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Study on a Novel Short-Term Load Forecasting Method Based on Improved PSO and FRBFNN

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Abstract

In order to accurately, fast and efficiently forecast the short-term load of power system, an improved particle swarm optimization algorithm is proposed to optimize the parameters of fuzzy radial basis function fuzzy neural network(FRBFNN) model in order to train the FRBFNN model for obtaining the optimized FRBFNN(IWPSRFN) method. In the proposed IWPSRFN method, the linear decreasing weight method is used to adjust the inertia weight of PSO algorithm. The global optimization ability of improved PSO algorithm is used to adjust the parameters of FRBFNN model by putting these parameters in the particle encoding, then the optimal values are found in the large number of viable solutions by continuous iteration of improved PSO algorithm. The found optimal values are regarded as the parameters of FRBFNN model to obtain the final IWPSRFN method for forecasting short-term load of power system. Finally, a certain region is selected to test the effectiveness of IWPSRFN method, the experiment results show that the improved PSO algorithm can effectively optimize the weights of FRBFNN and solve the slow convergence speed, and the IWPSRFN method can obtain the higher prediction accuracy and is an effective method for forecasting short-term load.

***Keywords**: Short-term load forecasting; PSO; fuzzy logic; RBF neural network; optimization; generalization ability*

1. Introduction

Electric power industry is a very important department in the national economy and closely related to the people's livelihood. In the power system, load is to refer to the electric power demand or power consumption [1]. Load forecasting results are used to determine the capacity of power generation equipment, corresponding transmission and distribution capacity. The load forecasting is to some mathematical methods to process the pasted and future load in order to forecast the load value under considering some important operating characteristics of the system, capacity decision and natural conditions [2]. The short-term load forecasting is an important part of load forecasting of power system and the basis of power plan and formulating operation mode of scheduling and planning department of power system [3-4]. It is great significance for reliable and economical operation of power system.

With the deepening of the reform of electric power market, the load forecasting becomes a important research field in the modern power systems. It also is an important part of the technical support system of power market. The load forecasting have played a extremely important role to meet the needs of the society and ensure safe and economic operation of power network. In recent years, the theories and methods of load forecasting of power system have great progress, all kinds of new theories and methods are constantly proposed, such as time series method, regression analysis method, expert system, grey theory, artificial neural networks, and support vector machine and so on. Park *et al.*, [5] presented an artificial neural network (ANN) approach to forecast electric load. The ANN is used to learn the relationship among past, current and future temperatures and loads. Ho

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et al., [6] presented a multilayer feedforward neural network for short-term load forecasting. Kim *et al.,* [7] presented a hybrid model for short-term load forecast that integrates artificial neural networks and fuzzy expert systems. Yang and Huang[8] presented a new self-organizing model of fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasting of power systems. Kim *et al.*[9] presented a new short-term load forecasting method based on ANN technique and fuzzy inference method for special days in anomalous load conditions. Khotanzad *et al.*[10] presented a new approach based on combining artificial neural network, PIS load forecaster and fuzzy logic (FL) system to short-term load forecasting in a deregulated and price-sensitive environment. Lopes *et al.*[11] presented a neural network based on the ART architecture (adaptive resonance theory), named fuzzy ART&ARTMAP neural network, applied to the electric load-forecasting problem. Pai and Hong [12] presented a recurrent support vector machines with genetic algorithms (RSVMG) to forecast electricity load. In addition, genetic algorithms (GAs) are used to determine free parameters of support vector machines. Pai and Hong[13] presented an electricity load method based on support vector machines and simulated annealing (SA) algorithm. Simulated annealing (SA) algorithms were employed to choose the parameters of a SVM model. Ulagammai *et al.*[14] presented a new load forecasting (LF) approach using bacterial foraging technique (BFT) trained wavelet neural network (WNN). Artificial neural network (ANN) is combined with wavelet transform called wavelet neural network is applied for LF. Zhang *et al.*[15] presented a model to forecast short-term load by combining the radial basis function (RBF) neural network with the adaptive neural fuzzy inference system (ANFIS). Xiao *et al.*[16] presented an approach of back propagation neural network with rough set (RSBP) for complicated STLF with dynamic and non-linear factors to develop the accuracy of predictions. Hinojosa and Hoese[17] presented a short-term load forecasting method based on fuzzy inductive reasoning(FIR) and local random controlled search simulated rebounding algorithm (SRA). The FIR and SRA methodology is applied to the Ecuadorian power system as an application example. Niu *et al.*[18] presented a power load forecasting method based on support vector machine and ant colony optimization. The present work is applied to complex systems monitoring, the ant colony optimization can mine the data more overall and accurate than the original fuzzy-rough method, an entropy-based feature selector, and a transformation-based reduction method, PCA. Niu *et al.*[19] presented a short term load forecasting model based on Bayesian neural network (shorted as BNN) learned by the Hybrid Monte Carlo (shorted as HMC) algorithm. The weight vector parameter of the Bayesian neural network is a multi-dimensional random variable. Sheikhan and Mohammadi[20] presented two hybrid models for short-term load forecasting (STLF). These models use "ant colony optimization (ACO)" and "combination of genetic algorithm (GA) and ACO (GA-ACO)" for feature selection and multi-layer perceptron (MLP) for hourly load prediction. Liu *et al.*[21] presented a load forecasting method for short-term load forecasting based on multi-wavelet transform and multiple neural networks. Ko and Lee[22] presented a hybrid algorithm which combines SVR (support vector regression), RBFNN (radial basis function neural network), and DEKF (dual extended Kalamn filter) to construct a prediction model (SVR-DEKF-RBFNN) for short-term load forecasting. Azadeh *et al.*[23] presented two different seasonal artificial neural networks (ANNs) in terms of model complexity, robustness, and forecasting accuracy. Liao[24] presented an air-conditioning load forecasting method based on wavelet neural network (WNN), improved differential evolution algorithm (IDEA) and fuzzy expert system. Quan *et al.*[25] presented a newly introduced method, called PSO-based lower upper bound estimation (LUBE) method for short-term load and wind power forecasting. Liu *et al.*[26] presented a new short-term load forecasting model based on ensemble empirical mode decomposition (EEMD) and sub-section particle swarm optimization (SS-PSO). Esener *et al.*[27] presented a short-term load forecasting method based on wavelet transform and

RBFNN. Jurado *et al.*[28] presented a hybrid methodology that combines feature selection based on entropies with soft computing and machine learning approaches, *i.e.* Fuzzy Inductive Reasoning, Random Forest and Neural Networks. Garulli *et al.*[29] presented an approach to load forecasting in the presence of AD, based on gray-box models where the seasonal component of the load is extracted by a suitable preprocessing and AD is considered as an exogenous input to a linear transfer function model. Khwaja *et al.*[30] presented an improved short-term load forecasting using bagged neural networks (BNNs). The BNNs consist of creating multiple sets of data by sampling randomly with replacement, training a neural network on each data set, and averaging the results obtained from each trained neural network. Lou and Dong[31] presented a novel integrated technique-Random fuzzy NN (RFNN) for electric load forecasting.

The time series method, regression analysis method and the state space method are simple, small calculation, fast speed and widely used, but because the model is too simple to simulate the complex and changeable power load. Although the expert system has achieved some results in the load forecasting, it has poor generality and lack of learning ability. Artificial neural network is regarded as the representative of the new artificial intelligence method, it has strong memory ability, nonlinear mapping ability and strong self-learning ability. Therefore, it can quickly used to fit the change curve of load. However, network training is usually a complex large-scale optimization problems, with the change of the training sample set and the initial weights of network, network training results takes on large randomness, it exists the shortcomings of slow convergence speed and easy falling into the local extremum, which bring certain difficulties for actual modeling. Because the power system load exists all kinds of uncertain and difficult describing nonlinear, the load forecasting is not only required the high prediction accuracy, but also required good robust, real-time and fault tolerance. So an improved PSO algorithm is introduced into fuzzy neural network (FNN) in order to propose an novel short-term load forecasting method in this paper, which is used for an actual short-term load forecasting system.

2. PSO Algorithm and Improved PSO Algorithm

2.1. PSO Algorithm

The PSO algorithm is a population-based search algorithm by simulating the social behavior of birds within a flock. In the PSO algorithm, individuals, referred to as particles, are “flown” through hyper dimensional search space. The particles positions within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity(v) and position(x) of each particle will be changed by the particle best value ($pbest$) and global best value ($gbest$). The velocity and position updating of particle are shown:

$$v_{ij}\left(t+1\right)=wv_{ij}\left(t\right)+c_1r_1\left(pbest_{ij}\left(t\right)-x_{ij}\left(t\right)\right)+c_2r_2\left(gbest_{ij}\left(t\right)-x_{ij}\left(t\right)\right) \tag{1}$$

$$x_{ij}\left(t+1\right)=x_{ij}\left(t\right)+v_{ij}\left(t+1\right) \tag{2}$$

Where $v_{ij}(t+1)$, velocity of particle i at iterations j, $x_{ij}(t+1)$, positions of particle i^{th} at iterations j^{th}. w is inertia weight, which is employed to control the impact of previous history of velocity. Accordingly, the parameter w regulates the trade-off between the global and local exploration abilities of the swarm. t denotes the iteration number, c_1 is cognition learning factor, c_2 is social learning factor, r_1 and r_2 are random numbers in [0, 1], which denote remembrance ability of study. Generally, the value of each component in V can be clamped to the range $[-V_{\max}, V_{\max}]$ to control excessive roaming of particles outside the search space. The PSO has shown its robustness and effectiveness in solving optimization problems in real number spaces.

The flow of basic PSO algorithm is shown in Figure 1.

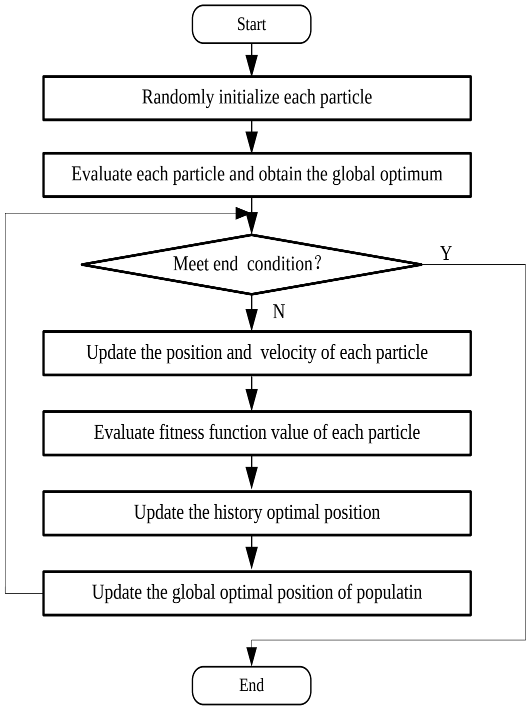

Figure 1. The Flow of Basic PSO Algorithm

2.2. An Improved PSO Algorithm

The value of inertia weight w will seriously affect the optimization performance of PSO algorithm. In general, the value of inertia weight w is bigger in the early search to guarantee the population search with larger search space and improve the convergence accuracy. The linear decreasing weight method is used to adjust the inertia weight w, it is described as follow:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}} \times t \tag{3}$$

where $w_{\max}$ is the maximum value of inertia weight and $w_{\min}$ is minimum value of inertia weight. $T_{\max}$ is the maximum number of iteration and t is the current number of iteration.

But in the actual application, the search process is a non-linear in the PSO algorithm, the dynamic changes of particles are complex. The linear decreasing weight can not better reflect the actual search process, which will result in the slow convergence speed and convergence precision. However the optimal gradient of linear decreasing weight relies on solving complex problem. So an adaptive dynamic adjusting strategy is used to control the inertia weight w for maintaining the diversity of population and reducing the probability of falling into the local optimum in the PSO algorithm. The adaptive dynamic adjusting strategy is described as follow:

$$w = \begin{cases} w_{\max} - \dfrac{w_{\max} - w_{\min}}{T_{\max}} \times t & f \geq f_{avg} \\ w_{\min} + (w_{\max} - w_{\min}) \times \dfrac{f_{avg} - 2f_{\min}}{2(f - f_{\min})} & \dfrac{f_{avg}}{2} \leq f < f_{avg} \\ w_{\min} + \dfrac{w_{\max} - w_{\min}}{T_{\max}} \times t & f < \dfrac{f_{avg}}{2} \end{cases} \tag{4}$$

where f is current fitness value of particle, $f_{\min}$ is global minimum fitness value of the particle, f_{avg} is global current average fitness value. This strategy makes full use of the current information and historical information to control the updating speed, better reduce the probability of falling into local optimum in the PSO algorithm.

3. Fuzzy Neural Network(FNN)

Fuzzy neural network(FNN) is a technology based on fuzzy system and neural network. The FNN integrates the accurate fitting ability and learning ability of neural network and strong structural knowledge expression ability of fuzzy logic. The structure and reasoning rules of FNN is deeply researched to determine the general structure of FNN. It has the characteristics of dealing with the non-linear and fuzziness. Each layer and each neuron have the relative physical meaning. In recent years, more and more experts contributed to researching the FNN model. The FNN model is composed of five layers, shown in Figure 2.

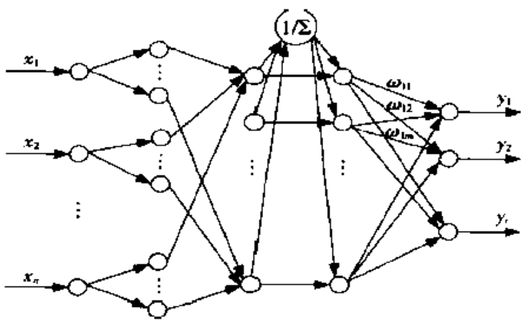

Figure 2. The Structure of the FNN

The each layer of FNN is described:

(1) The input Layer

The input vectors in the FNN are accurate numerical vector or fuzzy value. In general, the number of output nodes equals to the number of input nodes in this layer. The equation is given:

$$O_i^1 = I_i = x_i, i = 1,2,3,\cdots,n \tag{5}$$

(2) The Fuzzification Layer

The membership function of input variable and match the fuzzy control rules are realized in this layer. The number of nodes equals to all possible fuzzy rules based on the input variables. The output nodes are corresponding product of each Gaussian function. The equation is given:

$$\mu_{ij} = \exp[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}],\ i = 1,2,\cdots,r;\ j = 1,2,\cdots,u \tag{6}$$

where, r is the number of input vectors, u is the number of neuron, μ_{ij} is the i^{th} Gaussian function of the j^{th} neuron; c_{ij} is the i^{th} Gaussian function center of the j^{th} neuron; σ_{ij} is the i^{th} Gaussian function standard deviation of the j^{th} neuron.

The output equation of the j^{th} neuron is given:

$$O_j^2 = \exp[\sum_{i=1}^{r} \frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}],\ j = 1,2,\cdots,u \tag{7}$$

(3) The Fuzzy Reasoning Layer

In here, each neuron is a fuzzy rule. The reasoning takes advantage of fuzzy product reasoning for calculating the incentive intensity of fuzzy rule. The equation is given:

$$O_j^3 = \prod_{j=1}^{u} w_{aj} O_j^2 \tag{8}$$

(4) The Anti-Fuzzification Layer

The output of FNN is realized and the anti-fuzzification algorithm is used in this layer. The equation is given:

$$O_j^4 = \frac{O_j^3}{\sum_{j=1}^{u} O_j^3},\ j = 1,2,\cdots,u \tag{9}$$

(5) The Output Layer

The precision calculation is realized in this layer. The equation is given:

$$y = \sum_{j=1}^{u} w_{bj} O_j^4, \quad j = 1,2,\cdots,u \tag{10}$$

where w_{bj} is the connection weight of FNN model.

4. The IWPSRFN Model and Algorithm

4.1. The Optimized RBFFNN Model Based on Improved PSO Algorithm

Fuzzy logic and neural network both are based on mathematical models of dynamic characteristics. Fuzzy logic is used to describe expert knowledge, experience or data. The neural network is used to train sample data. The FNN combines the advantages of neural network and fuzzy logic, so it has good nonlinear function approximation ability, learning adaptability, parallel information processing ability, and been widely concerned in different application fields. The typical optimization process uses the gradient descent method and the least square method to adjust the parameters of FNN model. But this optimization strategy is easy to fall into local optimum and slow convergence speed. In the RBFFNN model, the values of output weight w_{ij}, the center of the membership function c_{ij} and width σ_{ij} have a great influence on the prediction performance of neural network. In the PSO algorithm, one particle corresponds to a feasible solution. So the improved PSO algorithm is used to adjust the parameters of RBFFNN model in order to obtain the optimized RBFFNN(IWPSRFN) model. In this method, the improved PSO algorithm is used to adjust the parameters of RBFFNN model by putting these parameters in the particle encoding, then the optimal values are found in the large number of viable solutions by continuous iteration of improved PSO algorithm. The found optimal values are selected as the parameters of RBFFNN model. After the RBFFNN model is learned, the final IWPSRFN model is obtained in this paper.

4.2. The Steps of IWPSRFN Model

In the process of model training, the improved PSO algorithm is used to train the parameters of RBFFNN model, the final IWPSRFN model is obtained. In here, mean square error(MSE) is selected as the training fitness function, which is described as follow:

$$f = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M}(q_{ij} - y_{ij})^2 \tag{11}$$

where N is the number of training samples, M is the number of output nodes, q_{ij} is target expectation value, y_{ij} is network computing value.

The flow of the IWPSRFN model is described as follows:

Step1: Initialize

Randomly initialize the connection weights(w_{ij}) in each layer of RBFNN, which are regarded as a population(m). Set the center of the membership function(c_{ij}) and width(σ_{ij}). Determine the search dimension of particle(n) and initialize the position(x_i) and velocity(v_i), $x_i \in [x_{\min}, x_{\max}]$, $v_i \in [v_{\min}, v_{\max}]$. Initialize the cognition learning factor (c_1), social learning factor(c_2), the initial inertia weight(ω),error accuracy of fitness(ε), the number of maximum iteration($T_{\max}$).

Step2: Calculate the fitness values

Calculate the fitness value of each particle according to fitness function(11). The position of the initial particle is recorded the local optimal value($pbest$), the found particle with minimum fitness value in the population is regarded the global optimal value($gbest$).

Step3: Compare

The improved PSO algorithm is used to search the optimal value. For each particle, the current fitness value is compared with the local optimal value ($pbest$). If the current fitness value is better than the local optimal value ($pbest$), the local optimal value ($pbest$) is replaced by the current fitness value. Then the local optimal value ($pbest$) is compared with the global optimal value($gbest$). If the local optimal value ($pbest$) is better than the global optimal value($gbest$),the global optimal value($gbest$) is replaced by the local optimal value ($pbest$).

Step4: After the each iteration is ended, the inertia weight w is adjusted according to the equation(4) and (5).

Step5: The current position and search velocity of particle are adjusted according to the equation(1) and (2).

Step6: If the number of iteration reaches the maximum number of iteration, or the error accuracy of current fitness value is less than the error accuracy of given fitness(ε),The IWPSRFN algorithm is terminated. Go to Step 7. Otherwise, go to Step 3.

Step7: Output the optimal result.

5. Application of the IWPSRFN Algorithm in Load Forecasting

The load change of power system is uncertainty, it is disturbed by changed climate and accident and so on. The load data of a certain area is used to test the proposed IWPSRFN model. All various affecting factors of cycle regularity and prediction of load are summarized. On the basis of these characteristics of load, a novel short-term load forecasting model and method based on IWPSRFN model are established in order to improve the prediction accuracy in this paper. The environments are followed: the Pentium CPU 2.40GHz, 2.0GB RAM with the Windows operating system, Matlab2012b. Because the initial values of parameters could seriously affect the experiment result, the most reasonable initial values of these parameters are obtained by testing and modifying. The obtained initial values of these parameters are: population size m = 40, iteration times $T_{\max}$ =1000, max velocity $v_{\max}$ =100, learning factor $c_1 = c_2$ =2.0, initial inertia weight w_0 =0.9, r_1 and $r_2 \in [0,1]$ .The number of neurons in hidden layer is determined by the improved PSO algorithm. In addition, FRBFNN and PSOFRBFNN are select to compare with the proposed IWPSRFN algorithm. Matlab2012b is used to realize the FRBFNN, PSOFRBFNN and IWPSRFN method. The forecasted results are shown in Table 1. The forecasted load curve and load curve are shown in Figure 2.

Table 1. The Forecasted Results for One Day

Time	Actual value(MW)	FRBFNN		PSOFRBFNN		IWPSRFN	
		Forecasted value(MW)	Error(	Forecasted value(MW)	Error(%)	Forecasted value(MW)	Error
1:00	180.35	173.38	-3.901%	177.35	-1.663%	178.67	-0.940%
2:00	172.24	167.43	-2.814%	170.02	-1.289%	170.95	-0.755%
3:00	163.62	160.16	-2.149%	161.54	-1.271%	161.02	-1.615%
4:00	160.37	164.37	2.450%	163.16	1.740%	163.27	1.776%
5:00	161.05	156.86	-2.606%	158.21	-1.763%	160.78	-0.168%
6:00	162.36	157.37	-3.118%	159.34	-1.860%	160.04	-1.450%
7:00	173.96	168.25	-3.339%	170.19	-2.167%	171.03	-1.713%
8:00	209.31	205.42	-1.870%	207.32	-0.951%	208.03	-0.615%
9:00	292.47	282.36	-3.494%	288.96	-1.200%	289.35	-1.078%
10:00	304.66	295.15	-3.163%	299.05	-1.841%	300.68	-1.324%
11:00	309.39	300.03	-3.056%	304.12	-1.703%	306.25	-1.025%
12:00	313.43	307.26	-1.943%	313.37	-0.019%	317.59	1.310%
13:00	214.04	222.42	3.851%	218.36	2.018%	217.63	1.650%
14:00	284.16	290.07	2.106%	288.15	1.404%	280.59	-1.272%
15:00	292.58	283.68	-3.087%	286.09	-2.218%	288.35	-1.467%
16:00	290.05	282.66	-2.528%	293.51	1.193%	292.36	0.790%
17:00	291.36	298.43	2.454%	287.86	-1.201%	288.05	-1.149%
18:00	288.21	280.62	-2.636%	287.07	-0.396%	287.93	-0.097%
19:00	258.37	264.43	2.331%	261.59	1.246%	259.96	0.612%
20:00	264.90	254.19	-4.109%	258.91	-2.261%	260.64	-1.634%
21:00	257.33	245.35	-4.776%	249.37	-3.093%	250.85	-2.583%
22:00	243.18	234.26	-3.721%	237.03	-2.529%	239.72	-1.443%
23:00	217.40	212.47	-2.287%	213.53	-1.780%	215.53	-0.868%
24:00	198.07	191.01	-3.611%	193.76	-2.176%	195.49	-1.320%

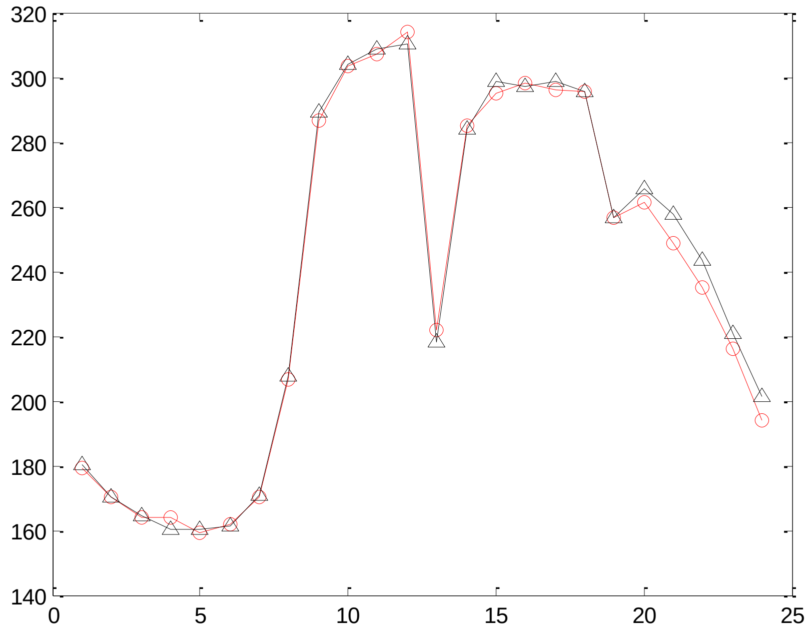

Figure 2. The Forecasted Values and Actual Values

As can be seen in Table 1, the proposed IWPSRFN algorithm can obtain better forecasted results than the FRBFNN and PSOFRBFNN for one day. The absolute average error of the FRBFNN is 2.975%, the absolute average error of the PSOFRBFNN is 1.624%, the absolute average error of the IWPSRFN is 1.194%. The Figure 2 is the fitting load curve and actual load curve, the curve with circle is the actual load curve, the curve with triangle is the forecasted curve. As can be seen in Figure 2, the proposed IWPSRFN algorithm is an effective and feasible forecasted method. As a result, improved PSO algorithm has better search ability and higher search accuracy. The proposed IWPSRFN algorithm significantly outperforms the FRBFNN and PSOFRBFNN for all forecasting. In a word, the proposed IWPSRFN algorithm can provide the higher forecasting accuracy than the FRBFNN and PSOFRBFNN.

6. Conclusion

Scientific and accurate short-term load forecasting is helpful to improve the economy and safety of power system operation. It is has very important significance for ensuring the healthy development of power industry and national economy. Due to the load complexity of power system, there exist many kinds of uncertainties and difficult describing nonlinear. So the PSO algorithm and fuzzy neural network is analyzed, an improved PSO algorithm based on the linear decreasing weight method is proposed in this paper, then the improved PSO algorithm is used to optimize the parameters of FRBFNN model by putting these parameters in the particle encoding. The optimal values are found in the large number of viable solutions to regard as the parameters of FRBFNN model in order to propose a short-term load method of power system. And a certain region is selected to test the effectiveness of IWPSRFN method, the experiment results show that the improved PSO algorithm can effectively optimize the weights of FRBFNN and improve the slow convergence speed, and the IWPSRFN method can Using this method can effectively improve the accuracy and validity of the power load forecasting, it has good engineering application value and practical guiding significance.

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