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Research on performance prediction of virtual power plant and multi-resource fusion system based on neural network

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ABSTRACT

In this paper, the modelling and fault monitoring methods of virtual power plants are investigated. Aiming at the risks faced by the virtual power plant, a virtual power plant dynamic model based on BPNN is proposed, which uses neural networks to establish the relationship between the uncertainty factors and the technical parameters of the virtual power plant, and adjusts the technical parameters of the virtual power plant in real time according to the size of the uncertainty factors. The technical parameters of the virtual power plant are optimised to obtain the parameters that maintain the optimal performance of the virtual power plant. At the same time, in order to be able to comprehensively monitor the failure of the virtual power plant, play a role in early warning, starting from the real-time database of the equipment, the data from a variety of sources to the equipment as the centre of the fusion. Multiple state parameters of the equipment are tracked in real time and displayed in the form of trend graphs, which completes the analysis of the parameters of the fault characteristics in the database and achieves a nonlinear mapping from characteristics and signs to the cause of the fault and the type of fault. Based on the BPNN dynamic model, the SMAPE is 6.51%, and after using the model constructed in this paper to monitor the virtual power plant, the failure rate of the virtual power plant decreases month by month, and the failure rate is much smaller than that before the model is used. It verifies the good performance of the method of this paper, and also shows that the method of this paper has a broad application prospect in the field of fault monitoring and warning of virtual power plant.

Keywords: virtual power plant, BP neural network, fault monitoring, multi-resource fusion

1. Introduction

In order to promote the effective consumption of clean and renewable energy and make full use of

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distributed resources at scale, virtual power plants have emerged. Virtual power plant includes not only power source, but also load-side resource integration, mainly demand response, energy storage, electric vehicle fleet, etc. [1-3], which integrates distributed power sources that are not directly connected physically into a whole through advanced measurement technology, communication technology, control technology, etc., and carries out control so as to realise orderly access to a large number of distributed power sources and to reduce the impact on the power grid [4-6]. Virtual power plants are an important solution to improve the rate of new energy consumption and energy utilisation, and their development is driven by the expectation of controlling climate change, security of energy supply and energy efficiency improvement by renewable energy scaling [7-9].

For the government, virtual power plants are a key driver for securing a safe supply of electricity and driving market and industry development. On the one hand, virtual power plants are an effective means to promote the coordinated development of all types of resources on the demand side, strengthen the interaction between supply and demand, and reduce the impact of large-scale new energy grid integration on system security [10-13]. On the other hand, as an emerging market player, virtual power plant can enrich the power market pattern, active market transactions, and its industrial chain includes collection terminals, operation and control software, digital platforms and other links, which is the key to promote the development of related industries [14-17]. For power grid enterprises, virtual power plants have the potential to support the safe and stable operation of power grids and delay power investment. And in the new period, the integration of virtual power plant and multiple resources is of great significance to promote the sustainable development of virtual power plant [18-20].

In this paper, we calculate the online parameters of the virtual power plant and construct a dynamic model, and train the relationship between uncertainty factors and capacity through BP neural network, so as to establish the dynamic model of the virtual power plant. Subsequently, a multi-resource fusion system is established to achieve the monitoring of virtual power plant equipment failures on the basis of neural network modelling, fusing the existing scattered and fragmented equipment data in the virtual power plant, and making full use of the data from the original information systems of the virtual power plant. It further promotes the development of virtual power plant condition maintenance, makes more faulty equipments in virtual power plant shift from planned maintenance to condition maintenance, gradually improves the equipment management level and reduces the failure rate.

2. Elements and forms of the virtual power plant

2.1. *Components of a virtual power plant*

1) The main body of energy supply. The main body of energy supply within a virtual power plant mostly consists of distributed generating units, which, according to the Measures for the Administration of Distributed Power Generation (hereinafter referred to as the Measures), are defined as small and medium-sized power generation facilities that are connected to and operated by distribution grids and whose power generation is consumed in close proximity to the grid, as well as comprehensive energy utilisation systems that have an output of electricity. At present, China is actively pursuing the development of distributed energy resources.

2) Energy Storage Resources. In addition to distributed energy supply equipment, the cooperation and application of energy storage resources will significantly enhance the ability of the virtual power plant to smooth out fluctuations in internal distributed wind power output and meet the demand for stable internal power consumption. The virtual power plant chooses to share energy storage to configure reasonable energy storage capacity, which can reduce construction costs and improve the economic efficiency of operation.

3) Load resources. Virtual power plants usually gather scattered load resources with large individual differences, small capacity and small regulation capability, and provide services such as energy hosting

and integration of power distribution and sale to these load resources. As the flexible loads in the loads have certain regulating ability, the virtual power plant can guide the users to change the electricity consumption behaviour and enrich the users' electricity consumption mode, on the one hand, to improve the terminal energy consumption efficiency and reduce the cost of energy services. On the other hand, it improves its own regulation elasticity and enhances the comprehensive benefits of cleanliness, economy and security. When the power system fluctuations, the power grid, power sales companies or some agent operators can release information to require users to respond according to the contract requirements, compared with the price-based demand response stronger autonomy, incentive-based demand response for the power grid, power sales companies or some agent operators to the degree of control over the load a little stronger. Load users in China can be divided into three categories: industrial load, commercial load, and residential load, and different types of loads have different demand response potentials.

2.2. Typical form of a virtual power plant

Virtual power plant does not have a unified form, according to the demand to determine their own in a certain time and space in a certain form, the following will focus on three aspects of the analysis of the typical form of the virtual power plant.

1) From the viewpoint of source and load characteristics, it can be divided into supply-type virtual power plant, demand-type virtual power plant and hybrid virtual power plant. Supply-type virtual power plant consists of a variety of distributed power sources and plays the role of a traditional power plant, through the provision of electric energy to obtain revenue. The demand-based virtual power plant is mainly composed of energy storage and load resources, and is equivalent to a large user for the power system. Hybrid virtual power plants include source, storage and load resources, which can be used as both power sources and loads, providing greater flexibility. Hybrid virtual power plants pay more attention to the coordination of internal resources for the vertical interaction of the source network, storage and load, in order to enrich the form of the existence of the power system to obtain more revenue, the current virtual power plant is mostly in the form of hybrid existence.

2) From the viewpoint of the composition of internal energy supply types, it can be divided into single-energy virtual power plants and multi-energy virtual power plants. Single-energy virtual power plant only has a kind of energy supply capacity. Multi-energy virtual power plant is mainly integrated with the supply of cold, heat, electricity and gas. With the continuous development of the concept and technology of the energy Internet and the diversification of load demand, the multi-energy complementary virtual power plant is gradually developed, which can realise the conversion of different types of energy, practice the idea of horizontal multi-energy complementarity, and improve the efficiency of energy use.

3) From the perspective of the development form, it can be divided into technical and commercial virtual power plants. Technical virtual power plants mainly connect and manage distributed resources physically, focusing on the safety and stability of their own operation. Commercial virtual power plants take on the responsibility of agency operation, aggregating, managing and coordinating small-capacity distributed resources that cannot participate in the market independently. On the one hand, the commercial virtual power plant participates in various markets in the form of an independent entity, and distributes the revenue to internal resources in a certain way.

3. Dynamic modelling of virtual power plants

3.1. Virtual power plant online parameters

For a traditional thermal power plant, the model and technical parameters of the plant are fixed values and are little affected by external factors. However, virtual power plants face a large amount of uncertainty, and in order to enable virtual power plants to participate in power system scheduling and operation like traditional thermal power plants, it is necessary to assess the risk based on the uncertainty and adjust the virtual power plant technical parameters in real time. For virtual power plant operation, risk refers to the economic loss suffered by a virtual power plant due to its own uncertainties that result in insufficient output to purchase power in the spot market to meet demand. The implementation of dynamic capacity values for virtual power plants can reduce the capacity of the virtual power plant when the risk increases, thus circumventing the underproduction of the virtual power plant. Due to the various types of uncertainty factors obtained through real-time measurement and forecasting techniques are inherently subject to a certain degree of error and the complexity of the impact of uncertainty factors on the virtual power plant capacity, it is difficult to directly establish an accurate expression of the virtual power plant's technical parameters. Therefore, this paper calculates the online parameters of the virtual power plant and constructs a dynamic model, and uses the big data processing capability of machine learning to establish the relationship between the parameters of the virtual power plant and the uncertainty factors using the data model.

3.2. Neural network based dynamic modelling

In this paper, the relationship between uncertainty factors and capacity is trained by BP neural network [21] as a way to build a dynamic model of virtual power plant.

Depending on the learning environment, supervised learning or unsupervised learning can be chosen to train the neural network. When using supervised learning, it is necessary to input a certain number of training samples, compare the output of the network with the actual output of the sample and adjust the network weights, and form the model beforehand after several trainings; while when using unsupervised learning, there is no need to give standard input and output samples beforehand, and the network will be placed in the actual environment directly, which is a good balance between the training of the network and the practical application. This paper adopts supervised learning for neural network modelling, and in the later operation of the virtual power plant, unsupervised learning can be used to continuously optimize and update the model, so as to realize the continuous upgrading of the dynamic model of the virtual power plant.

The first step in establishing the neural network is to determine the input and output signals of the model, and this paper selects three uncertainty factors as inputs, namely: the change value of the number of virtual air-conditioning units, the fluctuation of the outdoor temperature, and the actual error, and the output value is selected as the capacity value of the virtual power plant. The input signal is weighted and summed and placed in the activation function, and the output of the activation function is determined [22], which enables the nonlinear mapping of the input signal.

The schematic diagram of the neural network model is shown in Fig. 1, which establishes the relationship between the input and the output through the hidden layer neurons. The neural network training is divided into forward propagation process and error back propagation process, the forward propagation process is based on the input uncertainty factor signal to calculate the output capacity value signal and compare it with the expected output capacity value signal to find the error. And the error back propagation process is to adjust the network weights according to the size of the error. Through many cycles, it finally makes the parameters converge and stops the training.

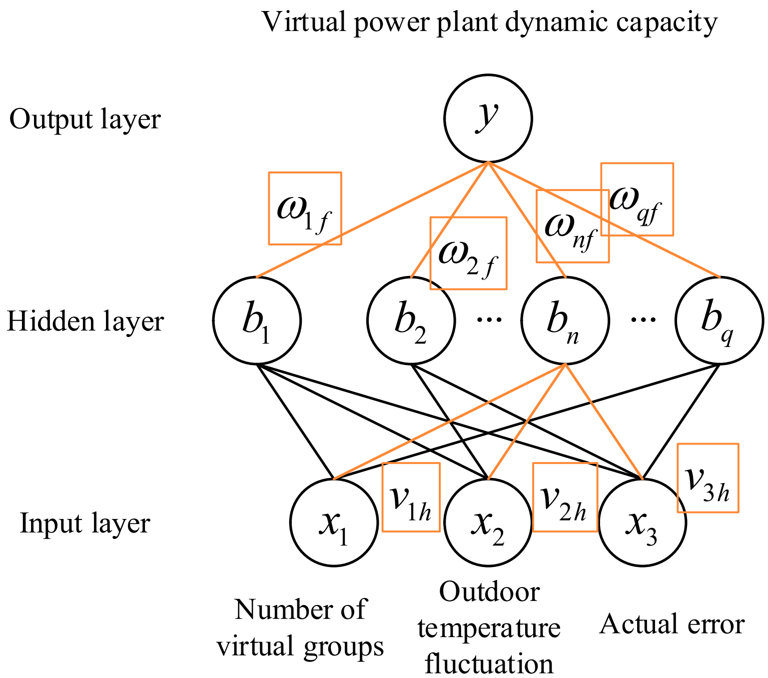

Fig. 1. Neural network diagram

$$a_h^k = \sum_{i=1}^{d} v_{ih} x_{ik} \tag{1}$$

$$A_h^k = f(a_h^k) \tag{2}$$

$$b_j^k = \sum_{h=1}^{d} w_{hj} A_h^k \tag{3}$$

$$\hat{y}_j^k = f(b_j^k) \tag{4}$$

The goal of training the BP neural network is to minimise the error of all input samples by adjusting parameters such as the network weights, and the degree of bias of all samples is better captured by using the mean square error. Equation (5) is the mean square error of the input and output of sample (x_k, y_k) [23].

$$E_k = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j^k - y_j^k)^2 \tag{5}$$

The error back propagation process uses a gradient descent algorithm to adjust the weights towards the negative gradient of the objective function.

$$\begin{gathered} w_{h,j} \rightarrow w_{h,j} - \eta \Delta w_{h,j} \\ \Delta w_{h,j} = -\frac{\partial E_k}{\partial w_{h,j}} \end{gathered} \tag{6}$$

where $w_{h,j}$ is the hidden layer neuron weights.

The process of updating the neural network parameters is shown in Eq. (7) to Eq. (10), and in order to improve the efficiency of the model operation, the neural network performance index shown in Eq. (11) is introduced.

$$w_{h,j:} = w_{h,j} - \eta \sum_{k=1}^{m} A_h^k (\hat{y}_j^k - y_j^k)\, \hat{y}_j^k (1 - \hat{y}_j^k) \tag{7}$$

$$\theta_{j:} = \theta_j - \eta \sum_{k=1}^{m} (\hat{y}_j^k - y_j^k)\, \hat{y}_j^k (1 - \hat{y}_j^k) \tag{8}$$

$$v_{i,k:} = v_{i,k:} - \eta \sum_{k=1}^{m} x_i^k A_i^k (1 - A_i^k) \sum_{j=1}^{l} w_{h,j} (\hat{y}_j^k - y_j^k)\, \hat{y}_j^k (1 - \hat{y}_j^k) \tag{9}$$

$$\delta_{i,h:} = \delta_{i,h:} - \eta \sum_{k=1}^{m} x_i^k A_i^k (1 - A_i^k) \sum_{j=1}^{l} w_{h,j} (\hat{y}_j^k - y_j^k)\, \hat{y}_j^k (1 - \hat{y}_j^k) \tag{10}$$

$$e_{MAPE} = \frac{1}{M} \sum_{i=1}^{M} \frac{|\hat{y}_i - y_i|}{y_i} \times 100\% \tag{11}$$

The selection of neural network parameters has a great impact on the performance of the model, the number of hidden layers and the number of neurons in each layer is too large, which will lead to model redundancy and increase the burden of the model, and the number of neurons is too small, which may not be able to respond to the complex relationship between the inputs and outputs, and affects the accuracy of the model. In this paper, the enumeration method is used to determine the number of hidden layers and the number of neurons in each layer, and the number of layers and neurons are selected according to the performance index and the model computing time.

The flow chart of model training is shown in Figure 2, for the virtual power plant has a large amount of historical data can be used to train the model, in order to ensure the accuracy of the model, 20% of the historical data can be reserved as a test set, and if the test results have a large error, the neural network model can be adjusted by adjusting the parameters of the neural network model, and re-training of the neural network model.

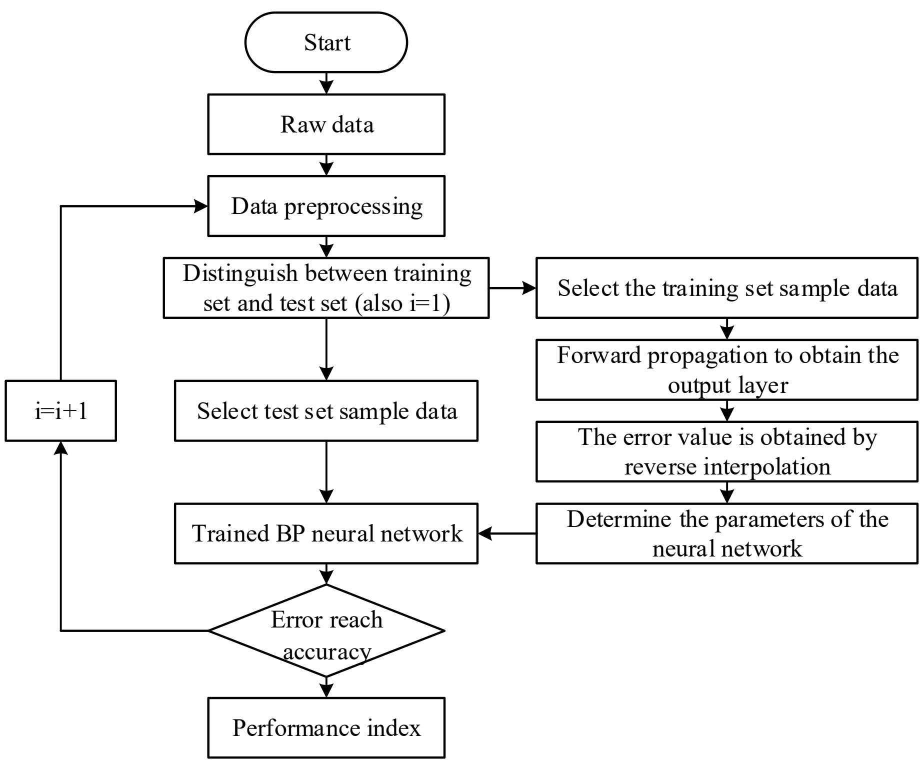

Fig. 2. Neural network training process flow chart

A BP neural network with the dynamic capacity of the virtual power plant as the output is built through machine learning to establish the relationship between input and output. When the virtual power plant is running, historical data is uploaded in real time to train the neural network model, and the data collected in real time is used to calculate the dynamic model. As the virtual power plant runs, the more historical data are accumulated, the neural network model is updated, and the dynamic model of the virtual power plant becomes more and more accurate.

4. Establishment of a multi-resource fusion system

With the increasing degree of automation of power station equipment, and a high degree of complexity between the equipment and the system itself, the power station itself is a place with high risk and high failure under high temperature and high pressure working conditions. Therefore, it is urgent to improve the safety and accelerate the fault monitoring method of power station equipment on the basis of the economy of power station operation. Using the BPNN dynamic model to achieve the modelling of the power plant, the existing scattered and fragmented equipment data within the virtual power plant can be fused and the data from the original information systems of the power plant can be fully utilised through a multi-resource fusion-based power plant equipment fault monitoring and optimisation system. The full application of such a system can also further promote the development of condition maintenance in thermal power plants, enabling more equipment to shift from planned maintenance to condition maintenance, and gradually improving the level of equipment management.

The main contents of the fault monitoring research based on multi-resource fusion include multi-resource access, component diagnosis list, equipment diagnosis list, multi-resource fusion display and the establishment of fault monitoring calculation model. The specific contents are as follows:

Multi-resource access. With the full cooperation of the owner and relevant vendors, the platform is proposed to access information such as equipment code information, equipment basic information, real-time data, monitoring data, equipment fixed value, performance deterioration index, equipment operating hours and start-up times, test and laboratory tests, etc., which will be applied and displayed in the system. By accessing multi-resource data, operators can simultaneously view the alarm status of multiple measurement points of a single device, and comprehensively analyse and judge the current status of the device according to the current multi-resource alarm situation of the device, which is convenient for maintenance personnel to carry out targeted maintenance. By modelling the similarity of one year's data of the power station, a prediction value is generated for each time point of each current measurement point, making it reliable and comparable when monitoring.

Component Diagnostic Sheet. Component diagnosis list is automatically generated according to the abnormal status of components, and can integrate relevant information of components, including component code, basic information of components, relevant real-time data, monitoring information of components, relevant fixed value, running hours and number of times of start-up of components, etc., record the analysis and processing process, accumulate diagnostic knowledge, and realise collaborative diagnostic and analysis of the status of equipment and components of multi-disciplines and multi-departments of the power plant. The processing flow of component diagnosis list is in line with the actual business analysis flow of the power plant. Through the creation of a personalised analysis process, to achieve multi-departmental and multi-disciplinary collaborative analysis work around the state of equipment components, the analysis process is shown in Figure 3.

Equipment diagnosis. Equipment diagnostic list of multiple key components of the state, combined with equipment operating hours and the number of start-ups, equipment performance indicators and other information, to achieve the comprehensiveness and objectivity of the equipment state diagnosis and quantification of state indicators. The processing flow of the equipment diagnosis list is configured according to the actual business process of equipment diagnosis in the power plant, so as to realise multi-departmental and multi-professional collaborative analysis operations around the equipment status.

Multi-source fusion display. Based on the fusion of data from multiple sources with equipment as the centre, equipment data from multiple sources are clearly displayed. Real-time tracking of multiple state parameters of the equipment and display them in the form of trend graphs. For the same kind of equipment, it is possible to call out the related multiple status parameters on the same page for comparison, which is more convenient for the operators to check the multiple status parameters of the same equipment, and to check the fault parameters and eliminate the safety parameters in time.

Establishment of fault monitoring calculation model. Research on fault monitoring and optimisation system of power station equipment based on multi-resource fusion. Project completion of the final configuration model needs to be based on the data sources as well as measurement points on site during project implementation, and may also be slightly adjusted.

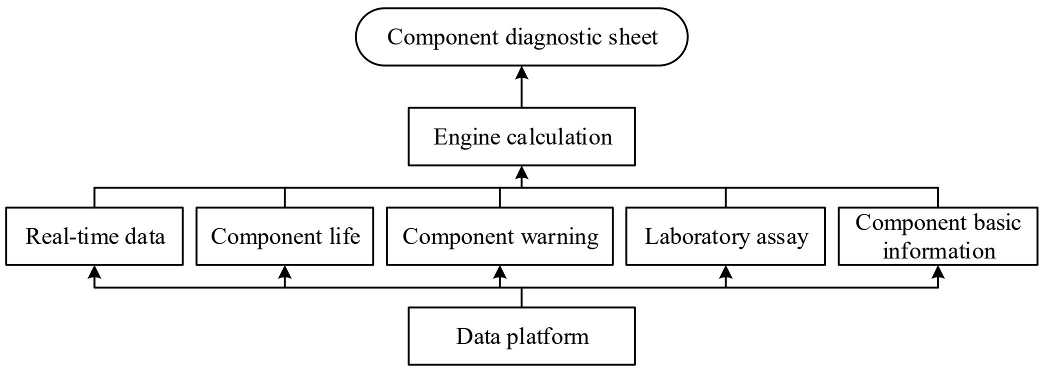

Fig. 3. Process of component diagnostic list analysis

5. Dynamic model building performance prediction analysis

In this section, several traditional prediction models are proposed to verify the prediction effect of different models and the dynamic model based on BPNN in this paper on short datasets. In order to accurately assess the merits of the model prediction results, various metrics have been proposed, including root mean squared error (RMSE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (SMAPE), etc., and these metrics have been widely used in various integrated and time series forecasting algorithms so that the same measurements can be applied in each case to ensure the accuracy of the prediction results. The output of the RMSE metric extracts predictor variables measured in kilowatt hours (kWh), while the output of the MAPE and SMAPE metrics are extracted on a percentage scale, which makes the results more comprehensive.

The parameter settings for each model are shown in Table 1, where LSTNet is run based on the Pytotch platform and the remaining algorithms are run based on the Tenserflow platform. The prediction results are shown in Fig. 4, from which it can be seen that the BPNN dynamic model has the smallest SMAPE, RMSE, and MAPE, which are 7.85%, 6.54kWh, and 6.72%, respectively. Fig. 5 shows the BPNN dynamic model training Loss decline graph. The above data can be seen for the prediction with small data samples, using the BPNN dynamic model based on the prediction of the smallest error, and the training Loss decline faster, the number of iterations of 10, the loss fell to 0.02, the training time is short, high efficiency, can be more efficient simulation of the virtual power plant, and the predicted data and the actual data similarity is very high.

Table 1. Model parameter Settings

Algorithm	Full junction	Neuron node	Epoch	Batchsize
LSTNet	/	/	200	20
Bi-LSTM	1	100	200	20

LSTM	1	100	200	10
SVM	7	100	200	00
BPNN	3	/	200	10

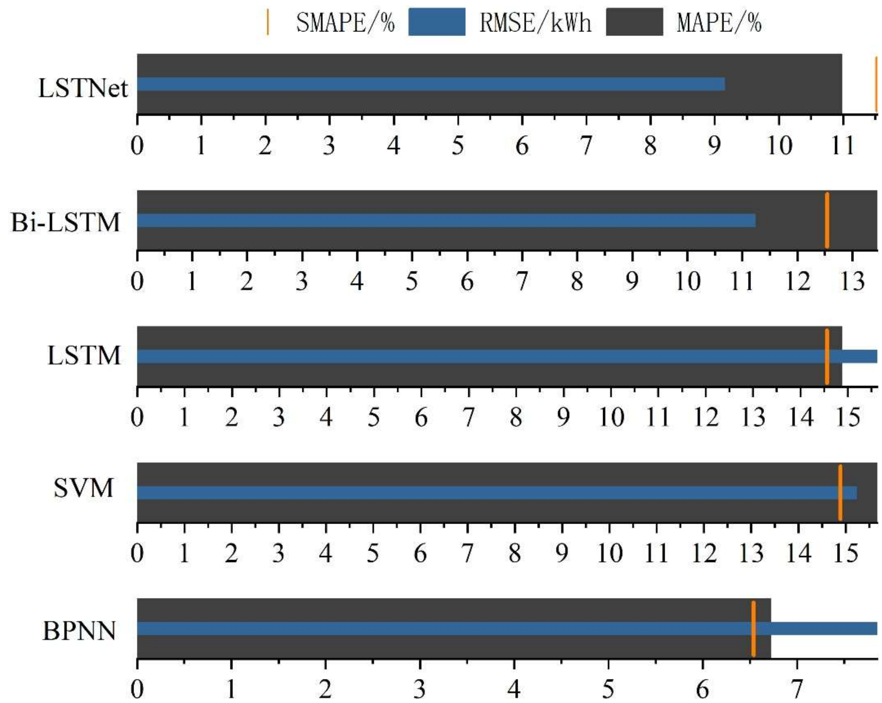

Fig. 4. Model prediction

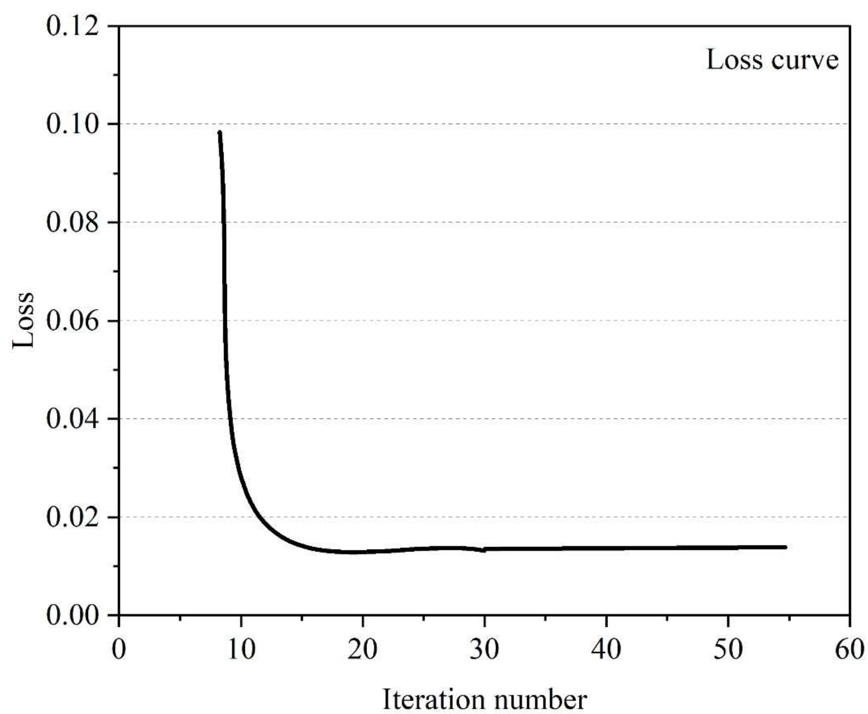

Fig. 5. Model loss curve

Since MAPE is not completely symmetric, it has limitations as it is much more sensitive to negative errors than positive errors. Therefore, SMAPE is used as the load prediction evaluation criterion in all the subsequent papers, and one of the advantages of SMAPE is that it can more easily analyse the output in a statistical manner.

In this section, the effects of the number of neurons and the number of training sessions on the prediction results are verified with specific analyses using examples.

1) Number of neurons. Experts began to study neurons at the beginning of the 20th century, when scholars already understood the composition of neurons and their structural distribution. Research shows that human beings think, learn, and hear, read and write are neurons in the brain is the result of the role of neurons, the human brain neurons more than 90 billion, determining the direction of human thinking changes, and the role of neural networks in computer science are mainly the following 3 aspects:

(1) Multiply the input values by their respective weights.

(2) Add up the results obtained.

(3) Finally, apply the activation function to the sum.

When training a neural network, it is essential that the input, hidden and output layers are connected to each other, and as the number of neurons increases, the weight coupling becomes tighter, allowing more complex functional relationships to be described. In addition, more neurons can classify complex data with clear boundaries, and nonlinear features can be extracted more easily. Therefore, increasing the number of neurons is beneficial for algorithm optimisation in practical training. In this example, the dynamic model based on BPNN is selected to verify the prediction of a power plant. Set the hidden layer parameter as 1, Epoch as 60, Timestep as 20, change the number of neuron nodes, in order to make the results more obvious, set the neural nodes as a group of 50 for observation, the experimental results are shown in Figure 6. From the experimental results, it can be seen that with the increase in the number of neurons, the prediction error gradually decreases, the number of neurons is 138, the error is 3.125% as the minimum, it can be seen that the more neurons, the stronger the learning ability of the model. However, when the number of neurons exceeds 138 gradually increases, the prediction effect gradually deteriorates again, indicating that more neurons will also increase the computational amount of the model, which will cause overfitting to the training data and affect the experimental results. Therefore, in practice, in order to meet the requirements of the model computing speed, but also to improve the model prediction accuracy, but also to ensure that the model generalisation ability is not destroyed, the number of neurons parameter should be set reasonably.

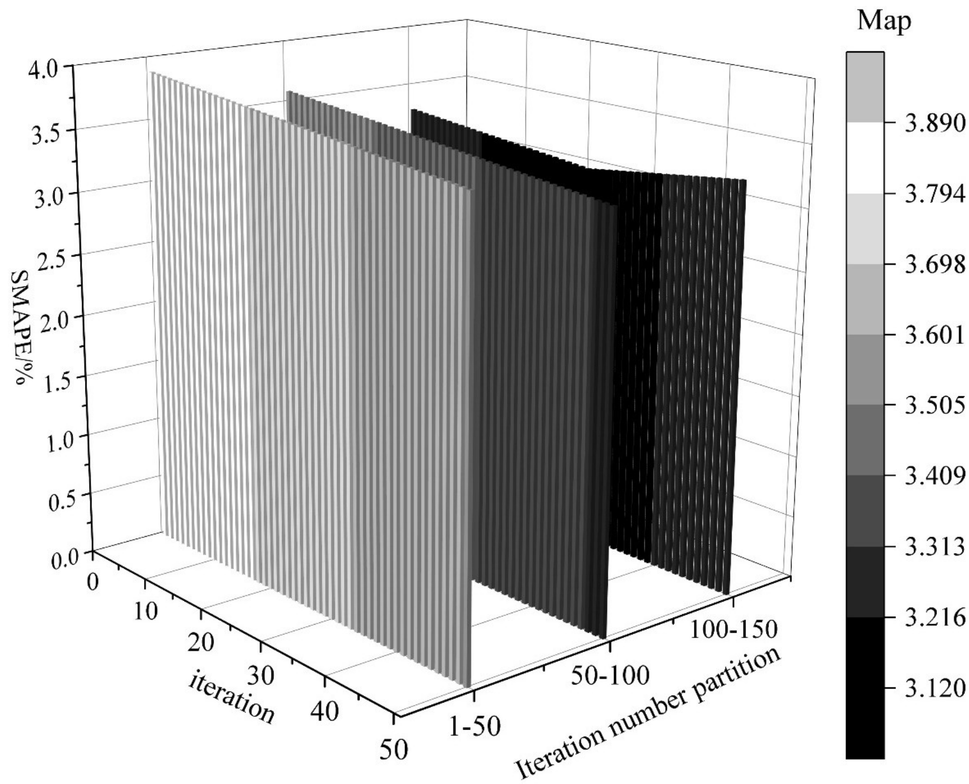

Fig. 6. Change the number of neurons

In neural network learning, all the samples are trained and this one training process is known as an Epoch. so in each Epoch, all the training samples undergo a forward propagation and a back propagation process in the neural network. However, it is not enough to pass the dataset just once, we also need to pass the complete dataset several times to better understand the model and make predictions. Therefore, the Epoch settings are not limited to just 1 pass. In this example, we set the hidden layer parameter to 1, the number of neuron nodes to 130, Timestep to 15, change the Epoch parameter, and the experimental results are shown in Figure 7.

From the experimental results, it can be seen that with the growth of Epoch, the prediction error becomes smaller and then larger, and it starts to become larger when Epoch is 140, which proves that the prediction accuracy becomes better and then worse. According to the theoretical analysis, due to the increase in the number of Epoch, the frequency of weight change will also increase accordingly, which leads to the prediction curve from underfitting to overfitting. In addition, the complexity of the sample data also affects the overall number of Epochs, so in order to obtain better prediction results, different parameters should be set according to different data sets to better meet the practical needs.

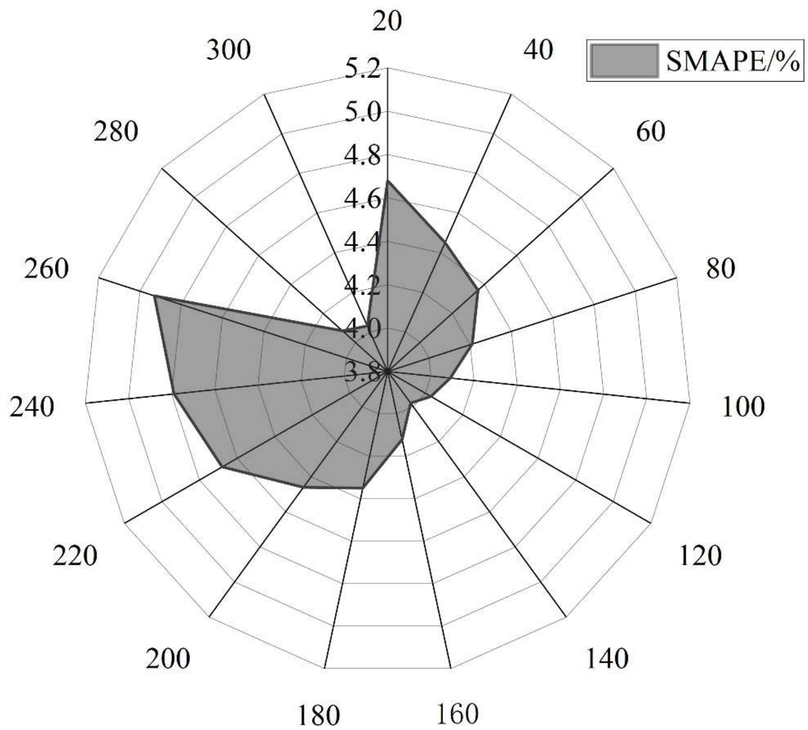

Fig. 7. The influence of epoch on SMAPE

6. System monitoring performance prediction and analysis

Based on the virtual power plant model constructed by BPNN, 8 nodes are randomly selected as targets, and the multi-resource fusion system constructed in this paper is used to carry out security monitoring of the 8 nodes in the virtual power plant to determine the security state under different moment conditions, and the results obtained are shown in Table 2. Analysis of Table 2 shows that the method of this paper is able to effectively analyse the security status of different monitoring nodes at different moments, and the results of the virtual power plant analysed by the method of this paper are completely consistent with the actual security status of the power plant, which shows that the method of this paper has a strong practical application value.

Table 2. Security at different times

Monitoring node	Monitoring moment	The method monitoring results of this article	Actual safe state
3	6:30	High safety	High safety
	9:36	Moderate risk	Moderate risk
	14:10	High safety	High safety
5	7:43	Moderate safety	Moderate safety
	11:15	High safety	High safety
	15:14	Moderate risk	Moderate risk
6	8:02	Moderate safety	Moderate safety
	10:09	High safety	High safety
	13:15	Moderate risk	Moderate risk
7	9:08	Critical safety	Critical safety
	15:25	Critical safety	Critical safety
	18:05	Moderate risk	Moderate risk
11	7:05	Critical safety	Critical safety
	11:09	Critical safety	Critical safety
	16:37	Critical safety	Critical safety
25	10:02	Moderate safety	Moderate safety
	14:21	High safety	High safety
	17:20	Moderate risk	Moderate risk
26	8:30	Critical safety	Critical safety
	11:30	Moderate risk	Moderate risk
	16:30	Moderate safety	Moderate safety
31	8:55	Moderate safety	Moderate safety
	15:09	High safety	High safety
	19:55	Moderate risk	Moderate risk

The following analyses the impact of different parameters on the accuracy of monitoring results in different data fusion processes.

In the fusion process, the setting of the weighting factor has an important impact on the data fusion accuracy. Figure 8 shows the fluctuation of data fusion accuracy under different weighting factor conditions. Analysing Figure 8, with the increase of data volume, the data fusion accuracy under different weighting factor conditions shows different degrees of decreasing trend. Under the condition of weighting factor of 0.7, the data fusion accuracy decreases from 100% to 29.63%. When the weighting factor decreased to 0.3, the data fusion accuracy decreased from the initial 100% to 69.56%. However, when the weighting factor decreased again to 0.1, the data fusion accuracy decreased to about 60.15%. The above data shows that under the condition of weighting factor of 0.3, the data fusion accuracy is significantly higher than other weighting factors, which indicates that the value of the weighting factor is set to be 0.3 in the adaptive weighted fusion process.

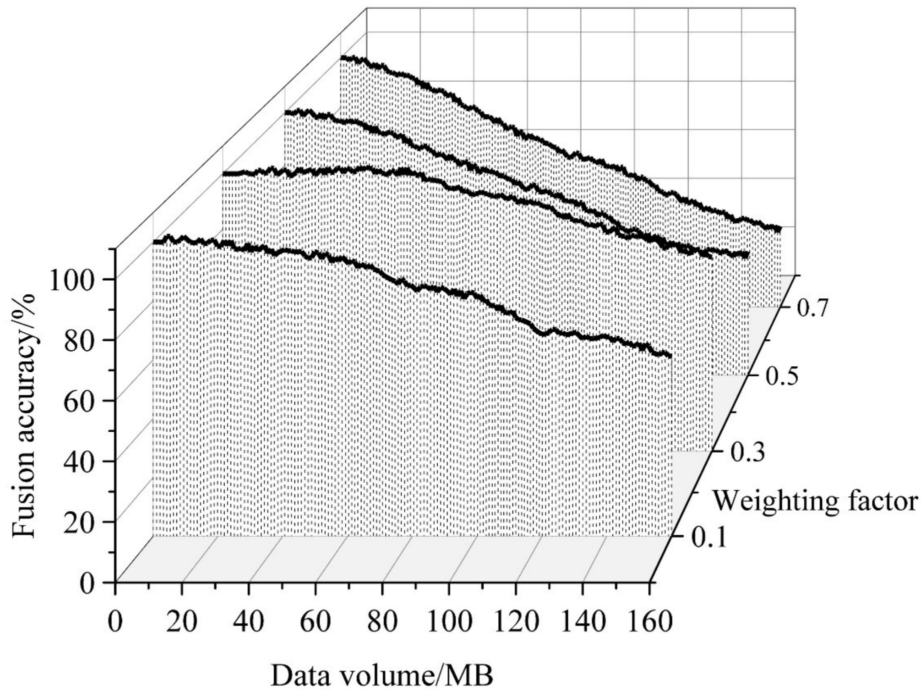

Fig. 8. Data fusion accuracy

In the process of BP neural network fusion, the number of nodes in the hidden layer has a direct impact on the accuracy of the monitoring results. Analyse the changes in the convergence accuracy of the BP neural network model under the condition of different number of nodes, and the results are shown in Figure 9. Analysing Figure 9, the convergence accuracy of the BP neural network shows a trend of gradual improvement as the number of nodes in the hidden layer increases. But at the same time, the improvement of the number of nodes in the hidden layer also makes the complexity of the BP neural network model calculation process and the time consumed increase significantly, combined with the related scholars on the analysis of the convergence speed of BP neural network, the comprehensive analysis of the BP neural network hidden layer node number of 5, BP neural network convergence accuracy and convergence speed is optimal, and the data fusion accuracy decreases from 100% to 60.23%, therefore, the data fusion accuracy is not as good as it should be. The data fusion accuracy decreases from 100% to about 60.23%, therefore, in the fusion process of this paper, it is most appropriate to set the number of nodes of the hidden layer in the BP neural network model to 5.

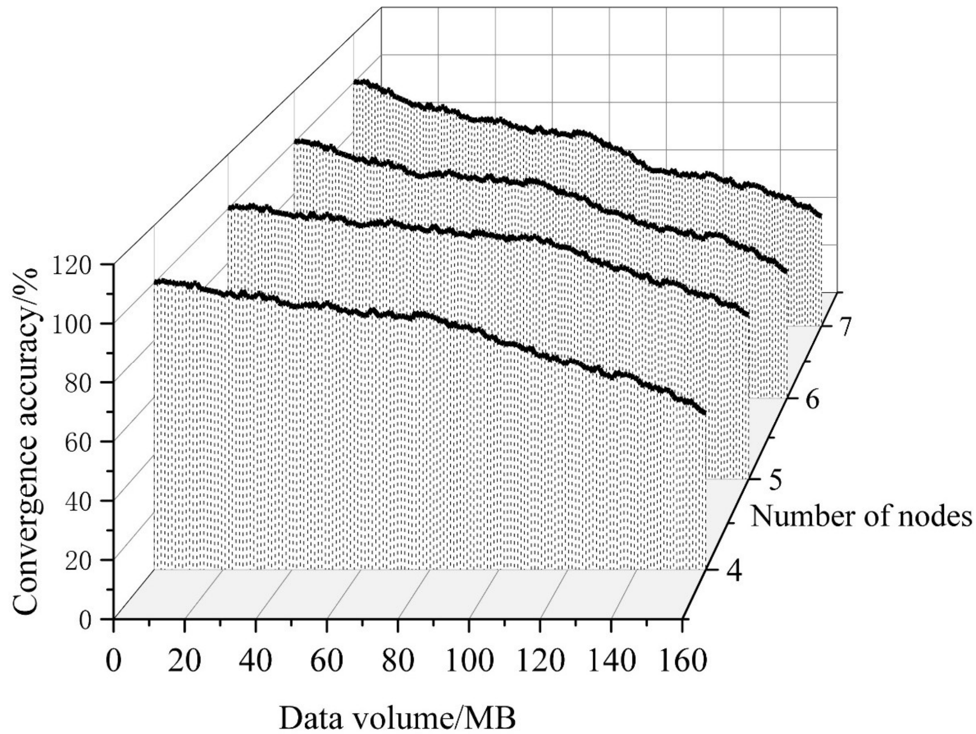

Fig. 9. Monitoring results analysis accuracy

The fluctuation of the overall failure rate of the power plant after using the method of this paper is shown in Fig. 10. After analysing Fig. 10, the failure rate of the virtual power plant is decreasing month by month after monitoring the safety status of the virtual power plant using the method of this paper, and the failure rate of each month after using the monitoring method of this paper is significantly lower than that of the month without using the monitoring method of this paper, and the failure rate of the virtual power plant before using the monitoring method is 4.6%, which is 1.9% lower after using the monitoring method of this paper. This shows that the use of the method in this paper can effectively monitor the safety status of the power plant and reduce the transmission line failure rate. Thus, the multi-resource fusion model can be used to monitor the safety of the virtual power plant constructed based on the neural network dynamic model.

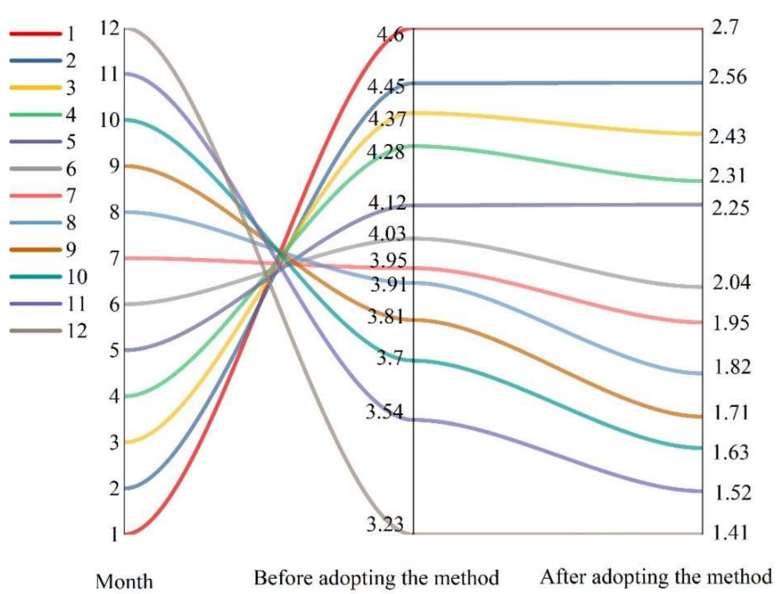

Fig. 10. Failure rate fluctuation result

7. Conclusion

In order to reduce the risk of occurrence of virtual power plant faults, BPNN neural network is used to model the power station equipment, and a multi-resource fusion system is used to monitor and analyse the relevant parameters of the equipment to achieve the purpose of fault early warning.

The SMAPE, RMSE and MAPE of the BPNN-based dynamic model have smaller correlation values than the other four models, and the prediction error is more obvious, only 6.51%. And the Loss of BPNN-based dynamic model training decreases faster, and the Loss decreases to 0.02 when the number of iterations is 10, which indicates that the BPNN-based dynamic model training time is short and efficient, and it can complete efficient and accurate modelling of the virtual power plant.

After using the multi-resource fusion model to monitor the safety status of the virtual power plant, the failure rate of the virtual power plant shows a decreasing trend month by month, and the failure rate has decreased significantly compared with the method before using, the failure rate in January is 4.6% before using the monitoring method, and after using the monitoring method, the failure rate is reduced by 1.9%. It shows that the method of this paper can effectively monitor the safety status of the virtual power plant and reduce the failure rate.

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