Eng Int Syst (2019) 4: 193–200

Engineering
Intelligent Systems

Reactive Power Optimization Control of Power Grid utilizing the Improved RBF Artificial Neural Network

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To optimize the management of the power grid and safeguard its operations, a design is presented under improved RBF artificial neural network (ANN) prediction of power grid reactive power optimization (PO) control to improve the traditional RBF ANN. The established genetic algorithm (GA), combined with the improved RBF artificial neural network (NN), uses the disorderly global optimization ability of GA to optimize the weights of RBF NN and narrow the search scope. The optimal solution is obtained by the accurate solution of RBF NN. On this basis, the improved RBF ANN is adopted to improve the power grid reactive power (RO) balance, forecast the grid voltage and power load values, and establish the objective function of minimum loss of transformer. The power load prediction is carried out in stages. The influence of average load, average temperature, rest day characteristic value and other data on load is considered. The load value, at the same time of the day before the prediction, is taken as the input, and the load value at the time to be tested on the day is taken as the output for prediction, for real-time monitoring and control. It shows that the improved RBF ANN can optimize the hidden layer neuron nodes, simplify the NN structure, improve the level of reactive PO, and reduce loss and save energy. Therefore, the method of improving RBF ANN can realize the nonlinear optimization problem of reactive PO of power grid and improve the quality and economic benefits of a power supply network.

Keywords: Reactive PO; ANN; Load forecasting; RBF; Substation

1. INTRODUCTION

With the development of the economy and society, the demand for electricity is increasing and the environment of electricity generation and distribution is becoming more and more complex. The safe operation of substations plays an increasingly important role in the power system [1]. A substation is an important piece of equipment in a power system, and the safety of the whole power grid depends on its safe operation. The voltage quality of the power grid is largely determined by the RO balance of the power grid system, and the reasonable distribution of RO is an important way to guarantee the voltage quality [2]. Voltage, as an important factor of power quality in power system, is closely related to the RO of power grid system. The change of RO directly affects the change of power grid voltage, which is especially necessary for the optimization of power grid voltage and RO.

Reactive PO control based on improved RBF ANN of power grid forecasts the power load through its integration with the substation of power grid by RBF ANN [3]. RBF ANN was established to obtain the model's prediction of the load and voltage of the power grid. The optimal solution for the objective function is achieved by segmenting the daily load with objective function and constraint conditions. Results show that the improved RBF ANN for the forecast of power grid system has obtained the good result, and load forecasting accuracy is higher. Compared with the traditional RBF ANN,

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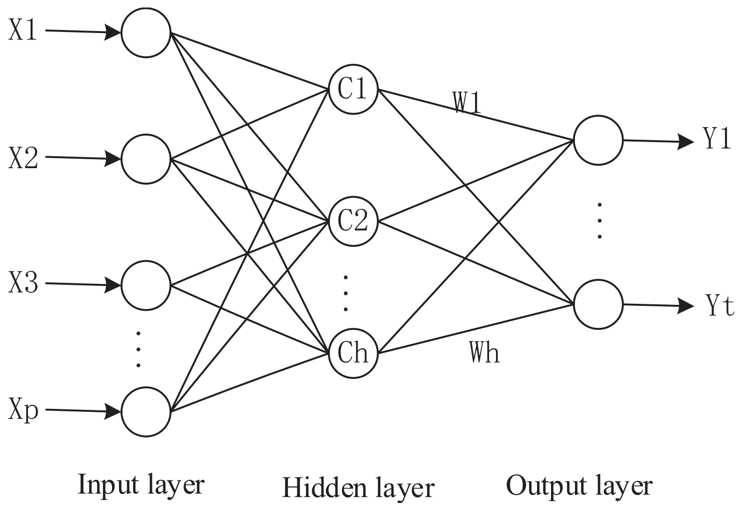

Figure 1 Three-layer feedforward NN.

the fitting curve has more similar advantages. It simplifies the structure of RBF ANN, reduces the loss of the system to the greatest extent when meeting the equipment operation times and voltage curve, realizes the technical optimization of the power grid system, and guarantees the power quality, which is of great significance to the security of the power grid.

2. METHODOLOGY

2.1 Improvement of RBF NN

RBF (ANN), namely radial basis function ANN, was proposed in the late 1980s. Its prototype is a three-layer feed forward NN, as shown in the topological structure diagram below. The hidden layer is the most important. RBF function is used to determine the number of nodes in the hidden layer [4]. The output layer is used to produce the final result, and linear combination is carried out. The number of nodes is determined by the number of final output results. RBF ANN not only imitates the local neural structure of human brain, but also imitates the sensory field NN structure of the human brain. RBF ANN is similar to Gaussian function, which approximates any continuous function through the NN structure of local approximation, and the accuracy of the function can be arbitrarily selected. RBF NN is a three-layer NN: input layer, hidden layer and output layer [5]. The transformation from the input space to the hidden layer space is non-linear, while the transformation from the hidden layer to the output layer is linear. RBF NN has more concise network structure and faster learning speed than BP NN. It is suitable for any continuous function to deal with large-scale, dynamic complex and irregular nonlinear problems.

The basic idea of RBF NN is to map the input layer node directly to the hidden layer, and its connection does not need the right of use. After determining the RBF center point, a certain mapping relationship is formed. The input layer to the hidden layer is a non-linear mapping, while the hidden layer to the output layer is a linear mapping [6]. The function of hidden layer is to map vectors from low-dimensional p to high-dimensional h, so that low-dimensional linear indivisibility can become linearly distinguished from high-dimensional, which is the mainly the idea of the kernel function. The linear characteristic of the output can be determined directly by the linear equations, so as to avoid the small local limitation. The activation function of RBF ANN is as follows:

$$\mathrm{R}(X_p - C_i) = \exp\left(-\frac{1}{2\sigma^2}\|X_p - C_i\|^2\right) \tag{1}$$

The xp structure of radial basis NN can obtain the output of the network as follows:

$$yj = \sum_{i=1}^{h} W_{ij} \exp\left(-\frac{1}{2\sigma^2}\|X_p - C_i\|^2\right) \qquad \mathrm{j} = 1, 2, 3 \ldots \mathrm{n} \tag{2}$$

The loss function of least square is adopted to express:

$$\sigma = \frac{1}{p}\sum \|d_j - y_j c_i\|^2 \tag{3}$$

The basis function of the network in the hidden layer adopts gaussian function:

$$\phi(x, \sigma) = \exp\left\lfloor -(x-c)^2/2\sigma^2 \right\rfloor \tag{4}$$

In formula (4), c is the center of the Gaussian function and sigma 2 represents the variance. The further away from the node center is the sample of input parameters, the smaller will be the output value. The output range of hidden layer neuron node is [0,1]. RBF network, the output of the ith hidden layer node is:

$$\mathrm{q_i} = \phi(//u - ci//) \tag{5}$$

The u is the input vector and ci is the center of the ith hidden node, represented as RBF function. The output of the output layer of RBF NN is expressed as the linear combination of hidden nodes, as shown below. Yt represents the output value of the TTH node.

$$y_t = \sum\nolimits_i W_{kj} q_i \tag{6}$$

Learning problem of RBF NN. There are three parameters to be solved: center of basis function, variance and weights from hidden layer to output layer.

Firstly, the self-organizing selection center learning method involves the following steps.

Step 1: Unsupervised learning process determines the center and variance of hidden layer base function; Step 2: there is a supervised learning process to determine the weights between the hidden layer and the output layer. First, h centers are selected for k-means clustering. For the radial basis of Gaussian kernel function, the variance is obtained by the formula:

$$\sigma_{\mathrm{i}} = \frac{c}{\sqrt{2h}} \qquad \mathrm{i} = 1, 2, \ldots, h \tag{7}$$

C_{max} is the maximum distance between the selected center points.

The connection weight of neurons between the hidden layer and the output layer can be directly calculated by the least square method, that is, the partial derivative of the loss function with respect to w can be obtained to make it equal to 0, and the calculation formula can be simplified as follows:

$$\mathrm{w} = \exp\left(\frac{h}{c^2 \max}\|x_p - c_i\|^2\right) \quad \mathrm{p} = 1, 2, \ldots, \mathrm{P}; \quad \mathrm{i} = 1, 2, \ldots, \mathrm{h} \tag{8}$$

Secondly, the direct computing method is applied.

The center of the hidden layer neuron is randomly selected from the input sample and the center is fixed. Once the center is fixed, the output of hidden layer neurons is known, and the connection weight of such NN can be determined by solving linear equations. The distribution applicable to the sample data is obviously representative.

Thirdly, supervised learning algorithms are applied.

By training the sample set, the network center and other weight parameters meeting the supervision requirements are obtained, and the error correction learning process is conducted. Similar to the learning principle of a BP network, the gradient descent method is also adopted. Therefore, RBF can also be regarded as a kind of BP NN.

In order to improve the performance of RBF ANN, the improved l-m algorithm is adopted to adjust the center, width and output weight of RBF training. However, the RBF ANN is only partially refined to improve the convergence speed and test accuracy. With the increase in the amount of RBF ANN training, the fitting the overall error of network becomes greater, and is not as good as expected, simply hovering near a constant value, so that the RBF ANN cannot reach the normal test precision of the rapid convergence or the network performs poorly so that an effective NN prediction cannot be achieved [7]. Because it is easy to fall into local minimum, the RBF ANN cannot cluster well. Therefore, the effective integration of GA and the RBF NN algorithm was considered so as to exploit the global optimization ability of GA to address the local minima problem of RBF ANN, enhance the overall performance of the RBF ANN, establish a GA to improve a power grid reactive PO RBF ANN prediction model, and improve power load prediction.

The fusion of GA and RBF ANN is based on the use of the global optimization ability of GA to optimize the weight of RBF ANN, reduce the search scope of the network, and then obtain an accurate optimization solution by means of the improved RBF ANN [8]. GA has incomparable advantages over other optimization algorithms. It is a global search method that simulates the evolution of nature, and it can find the best solution to optimization problems by applying the principle of survival of the fittest. The main characteristics of GA is not to function derivation, also not have the continuity, but directly on the coding parameters for high speed search object rather than the search for the parameter itself. Under the nonlinear rule, the search space and search direction can be adjusted automatically and randomly, and multiple initial data can be operated in parallel to avoid the problem of local minimum and local convergence in the search process. According to the uncertain rules with the ability of global search optimization, the search space and search direction can be adjusted automatically and randomly The process of GA can also be regarded as finding the optimal solution via a multivariate function. It is a search evolutionary algorithm used to find the optimal solution in the field of artificial intelligence. The great advantage of using GA is that it "rejects some bad individuals", weeding out the bad genes and leaving relatively good results [9]. GA includes the following stages: first, set the initial population. Each bit of the coding gene of each individual is selected randomly and uniformly within a certain range and the initial range of the parameters is established. Second is the fitness calculation. The fitness is calculated with formula (9). Fitness value is calculated through the objective function without other dependent information, so the little problem is posed as a result of lack of dependence has a small problem dependence. Third, genetic manipulation is designed. Traditional operations include selection, crossover, and mutation. The general step of GA is to randomly generate the population, and then judge the fitness of individuals according to the strategy to determine whether they meet the optimization criteria. If they do, the optimal individual and its optimal solution will be the output as the final stage. Otherwise, the next step will be carried out.

$$\mathrm{f}(m) = N * \left(\frac{1}{\sqrt{m}}\right) \Big/ \sum_{m=1}^{N} \left(\frac{1}{\sqrt{m}}\right) \tag{9}$$

In formula (9) above, f (m) represents the fitness of individuals ranked as m; M stands for individual ranking; N stands for group size.

GA is suitable for solving large-scale complex problems and enables global search. The core content of GA comprises five elements: parameter coding, initial population setting, fitness function calculation, genetic operation design and control parameter setting. Each chromosome in the GA corresponds to a solution of the GA. Generally, we use the fitness function to measure the advantages and disadvantages of the solution, mapping from a genome to the fitness of its solution. The combination of GA and improved RBF ANN shows that the possible weight range of RBF ANN is determined by GA, and the initial weight of the NN is generated randomly within this possible range. Then genetic coding was carried out, individual fitness value was calculated and used as the basis, and genetic selection, crossover and variation were carried out to produce a superior genetic population in the next generation [10]. The steps of the improved RBF ANN algorithm are as follows: first, determine

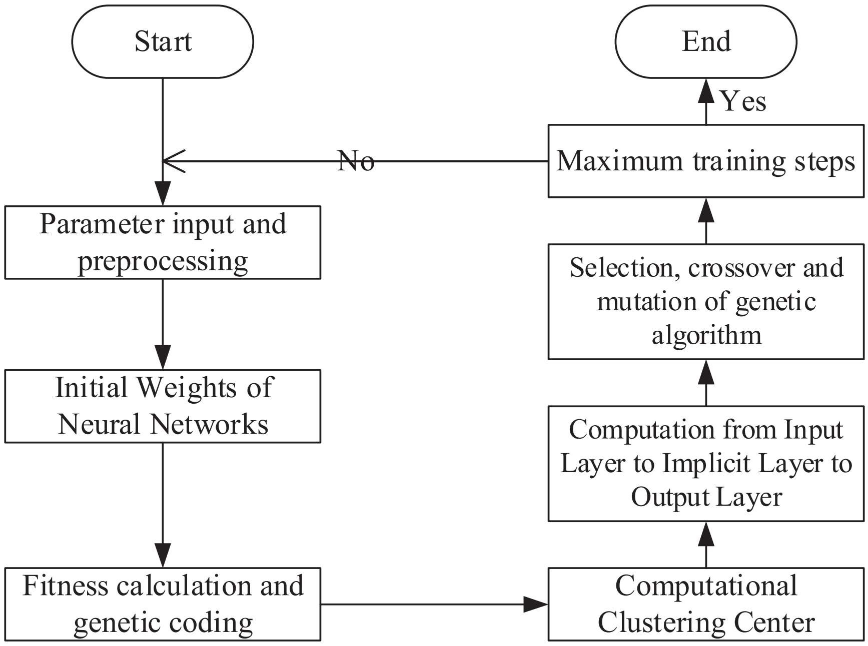

Figure 2 Improvement of the flow of RBF ANN.

the main input and output parameters of RBF NN, and obtain statistics such as mean value and variance based on the total data amount X recorded every day through processing. The degree of deviation of the data is determined, and the data close to the average value is defined as valid data, which is normalized and calculated and used as the input parameter of the network. Second, the initial weights of the NN are generated. The initial weights generated for a population consist of multiple groups of NN weights. Third, adaptive value is calculated. After RBF NN is used to calculate the training set data, the node error is obtained, indicating the adaptive value of the NN as follows:

$$z = \frac{1}{\frac{1}{2}\sum_{i=1}^{p}(t_i - y_i)^2 + 1} \tag{10}$$

The z represents an adaptation value, $z \in (0, 1)$; $\frac{1}{2}\sum_{i=1}^{p}(t_i - y_i)^2$ represents node error, p is the number of output nodes, yi is the calculated value of NN, and ti is the actual value. The smaller the node error, the closer the adaptive value is to 1, indicating that network is improved and the adaptive value is close to the maximum value 1 [11]. The largest of the adaptive values of the members of the generated new population is calculated and selected as the next generation population, and the new population is also operated with binary coding, so as to carry out genetic operations such as selection, crossover and variation on the weights of the corresponding RBF ANN [12]. In addition, the RBF NN is trained and the population binary code is decoded to obtain the weight of the decimal NN. Fourth, after determining the node h of the hidden layer of RBF ANN, the input parameter is taken as the clustering center, and this center is classified, processed and calculated. Fifth, the Gaussian function is used to calculate the input layer to the hidden layer, as shown in formula (4). Sixth, the calculation from the hidden layer to the output layer is obtained through the initial weight and the output of the hidden layer, that is, the linear mapping. Seventh, the selection of GA, the population fitness value and the total fitness value are calculated. The selection probability is higher with greater adaptive value. Eighth, the crossover of GA is performed [13]. If the random number generated by the population is less than the crossover probability, the crossover operation is carried out to randomly match and determine the crossover position. Ninth, GA variation, the random number generated by the population is compared with the mutation probability; the former is less than the latter for mutation operation. Tenth, the offspring population with the higher fitness value replaces the population with a lower fitness value in the parent generation, generates the optimized population, and the average fitness value is calculated. If the current evolutionary algebra is larger than the maximum evolutionary algebra, the fourth step is repeated, or the training is terminated, as shown in Figure 2.

3. REACTIVE PO CONTROL OF POWER GRID

Reactive PO of power grid involves dynamic, complex and non-linear factors, and takes the RO compensator, adjustable transformer, etc. as control variables, and RO output, voltage load, etc. as state variables. With the application of the improved RBF ANN algorithm, the RO capacity of load is satisfied [14], and the optimal solution is obtained. The linear programming method of the classical reactive PO method is relatively mature. The intelligent algorithm for reactive PO includes GA, ANN algorithm, etc. ANN (ANN) simulates the way the human brain processes information and comprises parallel processing, distributed storage, self-learning and self-adaptation, which gives it non-linear advantages and can be used for dynamic real-time operations in reactive PO.

In power system operations, the load value is constantly in a state of flux. The load at adjacent moments has a strong correlation. Dynamic reactive PO of substation means that based on the known daily load and power supply voltage curve [15], the optimal operating time and regulating amount of equipment can be obtained by using the optimization algorithm, so that the RO state of the power grid can be optimized. In reactive PO of a power grid, it is necessary to adjust the control parameters, and the upper and lower limits of voltage are operated by time-sharing and segmenting according to the maximum and minimum values of the load curve of the day.

The variable discretization and dynamics of reactive PO control of power grid is a multi-objective, multi-constraint and multi-variable nonlinear operation process that carries out load prediction according to the corresponding model. The bus voltage, as the support point of the grid voltage, must be within the qualified range, and can reduce the substation network loss to the greatest extent, so as to realize the value of reactive PO. Taking the minimum loss of the main transformer network as the objective function, the switching times of the capacitor and the adjusting times of the tap on the on-load regulating transformer as the means of reactive PO of the power grid, and the bus operation times as the constraint condition, the mathematical model is established as follows:

$$\mathrm{F} = \min \sum_{t=0}^{23} p_{loss}(T_t, Q_t) \tag{11}$$

The t represents 24 moments in a day, $t \in (0, 23)$; Tt represents the value of the transformer's gear position at time t; Qt represents the value of the reactive compensation amount of the reactive compensation device at time t; F is the reactive load at time t.

In the actual substation operations, the above means of reactive PO cannot be arbitrarily set, but should be tailored to specific situations. Therefore, the number of segments should not be maintained within a reasonable range. Too few segments will reduce the performance of reactive PO. The first piecewise optimization is divided into 24 segments, one segment per hour, and the optimal solution is calculated within the segment. Then, the optimal solution is gradually decreased. Among the 22 schemes of 23 segments, 22 segments and so on that are reduced to 3 segments, the one that meets the beam requirements of the objective function and reduces the loss least is selected. Then, the secondary segmenting optimization is carried out, and the RO is taken as the basis of the number of segmenting to increase from the third segment to the 24th segment. The loss reduction was calculated for the 22 cases respectively. Finally, the optimization scheme of capacitor bank and main variator is obtained 24 h after two optimizations.

In the research, the improved RBF ANN model is adopted for load prediction of the power system, predicting the active load value at 24 time points in a day. By comparing the difference between the actual value and the predicted value of the model, the actual load change is reflected, which provides a basis for short-term load prediction in the later stage [16]. RBF NN is suitable for a time-varying power system and is convenient for real-time monitoring and control. In general, the autogenous reasons that affect the load of the power system include: (1) weather factors on the day when electricity is used; (2) electricity consumption on the day; (3) power load at each time of the day; and (4) peak and trough values of power load on the same day. Therefore, when forecasting the load of the power system, the above factors should be fully considered and the RBF network prediction model should be adopted to determine the load value at the same time the day before the prediction, as the input and the load value at the time to be tested as the output for the prediction. In this research, average load values, average temperature values, characteristic rest day values and other data for 24 points in time were collected. These data were used to construct an operation model with improved RBF ANN. Each data sample M comprises 26 items of data. The input layer data is converted to the value within [−1, 1] by using the formula, which lays the foundation for neuron processing in the hidden layer. When the output value is obtained at the later stage of learning, it is then restored to the actual value by the formula (12).

$$x_{ij} = \frac{x`_{ij} - x'_{j\,\min}}{x`_{j\,\min} - x'j\,\min} \tag{12}$$

where X_{ij} represents the processed data; X'_{ij} stands for raw data; X'_{jmin} and X'_{jmax} are the maximum and minimum values in a series of X'_{ij} data. $I \in (1,n)$; $J \in (1, 26)$.

In the electric power system, people's productivity and lifestyles will be different according to the type of week they are having. On rest days, people may choose to travel or engage in other social activities. These various activities will indirectly lead to different daily load curves and sizes between weekdays and rest days. In addition, the influence of temperature on the power load is quite obvious. For example, in summer, when the temperature increases, the use of refrigeration equipment will increase, and the load will increase with the increase in temperature; in winter, when the temperature decreases, the use of heating equipment will increase, and the load will increase accordingly.

RO is an important factor affecting voltage. For a distribution network terminal system of a certain scale, when there is excessive RO, on the one hand, the operating voltage of the system will be increased, resulting in the operating voltage of the electrical equipment exceeding the rated working condition, shortening the service life of the equipment. On the other hand, RO surplus will also affect the security and stability of line transmission, leading to a decrease in the system's transmission capacity, which will have an adverse impact on power grid operations and scheduling [17]. The system's RO shortage, on the one hand, can reduce power grid voltage; on the other hand, the transfer in a power grid RO is increased when the electricity transmission network decreases, and the operating costs of the power grid are increased. An adequate power system reactive current distribution not only delivers a high-quality electricity supply to the users, but also directly affects the operational safety and economy of power grid itself. Therefore, solving the problem of RO compensation in a distribution network and optimizing RO are of great significance to the safety, loss reduction and energy saving of a power network.

Because the power system load can fluctuate, as shown in Figure 3 below, the load must be kept stable at each point in

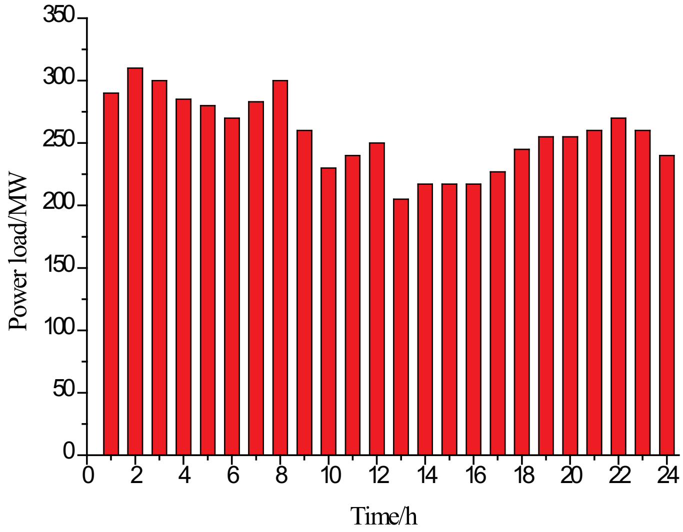

Figure 3 Power load curve.

time. Time segmentation is carried out to make the moment with little change in load as far as possible be divided into the same period, while the moment with great change is divided into different periods. Since the tap and capacitor bank of the main transformer can be adjusted in different sections, it is easy to ensure that the bus voltage is within the necessary range.

Reactive PO of a power grid can be achieved by adjusting the position of the on-load regulating transformer tap, switching the shunt capacitor bank, and seeking the optimal state of the RO of the power grid voltage taking into account the number of daily movements of the control equipment, which is vital to the optimal operation control of a substation power grid. In actual substations, the transformer has various operation modes such as independent operation, parallel operation and separate operation. When the high-voltage side of the transformer is connected in parallel, there are mutual influences among the transformers, and the assessment object of power factor is the total power factor of the high-voltage side of the substation, rather than the power factor of each high-voltage side of the transformer. The improved RBF ANN algorithm is adopted for the model, so as to improve the search efficiency of the algorithm.

4. RESULTS AND DISCUSSION

The improved RBF ANN is controlled by reactive PO. RBF NN is suitable for time-varying systems, and is convenient for the real-time monitoring of a power system and reactive PO.

Figure 3 above shows the power load curve at 24 points in time during the day. The load of the power system is continuously changing, and the load at each point in time basically maintains stability, so as to carry out segmented prediction of the power system and keep the voltage within the necessary range.

Figure 4 depicts the change curve of the average daily reactive load. During a day, at 12 and 18, the load curve shows regular changes. Before 12 o ’clock, the load curve shows a rising and then falling trend. These changes are related to people’s work and rest on the same day, and the rest day is relatively small compared with the load of the working day. Therefore, when carrying out reactive PO control of NN, it is necessary to consider the influence, on the prediction of RBF NN, of daily changes and the rest day changing load.

Figure 5 above shows the fitting curve of the traditional RBF ANN. The fitting data of the traditional RBF ANN fluctuates and is not obviously superior to the reactive PO of the power grid.

Figure 6 shows the fitting curve for the improved RBF ANN. The overall error of improved RBF NN is smaller than that of the traditional RBF NN, as it optimizes the hidden layer nodes, simplifies the structure of RBF NN and has a high degree of fit. Therefore, improved RBF ANN is better for power grid forecast, compared with the reactive PO control of the power grid.

As shown in Figure 7, the number of new substations of various specifications in China will increase from 2016 to 2020. Among them, 110KV and 220KV are still the key points of substation construction. The planned number of 110K/ specification smart substations is as high as 2300.

5. CONCLUSION

In this research, a reactive PO control system based on improved RBF ANN is established. Artificial intelligence technology was used to realize the real-time monitoring of the power grid in a substation. The application of RBF ANN in the design of a power grid reactive PO is described. The structure and principle of RBF ANN and GA are summarized to improve research. The global optimization ability of GA is used to optimize the weight of RBF NN. After narrowing its search range, the RBF NN was used to obtain a precise solution, which proved the effectiveness of the algorithm and obtained the optimal clustering result, simplified the network structure of RBF NN, and improved the degree of fitted NN. An improved RBF ANN was used in the power grid of reactive PO control to improve the control quality of the grid system and address the complicated uncertain object control

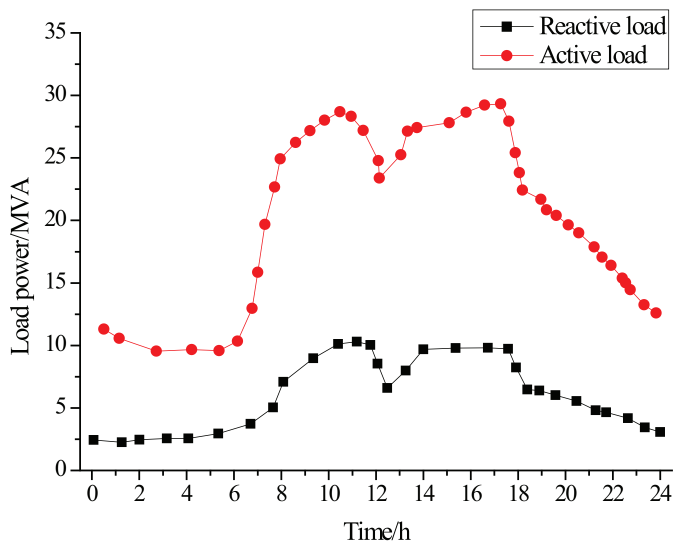

Figure 4 The average daily reactive load curve of the grid.

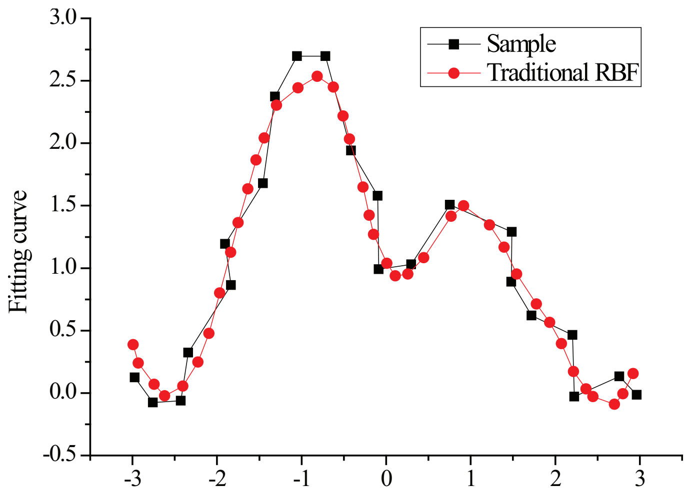

Figure 5 Traditional RBF ANN fitting curve effect diagram.

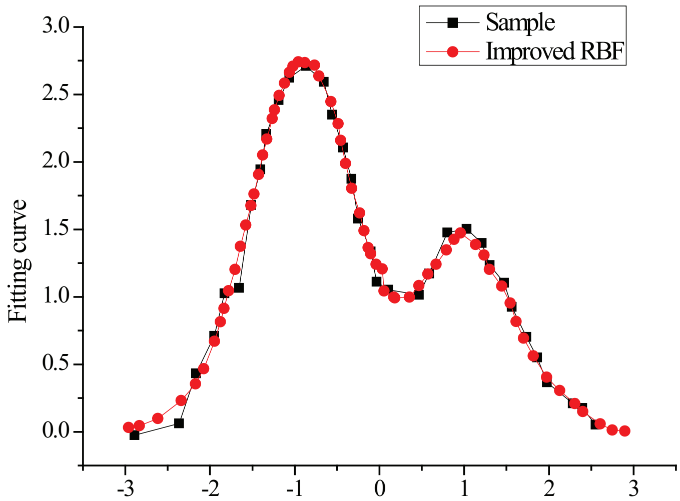

Figure 6 The improved RBF ANN fitting curve effect diagram.

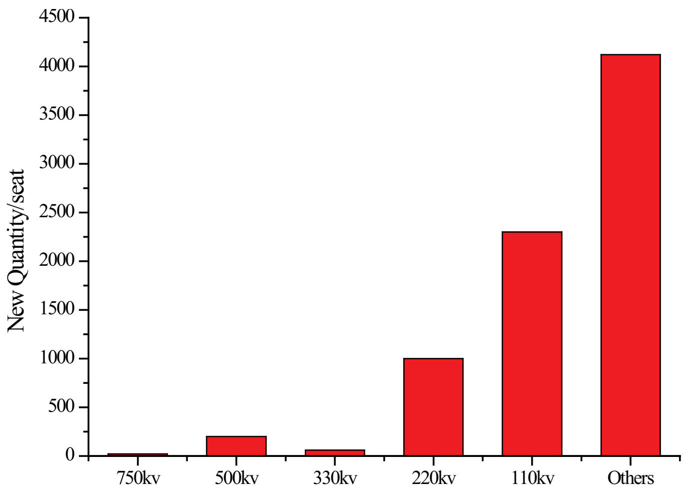

Figure 7 Planning of the number of substations with various specifications (RMB 100 million).

management. It was found that the improved RBF ANN for power load forecasting is effective, although it still needs further research and improvement to achieve maximum loss reduction and energy saving.

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