dimension reduction efficiency of Laplacian eigenmaps algorithm under different attributes, and then the performance of this algorithm is compared with the commonly used parallel dimension reduction algorithm according to the acceleration ratio. Finally, the data after cleaning is obtained through data duplication and error elimination, as shown in Figure 6. The reduction efficiency of the algorithm will increase with the increase of its parallelization. In order to verify the reduction efficiency of the Laplacian eigenmaps algorithm, 15 GB of transformer fault detection data are used to select 5, 10 and 15 nodes, respectively, for the Hadoop platform to conduct the time-effectiveness comparison experiment on the data sets of the same size. The data dimension reduction performance verification is in Figure 6. As is shown, when the number of nodes keeps increasing, the reduction efficiency of Laplacian eigenmaps algorithm will be improved accordingly. The performance advantages and disadvantages of the Laplacian eigenmaps algorithm and common parallel dimension reduction algorithms are analyzed in terms of time complexity, space complexity and algorithm accuracy. In order to further prove the effectiveness of this method, the performances of this method and the mainstream dimension reduction method are compared from the two aspects of reduction efficiency and acceleration ratio.

4.2. The accuracy verification of regression model

The hidden layer composed of 10 layers of LSTM is used in the test, and each layer has 128 nodes. The model was trained by stochastic gradient descent (SGD) with 500 rounds. The fitting effect of the unit is shown in Figure 7. When the number of training rounds is 500, the mean square error of the test set can be stable at 0.18 for the #1 unit and 0.06 for the #2 unit, which has achieved the expected fitting effect.

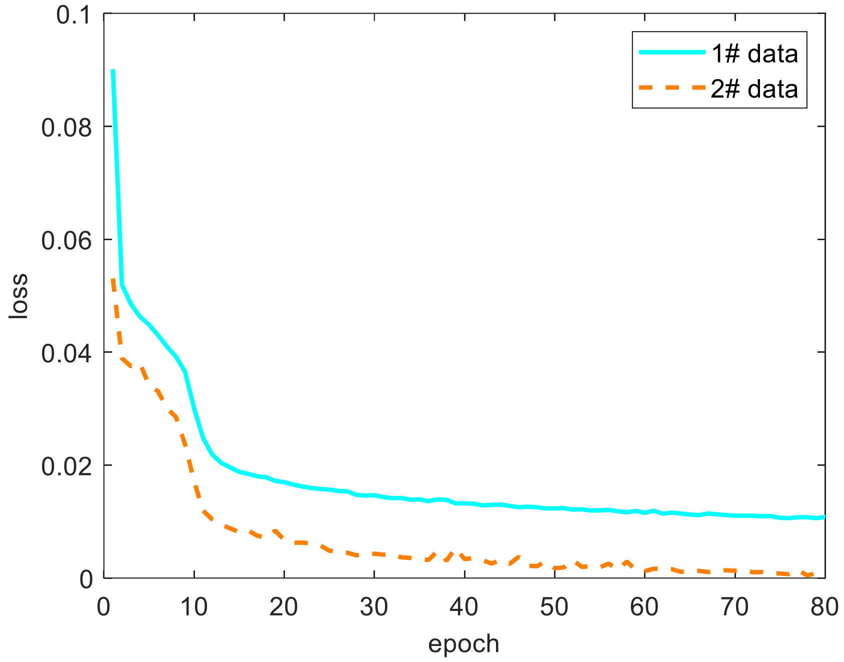

Figure 7. Prediction accuracy verification based on LSTM regression model.

The interval width of the proposed model is the narrowest, and the quantile score is the lowest. The main reason is that the convolutional neural network (CNN) in the LSTM model can extract the characteristic information of the original load related data and reduce the complexity of the information input to the prediction model. In addition, compared with the traditional regression model, LSTM can use its internal memory structure to continuously mine the time sequence compliance relationship within the time series under different loci, while the traditional RNN network model can only simply establish the mapping relationship between input variables and output variables and cannot use long-term historical input data information.

4.3. The influence factor results analysis based on partial relation coefficient

This paper mainly evaluates genetic algorithm, ant colony algorithm [38] and improved particle swarm optimization algorithm from the two aspects of time-consumption and scheduling effect. In practical application, in order to ensure the normal use of unit #1 and unit #2 of the power plant, the following restrictions are used. Micro gas turbine is used in the cogeneration unit in this paper. There are great differences in the thermal power load in the microgrid on the residential user side, and the thermal load demand will change significantly with the change of seasons. In summer, the average heat load demand in a week is only about the maximum heat load demand of the whole year, while the change of electric load demand is relatively small. In terms of one hour, the heat load demand is relatively stable, while the electric load demand fluctuates with the time period. In this paper, the generation cost of a microgrid in the future hours of a typical day in winter is selected as the research object for optimal control. The thermal power load prediction curve of a microgrid in the hours of that day is shown in the figure. Inputs are the forecast data of sunlight, temperature, wind speed, etc. The output forecast data of photovoltaic power generation can be obtained, respectively. The operation cost of a microgrid system under various dispatching strategies is shown in Figure 8.

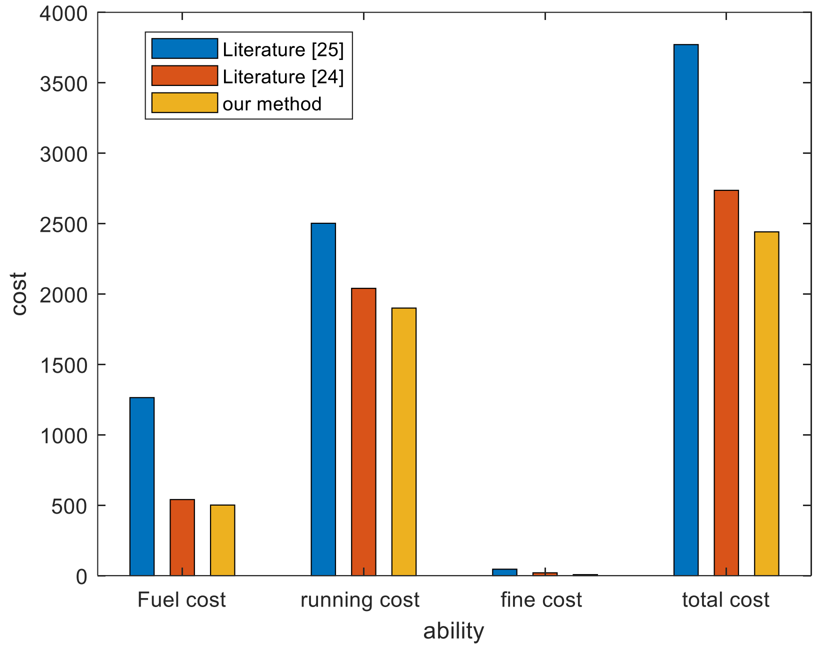

Figure 8. Superiority verification of the algorithm.

When the strategy is adopted, the power generation cost of the microgrid is the highest, in which the fuel cost accounts for the total cost, and the pollution penalty is also the highest compared with other strategies. Under the strategy, as the storage battery and the main network jointly participate in the system scheduling, the power generation cost is significantly reduced, which is slightly lower than the strategy. Meanwhile, the system fuel cost and pollution penalty are significantly reduced. Under the strategy, since the two-way interaction of electric energy with the main grid can be realized, when the microgrid has abundant electric energy, it can be sold to the main grid, so as to have a certain amount of electricity sales income and also make the power generation cost lower than that of the strategy, reducing about. On the basis of the strategy, the strategy considers the participation of controllable loads in the microgrid. It is found that when controllable loads in the microgrid participate in energy management, it is beneficial to improve the economy of microgrid system operation, and its power generation cost is the lowest compared with the first three dispatching strategies.

5. Conclusion

The smart grid dispatching control system is the backbone of the power system, and the premise is to ensure the stable and safe operation of the power grid. In recent years, due to the continuous expansion of the power system, power enterprises have gradually carried out the research and construction of the smart grid dispatching control system and developed from the traditional application architecture to the new application architecture. This paper presents an intelligent power plant scheduling algorithm based on LSTM algorithm and PSO algorithm. A pre-processing method of smart grid big data based on machine learning is proposed. Laplacian eigenmaps are used to adaptively learn and reduce the dimension of power grid big data, and then the reduced dimension data is used for analysis. The experimental analysis is carried out on the Hadoop platform. The results show that the Laplacian eigenmaps algorithm can be effectively applied to reduce the dimension of smart grid big data, and it has very broad application prospects. The coal consumption of the generating unit is accurately predicted by LSTM. Improved PSO is used to intelligently distribute the total power generation load, so that the total coal consumption of the whole plant is the lowest when the power generation index is completed. This method effectively improves the utilization rate of coal, improves the economic benefits of power plants, reduces the emission of pollutants and provides necessary support for economic and environmental protection with power plants. Due to the difference of regional power data, the dispatching methods in different regions are also different. It is important to try to achieve the collection of resources and forces to connect the grid and expand its coverage and scope. By breaking regional restrictions and barriers, this will provide more comprehensive social services, create a complete smart grid and improve the adaptability of the dispatching algorithm. .

Conflict of interest

All the authors declare no conflicts of interest in this paper.

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