Research on Wind Turbine Generator Selection and Comprehensive Evaluation Based on BPNN Optimized by PSO

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Abstract:-With the development of the of China's electric power system, wind power, as a clean energy, can be used to optimize the structure of electrical energy, thus can largely reduce the emission of pollutants and contribute to the sustainable development of the national economy. In wind power projects, scientific and rational choice for the wind turbine generator in actual wind farm is the core part, and it is directly related to the economic benefits of wind power projects. This paper analyze the status of current wind power capacity in global and China and reveals the regularity of the growing proportion of wind power in future energy. On this basis, this paper determines the comprehensive evaluation system of wind turbine generator selection and establishes a comprehensive evaluation model based on BP neural network which optimized by particle swarm optimization. A specific example verifies the validity of the proposed method, thus can provide guidance of the evaluation of the wind turbine generators selection in wind farms.
Key-Words: -Wind turbine generators selection; Comprehensive evaluation; BP neural network; Particle swarm optimization; Parameter optimization

1 Introduction

In recent years, wind power develops very quickly. By the end of 2013, global cumulative installed capacity reached 318137MW with an increase of 12.4%. According to the forecast of Global Wind Energy Council, the global cumulative installed wind power capacity is expected to exceed one million megawatts to 2020, at that time, wind power will meet approximately 11.5% ~ 12.3% of global energy demand [1,2]. As the core equipment of wind power, the comprehensive optimization selection of wind turbine generator needs to considerate a variety of factors and indicators under the construction and operation process of wind farm. It is not only the problem of wind power at the technical level, but also relates to many other disciplines, such as the environmental, economic, operational management and optimization [3,4]. The sustainable development of wind power industry constantly updated the technology type and design idea of wind turbine generators (WTG). Due to the complex and diverse selection of the wind turbines in the early wind farm construction, the research on wind turbine selection methods have emerged, and the wind turbine selection has become a relatively new field of scientific applications [5,6,7].

Jangamshetti SH and Rau VG [8] presented that the wind farm capacity factor should be determined as the evaluation of wind turbines selection. And found that the capacity factors computed from the Weibull statistical model using cubic mean of wind speed data fairly match the actual capacity factors. Based on the above, two researchers presented two new concepts, standardized power curve and matching coefficients. They pointed out that in order to achieve the best rated wind speed, its corresponding matching coefficient must be maximum. Thus, determine the best rated wind speed is a matter to be considered first in wind turbine selection [9]. Based on the two authors' research above, Shyh-JierHuang and Hsing-Ho Wan [10] pointed that the matching coefficient reaches the maximum when the rated is equal to the non-rated item value in the capacity factor equation. Furthermore, Ssu-yuan Hua and Jung-ho Cheng [11] modified the capacity factor formula, and derived its simple algorithm. The algorithm was used in the selection of 32 wind farms selection. Doddamani and Jangamshetti [12] simplified the algorithm of wind turbine composition, and used it to re-establish the technical and economic indicators. Li Wang [13] pointed out that the rated capacity and rated wind speed are the critical parameters in selection and set four technical and economic indicators as metrics. Albadi and El-Saadany [14] presented a new formulation for the turbine-site matching problem, based on wind speed characteristics at any site, the power performance curve parameters of any pitch-regulated wind turbine, as well as turbine size and tower height.

Although there are many literature about fan selection at home and abroad, we find they primarily focus on the research of wind turbine generator selection local algorithm and single required index, which are lack of comprehensive and systematic research on the entire wind turbine generator selection method by comparing these literature. Through analysis of some cases of wind turbine selection, several problems are exited as follows: I. There are few alternatives before work, so the choice is reduced which leads to the one-sidedness of the optimal solution. II. The operation performance and technical service quality after running of wind turbine generator are not fully considered and evaluated. III. The methods for evaluation of wind turbine generator selection are traditional and the evaluation is a bit subjective. Therefore, the paper constructs a comprehensive evaluation system of fan selection, and introduces the artificial intelligence algorithms to solve wind turbine generator selection evaluation problem.

2 The construction of WTG selection and comprehensive evaluation index system

Because there are lots of factors and indexes influencing fan selection, it has become an important and complicated problem prior to the construction of wind field. Therefore, it is necessary to establish a systematic index system for wind turbine generator selection so that it can fully and accurately reflect the indicators of wind turbine generator and compare the merits of the candidate models objectively and reasonably. The establishment of wind turbine generator selection index system should be guided by the following principles [15]: (1) Authenticity. In order to accurately reflect the fan indicator, the data collection should be as accurate and true as possible to avoid the wrong selection due to the data distortion. (2) Systematization. The whole index system should give due consideration to factors affecting fan operation and interlinkages among them, rather than simply list each index. (3) Independence. In order to reflect the actual status of the wind turbine, it shouldn’t have a containment relationship among the indexes of the same level, and the correlation among indicators should be reduced. (4) Operability. The indications of index system should be measurable or assessable, which not only exist in theory, and the establishment of indicators should reduce the difficulty of data collection as much as possible. (5)Quantitative and qualitative. When selecting indicators, we can’t take quantitative or qualitative one, which is likely to ignore more important data and make the selection result inaccurate, lack of comprehensiveness and scientific nature.

Based on the principle of wind turbine generator selection above and literature [16,17] at home and abroad, a wind turbine generator selection index system is established in this paper which contains five top grade indexes including wind turbine generator technical performance, wind field adaption performance, economic performance and the performance of products and technical service, thirteen second grade indexes and thirty-nine third indexes as shown in Table 1.

Table.1 Comprehensive evaluation index system of wind turbine generator selection

Technical performance of wind turbine A	Technical parameters of the main components A_1	Impeller A_{11} GearboxA_{12} Generator A_{13} Tower A_{14} Control system A_{15} Equipment weight A_{16}
	Global features A_2	Availability A_{21} Ways of power regulation A_{22} Guarabtee rate of power curve A_{23} The design lifetime of a wind turbine generator A_{24}
	Testing and certifications A_3	Wind turbine generator certification A_{31} Power curves testing A_{32} Load testing A_{33} Noise testing A_{34} Power quality testing A_{35} Low voltage ride through testing A_{36}
Adaptability of wind farm B	The fitness of wind resource B_1	Annual average wind speed B_{11} Wind speed measuring B_{12} IEC security level B_{13}
	The adaptability of special environment B_2 Grid compatibility B_3	Working environment B_{21} Special design B_{22}
Economic performance C	Project static investment C_1	Investment in equipment and installation items C_{11} Construction project investment C_{12} Other expense C_{13} Basic reserve funds C_{14}
	Project dynamic investment C_2	Operation cost C_{21} Maintenance cost C_{22} Failure cost C_{23} Recycle and disposal cost C_{24}
	Economic characteristics of the unit C_3	Power generation C_{31} Per kilowatt investment C_{32}

		Unit power investment C_{33} Internal rate of return C_{34}
Operation performance D	Operation performance of this unit D_1 Operation performance of the same capacity D_2	
Technical service capabilities E	Product supply E_1	Wind turbine generator manufacturer E_{11} Supply ability E_{12}
	Technology and service E_2	R & D capability E_{21} Technical support capability E_{22} Quality assurance and control capabilities E_{23} After service capability E_{24}

3 The comprehensive evaluation model of WTG selection based on BPNN optimized by PSO

3.1 BP neural network

Set $X_1, X_2, \cdots, X_n$ as BP neural network input vectors, $Y_1, Y_2, \cdots, Y_m$ as output vectors, w_{ij} and w_{jk} as weights. The typical BP neural network topology is shown in Fig.1.

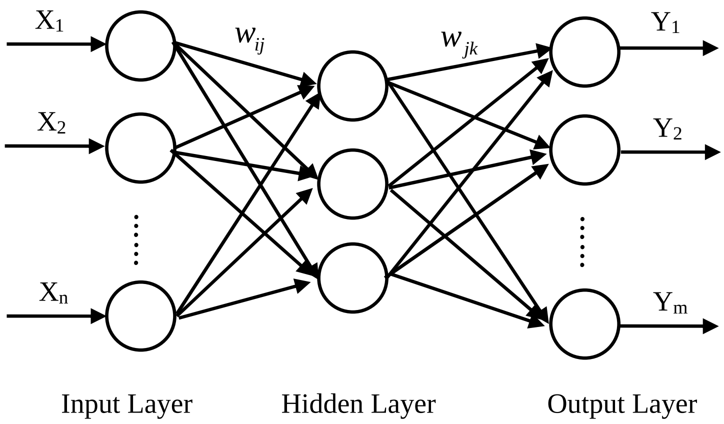

Fig.1 BP neural network structure

The input node *n* and the output node m reflect the mapping between the independent variables n and the dependent variables m. The prediction steps based on BP neural network include network architecture components, training and prediction. The basic work flow is shown in Fig.2 [18].

The construction phase of BP neural network model is primarily based primarily on system model and design goal to value assignment of the network parameters, which including: the input nodes n, the output nodes m, the hidden nodes l. What' s more, initialize the hidden layer threshold b_1 and output layer threshold b_2 according to the network forms and set the learning rate and neuronal activation function.

BP neural network training is a process of multiple cycles: First enter the training sample and calculate the output layers, then adjust the weights of each layer based on the output error and error in each layer which generate by the output error feedback, repeat this process until the end of the training [19].

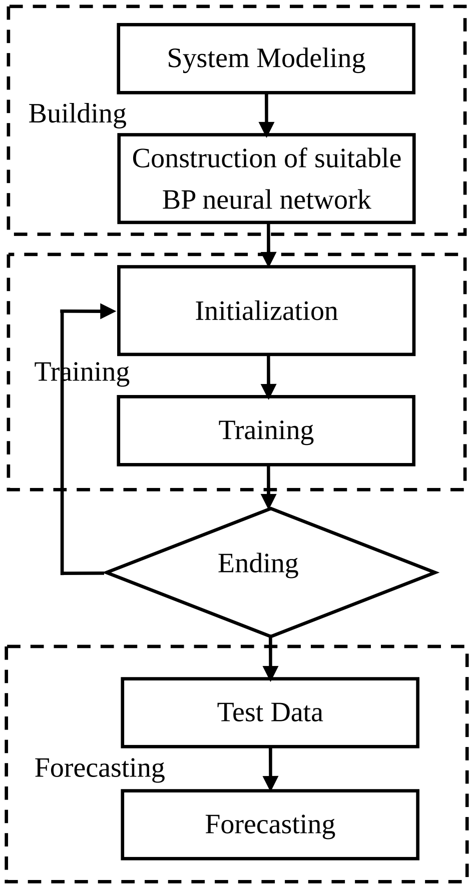

Fig.2 BPNN flow chart

3.2 Particle swarm optimization algorithm

Particle swarm optimization (PSO) algorithm is a swarm intelligence algorithm which simulates the behavior of bird flocking foraging and proposed by the American scholar R.C.Eberhart and J.Kennedy in1995 [20].

Particle swarm make up of N individual particles and search optimal solution iteratively in D-dimension space. Particles update themselves by tracking two "extremes", one is the best location of the particle $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$, another is the current optimal position of entire population $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$. When particles fly in the space, there exist position feature and velocity feature. Particles update the velocity v_{ij} and position x_{ij} in the process of iteration by using the following formula:

$$v_{ij}^{t+1} = \omega \cdot v_{ij}^t + c_1 r_1 (p_{ij} - x_{ij}^t) + c_2 r_2 (p_{gD} - x_{ij}^t) \quad (1)$$

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \quad (2)$$

Where t represents the maximum iteration, $i = 1,2,\cdots,N$, $j = 1,2,\cdots,D$. $v_{ij} \in [-v_{\max}, v_{\max}]$, $v_{\max}$ is a constant. $x_{ij} \in \lfloor X_{\min,j}, X_{\max,j} \rfloor$, in which $X_{\min,j}$ and $X_{\max,j}$ are constant. c_1 and c_2 is the learning factor, in general, $c_1 = c_2 = 2$. r_1 and r_2 are random numbers between 0 to 1. w represents inertia weight which means the new particle inherits its parent particle velocity and have a great impact on the convergence speed and accuracy of PSO, its formula is as follow:

$$w = (w_s - w_e)(t_m - t)/t_m + w_e \quad (3)$$

In which w_s, w_e represent the initial inertia weight and end weight respectively. t is the current iteration number. t_m represents the maximum iteration [21].

3.3 The comprehensive evaluation model of WTG selection

From the introduction and analysis of PSO and BPNN above, we can conclude that BPNN is expert in local search, but there exits the problems about slow training speed, falling into local minimum easily and being weak in global search; However, PSO proposes probability choice as the main idea and is good at global search which can easily find the global optimal solution or suboptimal solution that has a good performance, but for the local search ability is insufficient. Because of these reasons, we propose the model which combine the advantages of PSO and BPNN has a better performance. In this paper, the connection weights and thresholds of BPNN are optimized by PSO, then the samples of the wind turbine generator are training by the optimized BPNN and the comprehensive performance of wind turbine generators is obtained.

The steps of the comprehensive evaluation model of fan selecting based on this algorithm are as followings [22]:

(1) Initialize the parameters of BP neural network and PSO algorithm respectively, including the number of hidden layers, the number of nodes in the input, hidden and output layer, the maximum number of training, learning rate, the target error, the dimension of particles, iterations, population size, and initial position and velocity of particles.

(2) The learning samples are tested by BP neural network corresponding to each particle vector respectively and the test error value of the current position of each particle is obtained and regarded as the fitness value of the particles. The expression is as follows:

$$f_i = \frac{1}{n}\sum_{1}^{n}\left|\frac{R_i - F_i}{R_i}\right| \tag{4}$$

Where R_i is the desired output and F_i is the test output.

(3) The optimal fitness value of each particle is compared with the current fitness value, if better, the current position of the particle is updated as the optimal position of the particle.

(4) Compare the best fitness value of the swarm and all the optimal fitness value of each particle, if better, the best position of the particle with the best fitness value is updated as the best position of the swarm.

(5) Calculate the inertia weight according to equation (3) and use the formula (1) and (2) to update the velocity and position of particles.

(6) Check whether the termination condition is satisfied, if not return to step (2); or stop the computation and export the results.

4 Case study

This paper presents the wind farm which installed capacity is about 49.5MW is located in the Northern China, which has rich wind resource.

4.1 Data acquisition

According to the constraint conditions, which contain the wind resource condition, terrain condition, the requirements of technology development, the special requirements of wind power companies and the comprehensive strength of wind turbine generator manufactures, this paper select 60 kinds of wind turbine generators as the sample from the database which contains about 300 kinds of wind turbine generators.

Calculating the weights of indexes which is in the bottom of the comprehensive evaluation index system using the analytic hierarchy process [23], the result is shown in Table.2

Table.2 The weights of comprehensive evaluation indexes

Basic index	Weight	Basic index	Weight
A_{11}	0.0139	B_3	0.0834
A_{12}	0.0139	C_{11}	0.0208
A_{13}	0.0139	C_{12}	0.0208
A_{14}	0.0139	C_{13}	0.0208
A_{15}	0.0139	C_{14}	0.0208
A_{16}	0.0139	C_{21}	0.0208
A_{21}	0.0250	C_{22}	0.0208
A_{22}	0.0250	C_{23}	0.0208
A_{23}	0.0250	C_{24}	0.0208
A_{24}	0.0083	C_{31}	0.0104
A_{31}	0.0139	C_{32}	0.0104
A_{32}	0.0139	C_{33}	0.0313
A_{33}	0.0139	C_{34}	0.0313
A_{34}	0.0139	D_1	0.0694
A_{35}	0.0139	D_2	0.0139
A_{36}	0.0139	E_{11}	0.0208
B_{11}	0.0278	E_{12}	0.0625
B_{12}	0.0278	E_{21}	0.0083
B_{13}	0.0278	E_{22}	0.0250
B_{21}	0.0417	E_{23}	0.0250
B_{22}	0.0417	E_{24}	0.0250

Applying the method of expert scoring to estimate the quantitative indicators and qualitative indicators about wind turbine generator selection and the scoring range is in the scope [0,1], where [0,0.2) represents the performance is the worst, [0.2,0.4) means the result is worse, [0.4,0.6) shows that the performance is general, [0.6,0.8) represents the result is better and [0.8,1] means the performance is excellent. The higher the score is, the better the performance of index is. The average value of expert scoring is selected as the final result, and a part of evaluation results is shown in Table.3.

Table.3 The evaluation results of each WTG index

Index	W-01	W-02	⋯	W-59	W-60
A_{11}	0.93	0.91	⋯	0.76	0.66
A_{12}	0.96	0.92	⋯	0.88	0.60
A_{13}	0.65	0.67	⋯	0.66	0.91
⋮	⋮	⋮	⋯	⋮	⋮
E_{22}	0.61	0.93	⋯	0.68	0.77
E_{23}	0.78	0.83	⋯	0.84	0.74
E_{24}	0.75	0.82	⋯	0.82	0.82

According to the evaluation results and the weights which are mentioned above, calculating the comprehensive performance levels of various wind turbine generators based on the following formula and the results are regarded as the expected output value of sample.

$$E = \sum s \cdot w \tag{5}$$

In which E represents the expected output value, s means the score of each index and w is the weight of each index. The final sixty expected output values are shown in Table.4.

Table.4 The expected output values of sample

NO.	Expected output value	NO.	Expected output value	NO.	Expected output value
W-01	0.7947	W-21	0.7805	W-41	0.7872
W-02	0.8054	W-22	0.7946	W-42	0.8221
W-03	0.8000	W-23	0.8083	W-43	0.7939
W-04	0.7647	W-24	0.8100	W-44	0.7773
W-05	0.8069	W-25	0.7980	W-45	0.7971
W-06	0.7828	W-26	0.8345	W-46	0.8045
W-07	0.8220	W-27	0.7841	W-47	0.8001
W-08	0.7990	W-28	0.8452	W-48	0.7915
W-09	0.7855	W-29	0.8059	W-49	0.7963
W-10	0.7902	W-30	0.7990	W-50	0.8256
W-11	0.7826	W-31	0.8361	W-51	0.8002
W-12	0.8276	W-32	0.8413	W-52	0.7846
W-13	0.8065	W-33	0.8154	W-53	0.8095
W-14	0.8299	W-34	0.8397	W-54	0.7861
W-15	0.8345	W-35	0.7602	W-55	0.7815
W-16	0.7707	W-36	0.7793	W-56	0.8216
W-17	0.7911	W-37	0.7677	W-57	0.7974
W-18	0.7436	W-38	0.7981	W-58	0.7891
W-19	0.7953	W-39	0.7886	W-59	0.7776
W-20	0.7844	W-40	0.8083	W-60	0.7966

4.2 Parameters optimization

Before the optimization of connection weight and threshold, the parameters of BPNN and PSO should be initialized, which are shown in Table.5 and Table.6.

Table.5 Parameters setting of BPNN

Parameter	Initial value
Node point number of input layer	42
Number of hidden layer	1
Node in hidden layer	14
Node in output layer	1
The maximum training times	100
The accuracy of training error	0.001
Learning rate	0.1

Table.6 Parameters setting of PSO

Param-eters	N	t_m	c_1	c_2	w_s	w_e	$V_{\max}$
Value	20	500	2	2	0.3	0.9	1

Optimized the connection w_{ij}, w_{jk} and threshold b_1, b_2 of BPNN by using PSO. In the optimization process, the iterative curve of fitness value is shown in Fig.3.

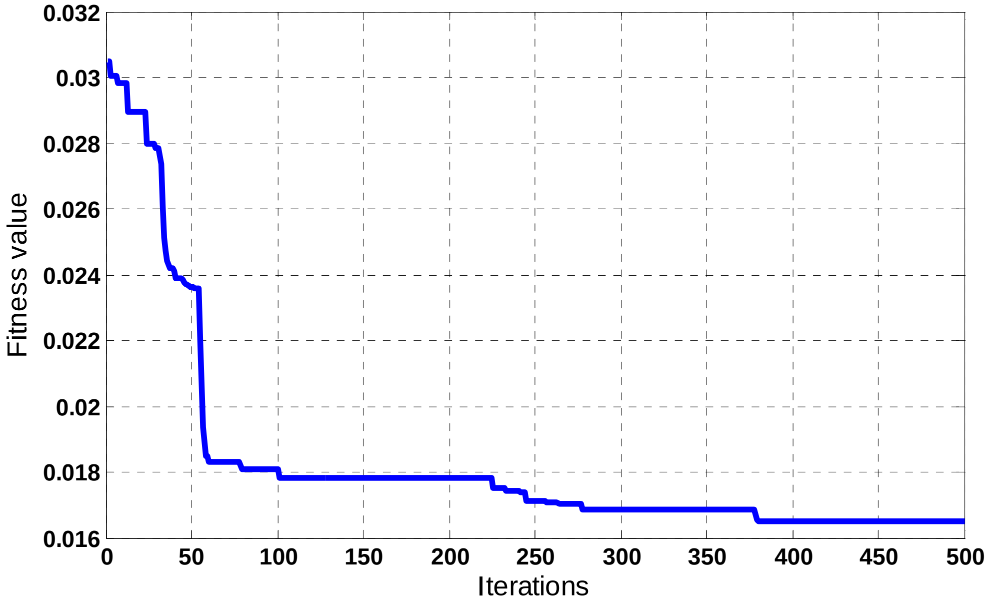

Fig.3 Iterative curve optimized by PSO

As is shown in Fig. 3, the fitness value of PSO is decreasing with the increase of the iteration. When the iteration time is 376, the iterative curve is converging. The optimal connection weights and thresholds which have been optimized by PSO are as follow:

The connection weights which are from input layer to output layer are as follow:

$$w_{ij} = \begin{bmatrix} 2.7088 & -1.7042 & \cdots & -0.9794 \\ -2.7807 & -0.8857 & \cdots & -2.8009 \\ \vdots & \vdots & \ddots & \vdots \\ -0.0070 & -0.918 & \cdots & 0.6040 \end{bmatrix}_{42\times 14}$$

The connection weights which are from hidden layer to output layer are as follow:

$$w_{jk} = [-0.9622 \quad 1.4796 \quad 1.4119 \quad -0.1438 \quad 2.5801 \quad -0.6229 \quad -2.9781 \quad -0.1273 \quad 1.0121 \quad 1.9607 \quad -1.5349 \quad -1.2857 \quad 0.4816 \quad -2.6472]_{14\times 1}$$

The thresholds which are from input layer to hidden layer are as follow:

$$b_1 = [2.3653 \quad 0.8208 \quad -0.2114 \quad 0.0477 \quad -0.3443 \quad -2.2215 \quad 1.6834 \quad -1.8436 \quad 1.8630 \quad 2.5066 \quad -1.4698 \quad 2.5942 \quad -0.6522 \quad -0.9447]_{14\times 1}$$

The threshold which is from hidden layer to output layer is as follow: $b_2 = 0.9183$

4.3 The training and testing of BPNN

The 60 samples of wind turbines are divided into two groups, which the former 40 are as the training data and the later 20 are as the testing data. Combining the parameters which have been set, the connection weights and thresholds which have been optimized and training data with BPNN for training. There exits two conditions when the process of training is stop: on the one hand, when the training error reaches the setting target 0.001, the process is stop; on the other hand, when the iteration time has reached the maximum iteration 100, the process is stop. The iterative curve of training error is shown in Fig.4.

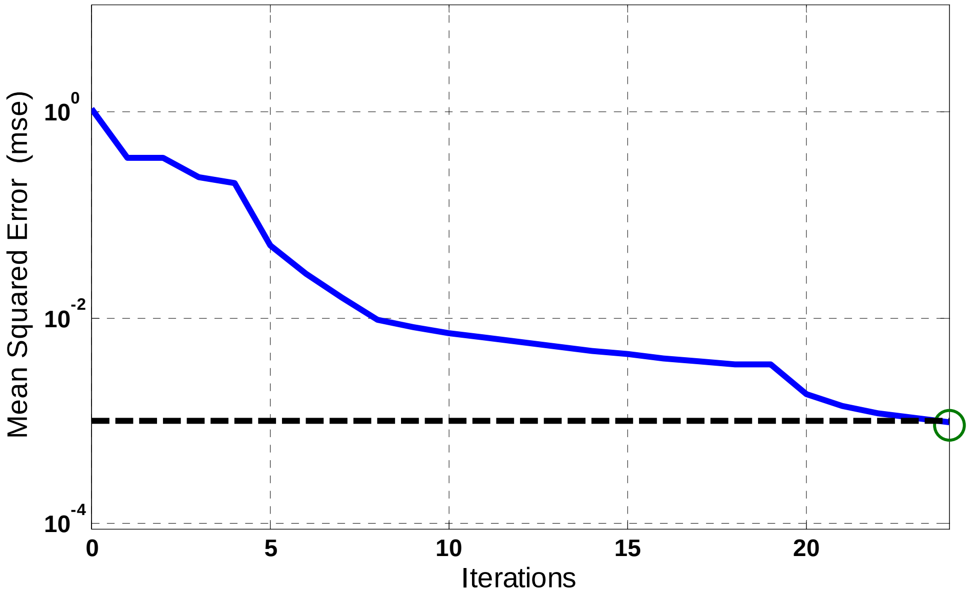

Fig.4 The iterative curve of PSO-BPNN training error

As it is shown in Fig.4, when the iteration time is 24, the error accuracy of BPNN training reaches the target error 0.001. The training results of BPNN are shown in Table.7 and Fig.5.

Table.7 the training results of PSO-BPNN

NO.	Expected output value	Training output value	NO.	Expected output value	Training output value
W-01	0.7947	0.7856	W-21	0.7805	0.7724
W-02	0.8054	0.7917	W-22	0.7946	0.8020
W-03	0.8000	0.8118	W-23	0.8083	0.8000
W-04	0.7647	0.7756	W-24	0.8100	0.8185
W-05	0.8069	0.8111	W-25	0.7980	0.7941
W-06	0.7828	0.7974	W-26	0.8345	0.8219
W-07	0.8220	0.8331	W-27	0.7841	0.7867
W-08	0.7990	0.7969	W-28	0.8452	0.8498
W-09	0.7855	0.7773	W-29	0.8059	0.8008
W-10	0.7902	0.7959	W-30	0.7990	0.7960
W-11	0.7826	0.7950	W-31	0.8361	0.8313
W-12	0.8276	0.8159	W-32	0.8413	0.8403
W-13	0.8065	0.8207	W-33	0.8154	0.8135
W-14	0.8299	0.8160	W-34	0.8397	0.8376

W-15	0.8345	0.8461	W-35	0.7602	0.7681
W-16	0.7707	0.7705	W-36	0.7793	0.7732
W-17	0.7911	0.8005	W-37	0.7677	0.7767
W-18	0.7436	0.7495	W-38	0.7981	0.7824
W-19	0.7953	0.7961	W-39	0.7886	0.7946
W-20	0.7844	0.7803	W-40	0.8083	0.7974

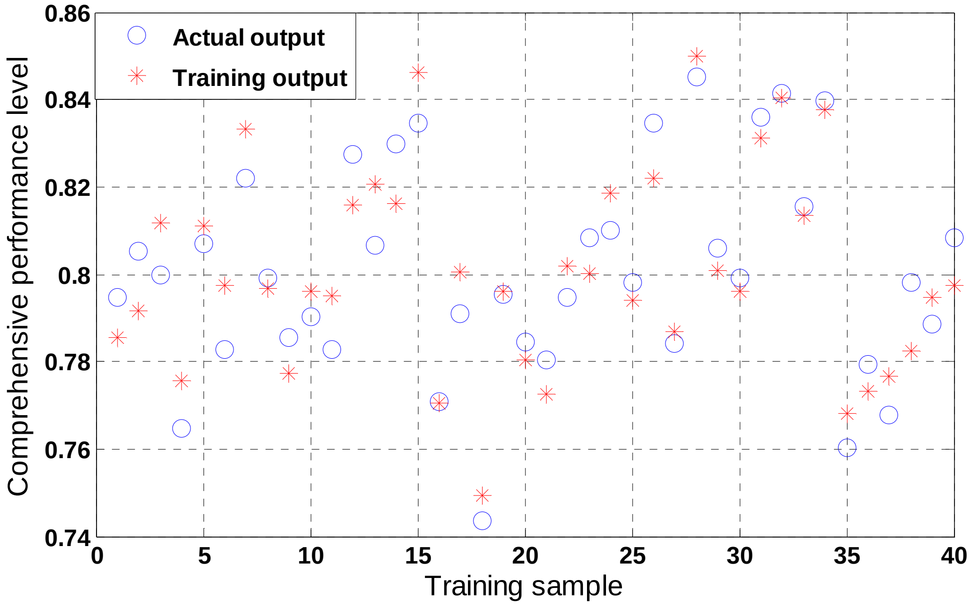

Fig.5 The training results of PSO-BPNN

From Table.7 and Fig.5, we can conclude that the training results of BPNN are satisfied, which the maximum relative error is 1.96% (sample number is W-38) and the minimum relative error is 0.03%(sample number is W-16) in the training sample. So, BPNN which has been trained can be test.

Add 20 samples into the trained BPNN for training, the testing results are shown in Table.8. The formula for calculating the relative error is as follow:

$$RE_i = \frac{P_i - R_i}{R_i} \times 100\% \tag{6}$$

Where R_i is the expected output value and F_i is the testing output value.

Table.8 The testing results of PSO-BPNN

NO.	Expected output value	Testing output value	Relative error（%）
W-41	0.7872	0.7897	0.32
W-42	0.8221	0.8099	-1.49
W-43	0.7939	0.7818	-1.52
W-44	0.7773	0.7655	-1.52
W-45	0.7971	0.8100	1.61
W-46	0.8045	0.8171	1.57
W-47	0.8001	0.8094	1.17
W-48	0.7915	0.8032	1.47
W-49	0.7963	0.7830	-1.68
W-50	0.8256	0.8306	0.60
W-51	0.8002	0.7937	-0.81
W-52	0.7846	0.7895	0.63
W-53	0.8095	0.8175	0.99
W-54	0.7861	0.8009	1.88
W-55	0.7815	0.7781	-0.44
W-56	0.8216	0.8136	-0.98
W-57	0.7974	0.7913	-0.76
W-58	0.7891	0.7818	-0.92
W-59	0.7776	0.7881	1.35

W-60	0.7966	0.7944	-0.27

4.4 Analysis of results

In order to estimate the ability of PSO-BPNN comprehensive evaluation model, this paper proposes the traditional BPNN for comparison. The parameters setting of single BPNN are same as above. The testing results of single BPNN are shown in Table.9.

Table.9 The testing results of single BPNN

NO.	Expected output value	Testing output value	Relative error（%）
W-41	0.7872	0.7681	-2.42
W-42	0.8221	0.7923	-3.62
W-43	0.7939	0.7668	-3.41
W-44	0.7773	0.7751	-0.29
W-45	0.7971	0.7853	-1.49
W-46	0.8045	0.7745	-3.73
W-47	0.8001	0.8108	1.34
W-48	0.7915	0.8018	1.30
W-49	0.7963	0.8133	2.13
W-50	0.8256	0.8258	0.02
W-51	0.8002	0.8023	0.26
W-52	0.7846	0.7790	-0.71
W-53	0.8095	0.8292	2.43
W-54	0.7861	0.7675	-2.37
W-55	0.7815	0.7572	-3.11
W-56	0.8216	0.8448	2.81
W-57	0.7974	0.7693	-3.52
W-58	0.7891	0.8063	2.18
W-59	0.7776	0.7761	-0.20
W-60	0.7966	0.7954	-0.15

Put the testing results of proposed model and single BPNN together to analyze and comparison. As is shown in Fig.6, for the proposed model, there exist 13 groups of testing results which have a better performance than single BPNN, 5 sets of testing results whose accuracy is lower than single BPNN and the rest of 2 sets testing results are worse than single BPNN obviously.

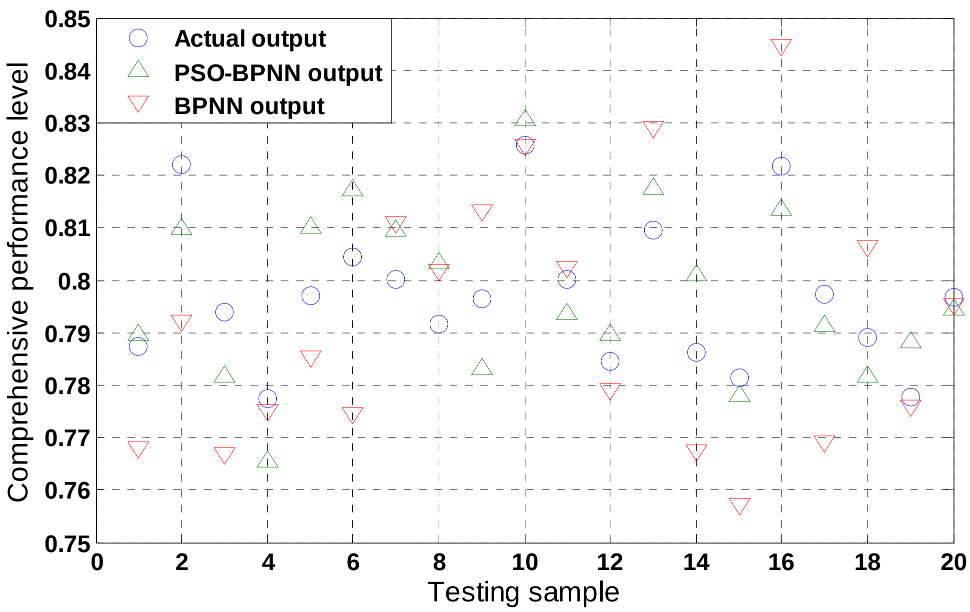

Fig.6 Comparison of testing results

As is shown in Fig.7, the relative errors of the proposed model are less fluctuant than the single BPNN, and that represents PSO-BPNN comprehensive evaluation model has a better generalization ability and lead to high tolerance rate.

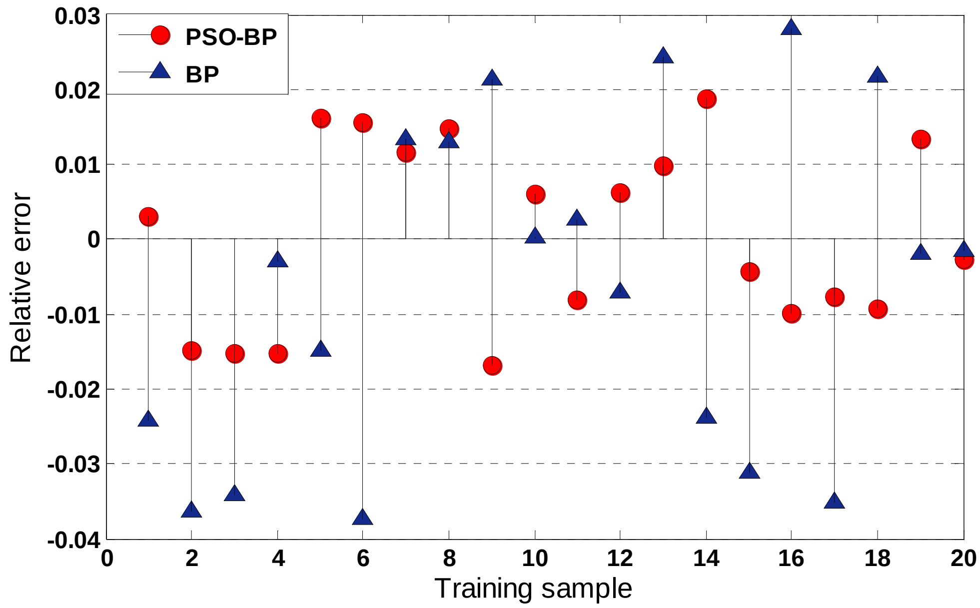

Fig.7 Relative error of PSO-BPNN and single BPNN

Above all, the proposed model has a better performance, which has a higher accuracy and better generalization ability, than single BPNN in comprehensive evaluation of fan selection. For the problem of wind turbine generator selection in the future, PSO-BPNN comprehensive evaluation model can be used widely by putting the parameters of each wind turbine generator and the connection weights and thresholds which have been optimized into the proposed model, after training the model, then we can obtain the comprehensive evaluation results which is the standard of wind turbine generator selection.

5 Conclusion

With the target of wind turbine selection comprehensive evaluation, this paper establishes the hierarchy model of wind turbine generator selection comprehensive evaluation index system and takes the wind turbine generator indicators during the construction and operation of wind field into account, which contain the wind turbine technical performance, wind field adaption performance, economic performance, wind turbine generator operation performance and the performance of products and technical service. We use PSO to optimize the connection weights and thresholds of BP neural network, then put the optimized parameters, various types of initialization parameters and wind turbine generator samples into BP neural network for training and testing. Based on analysis of cases, it has been validated that BP neural network which is optimized by PSO can accurately assess the performance level of wind turbine generator, and the proposed model is superior to traditional single BP neural network model and can be used in actual wind turbine generator selection comprehensive evaluation problems.

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