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Intelligent Analysis of Power Transmission Quota for Multi-energy Power System External Transmission Section Based on Neural Network

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ABSTRACT

In order to solve the problem of renewable energy consumption, this paper focuses on the study of dynamic adjustment methods of maximum transmission power capacity for the key transmission sections. Firstly, based on the current power grid company's simulation ideas for solving cross-sectional quotas, a step-size search simulation sample generation method is proposed. Then based on the BP neural network optimized by the LM algorithm, a model that can quickly determine the transmission section quota is established. Finally, the effectiveness of the model is verified through the operating data of the Western China Power Grid. The results show that the model can fit the non-linear relationship between the generator output combination and the section transmission quota well, and has great practical value.

Keywords: wind power system, BP neural network, Sample data generation, Power transmission Quota

NONMENCLATURE

Abbreviations	
BPNN	Back Propagation Neural Network
LM	Levenberg—Marquardt
PSASP	Power System Analysis Synthesis Program

1. INTRODUCTION

In recent years, global energy security and environmental protection issues have received extensive attention. Relying on the advantages of mature technology, large-scale development conditions and commercial development prospects, wind power has developed rapidly in installed capacity worldwide. However, due to the difference of its own structure, wind turbines show different dynamic characteristics from synchronous generators during grid failures. As more and more doubly-fed units are being integrated into the grid, the dynamic characteristics of the power system will change. It will definitely cause new changes to the stability of the power grid[1].

In [2], the equivalent external characteristics of doubly-fed wind turbines based on the equivalent power angle characteristics of doubly-fed wind turbines. It is found that the deceleration area of the single-ended system is increased during the fault period and the early stage after the fault is cleared, and the head swing amplitude of the power angle of the sending-end system is reduced. The access of doubly-fed units increases the power limit of single-ended systems. However, it is still very difficult to calculate the safe schedulable interval considering the transient stability problem[3]. The power dispatching department usually takes one or several conservative fixed values as the key transmission section limits, which has led to increasingly prominent contradictions in the consumption of renewable energy[4]. How to quickly and accurately calculate the dynamic safe schedulable interval has become one of the urgent problems to be solved.

Many scholars have carried out research on solving methods of power system transmission capacity, which are mainly divided into deterministic methods and probabilistic methods. Deterministic methods mainly include RPF (Repeated Power Flow), CPF (Continuation Power Flow), and OPF (optimal power flow). However, the number of iterations is large and the calculation time is long. Probabilistic methods mainly include stochastic planning method, enumeration method and Monte Carlo simulation method, but their adaptability to large-scale power grids is relatively poor. Using data mining

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methods to solve or simulate power system security domains is a new type of thinking in security domain analysis in recent years[5]. Data mining methods can be used to discover many important potential changes from a large amount of historical data in the power system security and stability analysis. For example, decision trees can be used to divide the power system into stable and unstable states[6]. However, there are few reports on the research on the safe dispatchable interval of multi-energy power system.

With the help of BPNN, this paper can learn and construct the model characteristics of nonlinear complex relationships, excavate the internal relationship between unit commitment and transmission section limits, and analyze the potential physical laws of complex systems. A method that can quickly give section quotas based on the unit commitment plan of the power dispatching department is proposed. First, a large number of simulation samples are obtained by the method of step search. Secondly, a BP neural network model optimized by the LM algorithm is established, which is used for the budget of the external transmission section transmission quota. Finally, through the actual grid operation data of a province in western China, the validity of the model was verified, and the influence of different wind power output proportions on the export quota was analyzed, and the export potential was further explored to increase the capacity of new energy consumption.

2. INTELLIGENT ANALYSIS MODEL OF SECTIONAL TRANSMISSION QUOTA

2.1 Sample data generation

At present, there are generally two sources of data samples for the application of artificial intelligence algorithms in the power field. One is from historical data generated during the operation of the power system. Another data source can obtain a large number of samples for simulation by performing transient stability simulation. This article focuses on the critical section transmission quota considering transient faults and draws on the method of calculating section quotas in traditional power systems. The method of small-step search simulation is used to provide sample data for the algorithm proposed in this paper. The specific data generation process of this article as follows:

1) First of all, we should choose an actual operating mode as the power flow benchmark.

2) Get the selected power flow result. Retain the power system topology, and re-set the active power of the generator and load. ① The total load amount fluctuates randomly by 10% up and down the base amount, and the fluctuation amount of the total power generation is set to be equivalent to the total load. ② Distribute the adjusted amount to generator sets and regional loads. ③Calculate the power flow and get the new power flow result.

3) Consider the various AC N-1 and N-2 faults of the cross section, and conduct stability calculations for the convergent power flow.

4) If the calculation result is stable, adjust the power of the section. By changing the output of the generators near the section, the actual power grid generally considers the adjustment to be 1% of the existing transmission capacity of the section, and obtains new power flow data. Repeat step 3 until the result Instability boundary, the output includes the output of the unit, constraint failures, the proportion of wind turbines, the section limit, etc., and forms a sample. And repeat step 2 to get the next trend.

5) Repeat steps 2-4 until the number of generated samples meets the requirements.

The sample data generation process is shown in Figure 1.

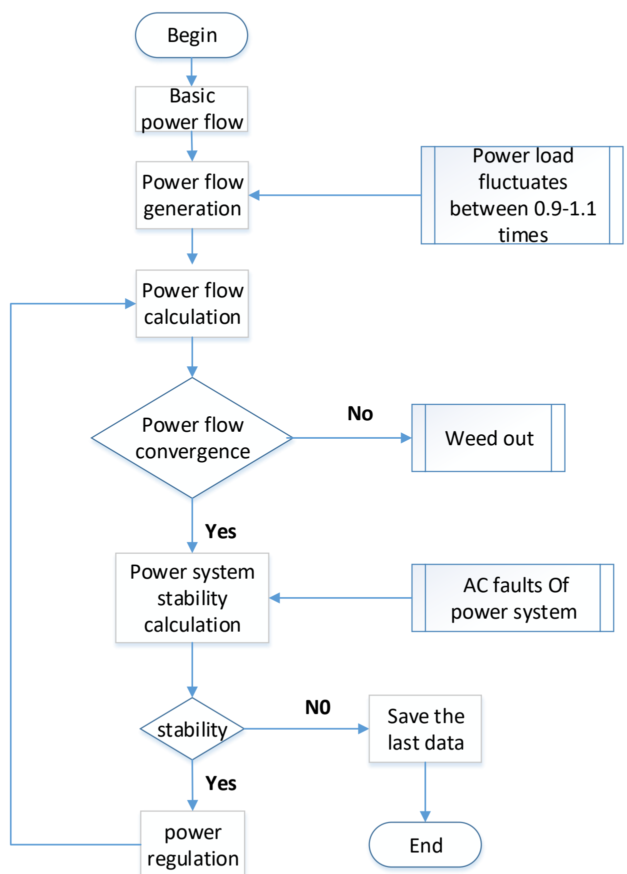

Fig 1 The generation process of sample data

2.2 The structure and algorithm of BP neural network

The model structure of the BP neural network is shown in Figure 2, which consists of three parts: the input layer, the hidden layer and the output layer[7]. The hidden layer can contain a multi-layer structure, while the input layer and output layer only contain one layer. Under normal circumstances, the selected transfer function is the Sigmoid function,as shown in equation (1):

$$f(x)=\frac{1}{1+e^{-x}} \qquad (1)$$

The learning process of BP algorithm consists of two parts: forward propagation of signal and back propagation of error. Forward propagation means that the input samples are input from the input layer and passed to the output layer through various hidden layers. If the output of the output layer does not reach the expected value, then go to the back propagation of the error. Error backpropagation is to pass the output error back layer by layer through the hidden layer, and adjust the weight and threshold of each neuron. The process of constant adjustment of weights and thresholds is the learning and training process of the network until the error reaches the expected range or reaches the set number of learning times.

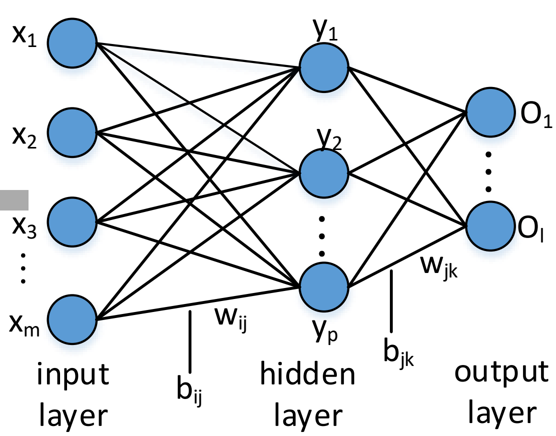

Fig 2 Structure of BP neural network

The forward propagation process of the BP algorithm as shown in equation (2) and (3):

$$y_j = f[\sum_{i=1}^{m}(w_{ij}x_i+b_{ij})],\ \ j=1,2,\cdots,p \qquad (2)$$

$$o_k = f[\sum_{j=1}^{p}(w_{jk}y_j+b_{jk})],\ \ k=1,2,\cdots,l \qquad (3)$$

Where $X_r=(x_1, x_2,...,x_m)^T$ is the input layer input vector, $Y_r=(y_1, y_2,..., y_p)^T$ is the hidden layer output Vector, $O_r=(o_1,o_2,..., o_l)^T$ is the output vector of the output layer, $D_r=(d_1, d_2,...,d_l)^T$ is the desired output vector; the weight from the input layer to the hidden layer is w_{ij} $(i=1,2,...,m; j=1,2,...,p)$, the threshold is $b_{ij}(i=1,2,...,m; j=1, 2,...,p)$. The weights and thresholds from the hidden layer to the output layer are $w_{jk}(j=1,2,...,p; k=1,2,...,l)$, $b_{jk}(j=1,2,...,p; k=1,2,...,l)$.

The output error e is the distance between the output vector O of the output layer and the expected output vector D, as shown in equation (4):

$$\begin{aligned} e &= \frac{1}{2}(\boldsymbol{D}-\boldsymbol{O})^2=\frac{1}{2}\sum_{k=1}^{l}(d_k-o_k)^2=\frac{1}{2}\sum_{k=1}^{l}\{d_k- \\ &f[\sum_{j=1}^{p}(w_{jk}y_j+b_{jk})]\}^2=\frac{1}{2}\sum_{k=1}^{l}\{d_k- \\ &f[\sum_{j=1}^{p}(w_{jk}f[\sum_{i=1}^{m}(w_{ij}x_i+b_{ij})]+b_{jk})]\}^2 \end{aligned} \qquad (4)$$

In the process of error back propagation, the standard BP algorithm uses gradient descent to adjust the weight and threshold, so that the error is continuously reduced. It can be seen from equation (5) and (6) that the error e is a function of the weight and the threshold, and the adjustment amount of the weight and the threshold is as follows:

$$\Delta w=-\eta\partial e/\partial w \qquad (5)$$

$$\Delta b=-\eta\partial e/\partial b \qquad (6)$$

Where η is learning rate, which is a constant between 0 and 1.

The learning rate is one of the important factors affecting the convergence speed of the algorithm. Too much learning rate will lead to instability of the neural network model, and too small learning rate will lead to slow convergence.

The BP neural network model will get different calculation results under different training target errors. The larger the training target error, the shorter the training time, but the calculation accuracy may not reach the expected value; the smaller the training target error, the longer the training time and the higher the calculation accuracy, but the algorithm may not converge.

2.3 The structure and algorithm of BP neural network

In order to overcome the shortcoming of the standard BP neural network algorithm that it is easy to fall into the minimum point and stop the iterative calculation and the convergence speed is slow, many improved algorithms have been proposed, such as the quasi-Newton method, the conjugate gradient method and the Levenberg-Marquardt algorithm.

The BP neural network optimized by the LM algorithm uses the method of finding the minimum value of the error function e in the process of error back propagation to continuously modify the network weights and thresholds. The following takes the weight correction process as an example to introduce.

Expand *e(w(n+1))* according to Taylor's formula to get:

$$e[w(n+1)] = e[w(n)] + \boldsymbol{g}^{\mathrm{T}}(n)\Delta w(n) + 0.5\Delta w^{\mathrm{T}}(n)\boldsymbol{A}(n)\Delta w(n) \tag{7}$$

Where *g(n)* is the gradient vector; *A(n)* is the Hessian matrix.

In order to avoid calculating the Hessian matrix directly, the LM algorithm approximates the Hessian matrix as shown in equation (8):

$$\boldsymbol{A} = \boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} \tag{8}$$

Where *J* is the Jacobian matrix.

Gradient vector as shown in equation (9):

$$\boldsymbol{g} = \boldsymbol{J}^{\mathrm{T}}\mathrm{e} \tag{9}$$

The weights are revised as follows:

$$w(k+1) = w(k) - [\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} + \mu \boldsymbol{I}]^{-1}\boldsymbol{J}^{\mathrm{T}}\mathrm{e} \tag{10}$$

In the same way, the threshold correction method can be obtained as follows:

$$b(k+1) = b(k) - [\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} + \mu \boldsymbol{I}]^{-1}\boldsymbol{J}^{\mathrm{T}}\mathrm{e} \tag{11}$$

The application of LM algorithm has obvious advantages in function approximation. When performing function approximation for neural networks containing hundreds of weights, the LM algorithm has the fastest convergence speed and higher calculation accuracy. Therefore, the LM algorithm can be used as the learning rule of the neural network for practical problems with high accuracy requirements. However, with the further expansion of the network, the advantages of the LM algorithm gradually weaken. In addition, the LM algorithm has almost no advantage when dealing with practical problems of pattern recognition, and it requires more storage space than other algorithms.

The quasi-Newton method is similar to the LM algorithm. Since the inverse matrix of the corresponding matrix is calculated in each iteration, the amount of calculation will increase geometrically as the network expands. But the storage space required by the algorithm is smaller than that of the LM algorithm.

The actual problem of section transmission quota involved in this article is a function approximation problem. The neural network required is not very large, but requires relatively high calculation accuracy. In summary, it is most reasonable to choose LM algorithm as the learning rule of BP neural network. Therefore, the model established in this paper is a BP neural network model optimized based on the LM algorithm, which is used to predict section transmission quotas.

3. CASE ANALYSIS

Considering the rich wind power resources in western China, the method proposed in this paper is verified with data from a provincial power grid in western China.

This basic power flow selects the 2018 high-load operation mode. And take a new energy power generation base in the province as the research object. The base has abundant scenery and water resources, and power is sent out through 8 pieces 500KV AC lines.

Using PSASP7.35 to obtain 600 samples through the sample generation method proposed in section 2.1. And randomly divided according to the ratio of 0.95, divided into 570 training set samples, 30 test set samples. In order to enhance the practical value of the research results of the project and realize the function of adaptive prediction of the cross-section transmission quota using the dispatch power generation plan. Therefore, the samples generated in this article only retain the active power output of the generating units and target attributes (transmission quotas). By using BPNN to learn the data, the fine rules of the safe schedulable interval are obtained. And through the test set 30 samples to predict the cross-section quota, and compare and analyze the cross-section transmission quota during the sample generation process.

As shown in Figure 3, through comparative analysis, it can be seen that due to the number of training samples and the accuracy of the model itself, although the predicted value cannot be completely accurate, the predicted result of the transmission interval quota is basically consistent with the calculated result. It shows that the model can adaptively give interval quotas according to different unit combinations. With the increase in the proportion of wind power, the section limit has increased, the proportion of wind turbines has risen from 8% to about 11%, and the section limit has increased by about 500MW.

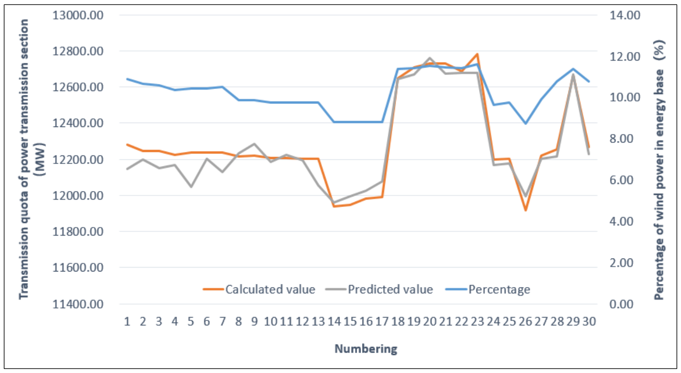

Fig 3 Comparison of predicted value and calculated value of section quota

4. CONCLUSIONS

This paper proposes a calculation method for cross-section transmission quota, and verifies it with actual grid data of an energy base in western China, and obtains the following conclusions:

1) This paper explores the application of data mining algorithms in the direction of cross-section transmission quotas. It is found that neural networks can fit the data relationship between unit combinations and cross-section transmission quotas well, and its fast and accurate solution characteristics can fully explore grid security Scheduling interval.

2) In terms of the input characteristics of the sample, no voltage, reactive power and other characteristics are added, and only the active characteristics of the unit combination are used for learning and prediction, and high accuracy is achieved, which further enhances the practicability of the method.

3) The model has a strong dependence on data and its generalization ability is poor. How to enhance its generalization ability is an important direction for future research.

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