Teaching Quality Evaluation of BP Neural Network Optimized by FOA based on Human-Computer Interaction

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***Abstract* — Background: Since the existing teaching quality evaluation method is rather troublesome and cumbersome, a teaching quality evaluation method of BP neural network optimized by FOA based on human-computer interaction is proposed by introducing the attribute mathematics theory into teaching quality evaluation and using the good global optimization ability of FOA based on experts' scores. Methods: The single-index evaluation and multi-index evaluation of teaching quality are realized through the attribute mathematics theory. The teaching courses of Basis of Computer Engineering of 100 universities of "211 projects" such as Tsinghua University and Peking University were selected as the objects of study. Results: As shown in the experimental result, the effect of teaching quality evaluation by using the FOA-BP neural network is rather good and better than the evaluation result by using BP; with the average relative error of prediction of 0.5%, its effect is good; meanwhile, the BP neural network optimized by FOA has a quick convergence rate, which is better than that of the BP algorithm. Conclusion: The validity and reliability of teaching quality evaluation by using FOA-BP is verified.**

Keywords - BP neural network; FOA; Human-Computer Interaction; Teaching Quality; Experts Grading Method

I. INTRODUCTION

As teaching quality, which directly concerns the educational competitiveness, is an important cornerstone and precondition of sustainable development of education, how to improve the teaching quality of institutions of higher education is a current research hotspot. At present, research methods for teaching quality evaluation mainly include the questionnaire method [1], experts grading method [2] and comprehensive evaluation method [3]. Even though the questionnaire method is simple, practicable and strongly operational, its evaluation result is easily to be influenced by the questionnaire design level, sample distribution and quantity etc. Even though the experts grading method has the advantages such as strong authority, no need to collect a large number of sample data and short evaluation time, its evaluation result excessively relies on experts' experience and level. In spite of the advantages of both the experts grading method and questionnaire method combined in the comprehensive evaluation method, its whole evaluation process is time-consuming and troublesome.

In view of the weaknesses such as poor generalization ability and local optimum in BP neural network, a teaching quality evaluation method of BP neural network optimized by FOA based on human-computer interaction was proposed by introducing the attribute mathematics theory into teaching quality evaluation according to the attributes of all indexes of teaching quality evaluation and based on experts grading method.

II. EVALUATION THEORY OF ATTRIBUTE MATHEMATICAL MODEL

Suppose the data set of an evaluation object of teaching quality is *Z*, each element *x* in the data set Z needs to measure *m* indexes I_1, …, I_m. The evaluation set of elements in data set *Z* is (C_1, C_2,…, C_K). C_K (1≤k≤K) signifies the teaching quality grade or evaluation. The evaluation standards for teaching quality are shown in Table 1 [3].

TABLE 1 EVALUATION STANDARDS FOR TEACHING QUALITY

	C_1	C_2	…	C_K
I_1	$a_{10}-a_{11}$	$a_{11}-a_{12}$	⋯	$a_{1K-1}-a_{1K}$
I_2	$a_{20}-a_{21}$	$a_{21}-a_{22}$	⋯	$a_{2K-1}-a_{2K}$
…	⋯	⋯	⋯	⋯
I_m	$a_{m0}-a_{m1}$	$a_{m1}-a_{m2}$	⋯	$a_{mK-1}-a_{mK}$

A certain kind of evaluation results of elements in data set *Z* is called the attribute space *F*; the evaluation set ($C_1, C_2, \cdots, C_K$) signifies the partition of attribute space *F*; C_K signifies an attribute set or an evaluation level. $\mu_{xk} = \mu(x \in C_k)$ means that the level C_K of the judged object *x* is measured with attributes. μ_{xjk} means that level C_K of j[th] index value t_j of *x* is measured by attributes.

According to the attribute set and attribute measurement theory, μ_{xjk} and μ_{xjk} shall meet the conditions required by formula [4] (1):

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$$\mu_{xk} \geq 0, \sum_{k=1}^{K} \mu_{xk} = 1, \ \mu_{xjk} \geq 0, \sum_{k=1}^{K} \mu_{xjk} = 1 \quad (1)$$

A. Analysis on single-index attribute measurement

Let *x*'s *j*th index value is t_j. The single-index attribute measurement function of teaching quality can be determined according to Table 1, where $\mu_{xjk(t)}$ shall meet $a_{j0} < a_{j1} < \ldots < a_{jK}$ or $a_{j0} > a_{j1} > \ldots > a_{jK}$.

In this paper, let $a_{j0} < a_{j1} < \ldots < a_{jK}$ and let

$$b_{jk} = \frac{a_{jk-1} + a_{jk}}{2}, k = 1, 2, \cdots, K,$$

$$d_{jk} = \min(|b_{jk} - a_{jk}|, |b_{jk+1} - a_{jk}|), k = 1, 2, \cdots, K-1 \quad (2)$$

Then, $\mu_{xjk}(t)$, the single-index attribute measurement function of teaching quality evaluation can be expressed by the formula below [5]. In the formula, when $j = 1, 2, \ldots, m; k = 2, 3, \ldots, K-1$, any t and $\mu_{xjk}(t)$ can meet the above-mentioned relation. Write $\mu_{xjk}(t)$ as μ_{xjk}.

$$\mu_{xj1}(t) = \begin{cases} 1 & t < a_{j1} - d_{j1} \\ \dfrac{|t - a_{i1} - d_{i1}|}{2d_{j1}} & a_{j1} - d_{j1} \leq t \leq a_{j1} + d_{j1} \\ 0 & a_{j1} + d_{j1} < t \end{cases} \quad (3)$$

$$\mu_{xjK}(t) = \begin{cases} 1 & a_{jK-1} + d_{jK-1} < t \\ \dfrac{|t - a_{iK-1} - d_{iK-1}|}{2d_{jK-1}} & a_{jK-1} - d_{jK-1} \leq t \leq a_{jK-1} + d_{jK-1} \\ 0 & t < a_{jK-1} - d_{jK-1} \end{cases} \quad (4)$$

$$\mu_{xjk}(t) = \begin{cases} 0 & a_{jK-1} + d_{jK-1} < t \\ \dfrac{|t - a_{ik-1} + d_{ik-1}|}{2d_{jk-1}} & a_{jK-1} - d_{jK-1} \leq t \leq a_{jK-1} + d_{jK-1} \\ 1 & a_{jk-1} + d_{jk-1} < t < a_{jk} - d_{jk} \\ \dfrac{|t - a_{jk} - d_{jk}|}{2d_{jk}} & a_{jk} - d_{jk} \leq t \leq a_{jk} + d_{jk} \\ 0 & a_{jk} + d_{jk} < t \end{cases} \quad (5)$$

B. Analysis on multi-index comprehensive attribute measurement

Since every evaluation index has a different function in the process of teaching quality evaluation, the weight w_j will meet formula (6) when w_j is used to signify the weight of the j_{th} index. The multi-index comprehensive attribute measurement of teaching quality evaluation μ_{xk} can be deduced based on the weight of evaluation index of teaching quality w_j and the single-index attribute measurement μ_{xjk}. The comprehensive attribute measurement μ_{xk} can be expressed by formula (7) [1]:

$$w_j \geq \sum_{j=1}^{m} w_j = 1 \quad (6)$$

$$\mu_{xk} = \sum_{j=1}^{m} w_j \mu_{xjk} \quad (7)$$

To realize the attribute identification of teaching quality, all single indexes or comprehensive indexes of evaluated courses can be determined in accordance with the confidence criteria. Let the confidence no less than 80%. Judge the categories of teaching qualities evaluated to be good, moderate and poor within the confidence interval greater than 80%.

The attribute identification criteria for teaching quality are as follows [2]: generally, the evaluation set $C_1, C_2, \ldots, C_n$ is an ordered set. Set the evaluation set as C_1, C_2, C_3 as required. $C_1 = \{\text{good}\}$; $C_2 = \{\text{moderate}\}$; $C_3 = \{\text{poor}\}$. If "good" is better or stronger than "moderate", $C_1 > C_2, C_2 > C_3$. If $C_1 = \{\text{poor}\}, C_2 = \{\text{moderate}\}$ and $C_3 = \{\text{good}\}$, $C_1 < C_2 < C_3$. Suppose $C_1 > C_2 > C_3$ for the evaluation set $C_1, C_2, \ldots, C_K$. If the evaluation set $C_1, C_2, \ldots, C_K$ is an ordered set and λ is the confidence, we can know that $0.8 < \lambda \leq 1$ as per the confidence criteria. If $k_0 = \min\{\sum_{l=1}^{k} \mu_{xl} \geq \lambda, 1 \leq k \leq K\}$, it can be determined that x belongs to grade C_{k_0} or type C_{k_0}.

III. Learning Algorithm Of Bp Neural Network Optimized By FOA

A. BP neural network

BP neural network, which was first put forward by *Rumelhart* and *McCelland* [2,3], is a neural network based on reverse error propagation; its model structure is shown in Fig. 1.

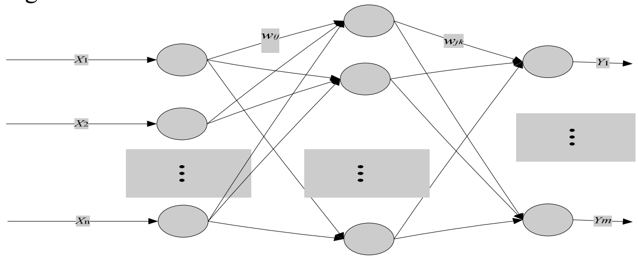

Figure. 1 BP neural network structure diagram

In Fig. 1, $X = (X_1, X_2, \ldots, X_n)$ signifies the input value of BP neural network; $Y = (Y_1, Y_2, \ldots, Y_m)$ signifies the predicated value of neural network; the algorithm flow is shown below:

Step 1: Initialize the network. Determine the number of nodes of input layer n, number of nodes of hidden layer l and number of nodes of output layer m in the neural network according to the input $X = (X_1, X_2, \ldots, X_n)$ and output $Y = (Y_1, Y_2, \ldots, Y_m)$ of neural network; initialize the connection weights between neurons of the input layer, hidden layer and output layer w_{ij}, w_{jk}; initialize the threshold value of input layer and threshold value of output layer to be a and b respectively; set the learning rate and neuron excitation function;

Step 2: Calculate the output of hidden layer. Calculate the output of hidden layer H according to the output variable X, the connection weight between the input layer and hidden layer w_{ij} and the threshold value of hidden layer a;

$$H_j = f\left(\sum_{i=1}^{n} w_{ij} x_i - a_j\right) \quad j = 1, 2, \ldots, l \qquad (8)$$

In formula (2), l signifies the number of nodes of hidden layer; f signifies the excitation function of hidden layer; set $f(x) = \frac{1}{1+e^{-x}}$ in this paper.

Step 3: Calculate the output of output layer. Calculate the predicated value of BP neural network O according to the output of hidden layer H, connection weight w_{jk} and threshold value b;

$$O_k = f\left(\sum_{j=1}^{l} H_j w_{jk} - b_j\right) \quad k = 1, 2, \ldots, m \qquad (9)$$

Step 4: Calculate the error e;

$$e = Y_k - O_k \quad k = 1, 2, \ldots, m \qquad (10)$$

Step 5: Update the weights:

$$w_{ij} = w_{ij} + \eta H_j (1 - H_j) x(i) \sum_{k=1}^{m} w_{jk} e_k \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, l \qquad (11)$$

$$w_{jk} = w_{jk} + \eta H_j e_k \quad j = 1, 2, \ldots, l; k = 1, 2, \ldots, m \qquad (12)$$

In formula (11) and formula (12), η signifies the learning rate.

Step 6: Update the threshold value;

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^{m} w_{jk} e_k \quad j = 1, 2, \ldots, l \qquad (13)$$

$$b_k = b_k + e_k \quad k = 1, 2, \ldots, m \qquad (14)$$

Step 7: Is the stopping condition for algorithm satisfied? If so, stop the algorithm; if not, return to Step 2.

B. FOA

As the Fruit Fly Optimization Algorithm (FOA), a biological optimization algorithm proposed under the enlightenment of fruit flies' foraging behavior, has the advantages such as few control parameters and quick convergence rate, it has been widely used in scientific research and engineering application currently. Its algorithm flow is as follows [6]:

(1) Set the $popsize$ of fruit flies and the maximum $Iteration$ of FOA; randomly initialize the location of fruit fly populations; the initialization results are signified respectively with X_begin and Y_begin;

(2) Determine the random optimization direction and distance of an individual fruit fly according to formula (15) and formula (16);

$$x_i = X\_begin + Value \times rand() \qquad (15)$$

$$y_i = Y\_begin + Value \times rand() \qquad (16)$$

In the formulas above, $Value$ signifies the scouting distance of fruit fly; x_i and y_i signify the location of individual fruit fly in next moment.

(3) Estimate the distance d_i between an individual fruit fly and the original point according to formula (17); later, calculate the smell concentration s_i of individual fruit fly by using formula (18);

$$d_i = \sqrt{x_i^2 + y_i^2} \qquad (17)$$

$$s_i = \frac{1}{d_i} \qquad (18)$$

(4) The smell concentration s_i is substituted into the smell concentration decision function in formula (19) to calculate the smell concentration of the current location of the individual fruit fly;

$$Smell_i = Function(s_i) \qquad (19)$$

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(5) Find out the optimum smell concentration value and optimum location in the fruit fly population; the optimum smell concentration is signified with $Smell_b$; the optimum location is signified with x_b and y_b;

(6) Keep and record the optimum location and optimum smell concentration of fruit fly; the optimum smell concentration $Smellbest = Smell_b$; the initial position of fruit fly $X\_begin = x_b$ and $Y\_begin = y_b$; meanwhile, the fruit fly population searches for the optimum location;

(7) Start the iterative optimization and repeat the iterative steps (2) – (5); meanwhile, judge whether the smell concentration is better than the iterative smell concentration of the previous generation; if so, carry out step (6).

C. Mathematical model of FOA-BP BP neural network

Due to the weight and threshold value of BP optimized by FOA, its fitness function is [7-9] to achieve the self-adaptive selection of w_{ij}, b_j on the premise of minimizing the scoring error in teaching quality.

$$Minimize\ Fitness(w_{ij}, b_j) = \sum_{i=1}^{m}(o_i^k - d_i^k) \quad (20)$$

D. FOA-BP-based teaching quality evaluation

The algorithm for teaching quality evaluation based on FOA-BP neural network is as follows [10]:

Step 1: normalize the evaluation data of teaching quality;

Step 2: set the maximum iteration (*maxgen*) and the population size (*popsize*) of FOA;

Step 3: input the constructed training samples into BP; calculate the fitness function value of individual fruit fly according to the fitness function formula (20); look for individual fruit flies and the locations and optimum values of global optimum individual fruit fly;

Step 4: update the speed and location of fruit fly;

Step 5: calculate and evaluate the fitness size and update the location and speed of fruit fly;

Step 6: if *gen>maxgen*, preserve the optimal solution; on the contrary, if *gen=gen+1*, go to Step 4;

Step 7: achieve the teaching quality evaluation according to the optimum parameters w_{ij} and b_j corresponding to the optimum location of individual fruit fly.

IV. Comprehensive Evaluation System Of Image Quality Based On Human-Computer Interaction

A. Human-computer interaction

The human-computer interaction optimization method is a method to achieve the algorithm optimization through quantitative and qualitative expressions by combining human with the computer and by utilizing the logical reasoning ability of overall effect of human's qualitative understanding and computer's qualitative expression so as to give full play to the mutual advantages of human and computer [11, 12].

B. Design framework

The diagram for design module of comprehensive evaluation system of teaching quality based on human-computer interaction is shown in Fig. 2. The comprehensive evaluation system of teaching quality based on human-computer interaction mainly consists of four modules, which are respectively the graphic interface module, index loading module, index calculation module and quality assessment.

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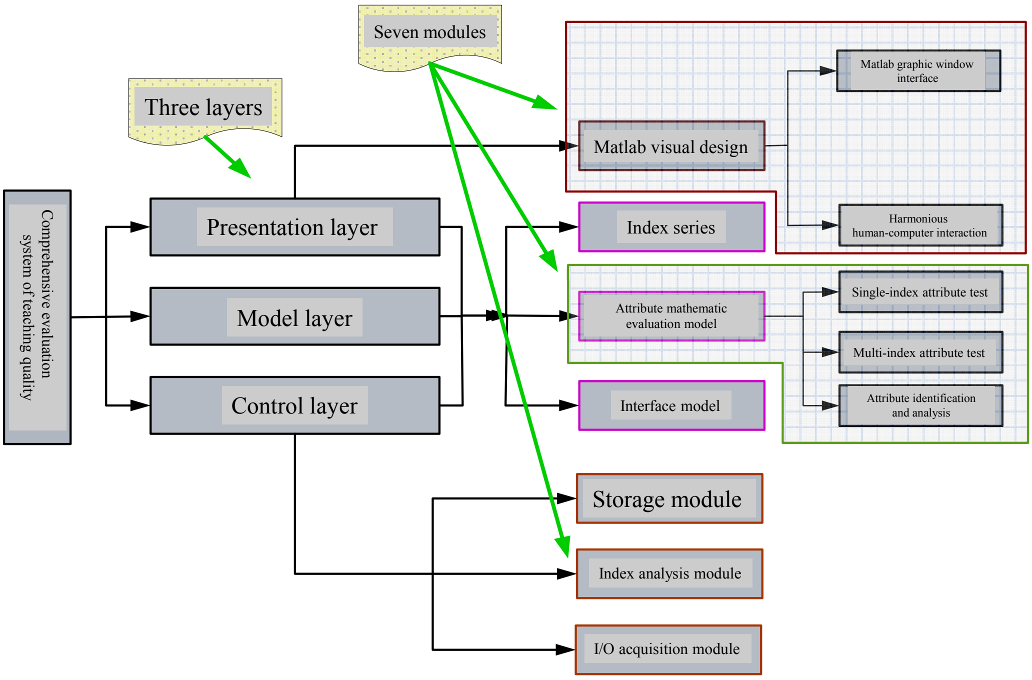

Figure 2 Evaluation system modules of image quality

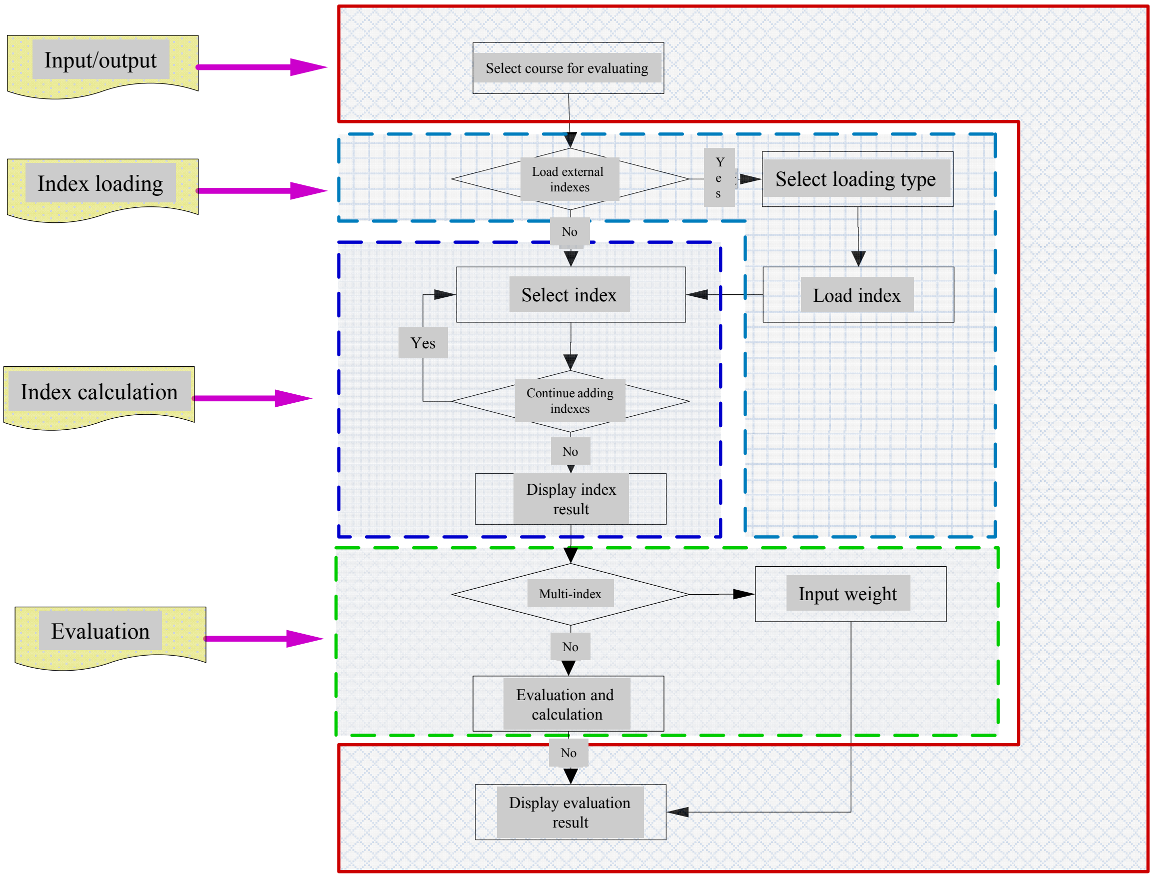

Figure 3 Diagram for functional description of comprehensive evaluation system of teaching quality

(1) Graphic interface module: mainly used to provide human-computer interactions and realize the teaching course loading, index selection, index calculation, teaching quality evaluation, result display and other functions.

(2) Index loading module: mainly used to load the evaluation indexes for teaching course, primarily including single indexes and comprehensive indexes etc.

(3) Index calculation module: mainly used to calculate the evaluation indexes of teaching quality.

(4) Quality assessment module: mainly used to realize the judgment of teaching quality grades by using the analytical results of index analysis module and by combining the attribute identification method and teaching quality evaluation set (good, moderate and poor).

V. EMPIRICAL STUDY

A. Data source

To verify the validity and reliability of this algorithm in this paper, the teaching courses of *Basis of Computer Engineering* in 100 universities of “211 project” such as Tsinghua University, Peking University, Fudan University and University of Science and Technology of China from March 2015 to June 2015 were selected as the objects of study. The evaluation indexes include the supervising experts’ teaching evaluation index system, fellow teachers’ teaching evaluation index system and students’ teaching evaluation index system [13,14]; there are 20 first-class indexes and 35 second-class evaluation indexes in total. The evaluation data about course teaching of *Basis of Computer Engineering* were obtained through experts’ grading [11] and normalized processing was carried out.

B. Evaluation indexes

To verify the validity of teaching quality evaluation by using the FOA-BP and BP algorithms, the mean square error (MSE) is used as the evaluation index; the evaluation formula [15,16] is shown below:

$$MSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K}(x_i - \hat{x}_i)^2} \qquad (21)$$

In formula (21), x_i and x_i are respectively used to signify the actual score and predicated score of teaching quality.

C. Empirical analysis

The 100 groups of evaluation data of teaching quality are divided into training samples [17,18] with 90 groups of data and test samples with 10 data. The training samples are used to build the BP neural network model while the test samples are used to verify the correctness of this model.

Set the parameters of FOA algorithm and BP neural network as follows: maximum iteration is 100; the popsize is 20; the error goal =0.0001; the maximum iteration is 10000; the prediction results are shown in Fig. 4 and Fig. 5:

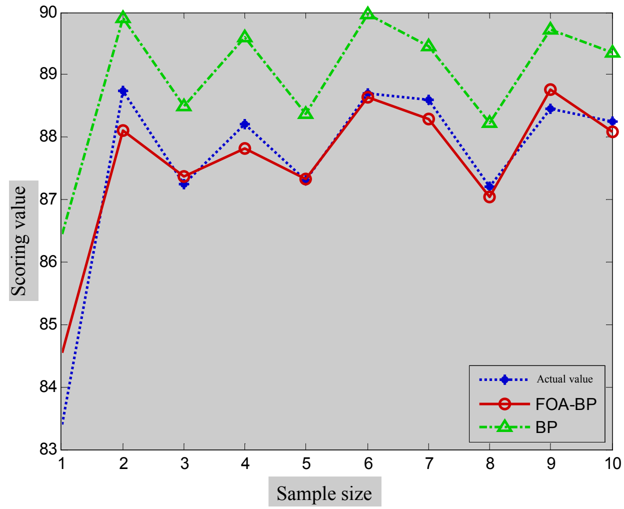

Figure 4 Evaluation results of FOA-BP and BP

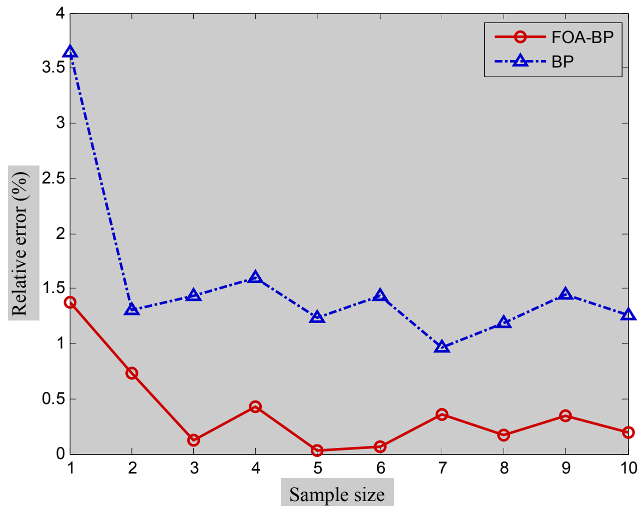

Figure 5 Evaluation errors of FOA-BP and BP

It can be seen from the prediction results in Fig. 4 and Fig. 5 that the evaluation effect of teaching quality by using the FOA-BP neural network is good and is better than the evaluation result of BP; its effect is good with the mean relative error in prediction of 0.5%. It is clear from Fig. 6 that the BP neural network optimized by FOA is quick in convergence rate and has a better result of teaching quality evaluation than BP.

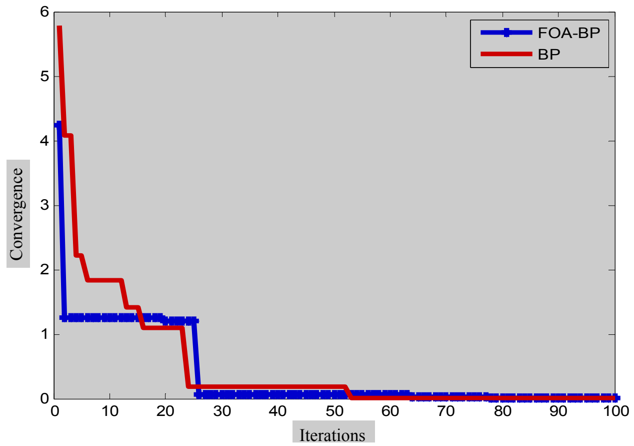

Figure 6 Diagram for convergence iteration

VI. CONCLUSIONS

The teaching quality, which directly concerns the educational competitiveness, is an important cornerstone and precondition of sustainable development of education. Since the existing teaching quality evaluation method is rather troublesome and cumbersome, a teaching quality evaluation method of BP neural network optimized by FOA based on human-computer interaction is proposed by introducing the attribute mathematics theory into teaching quality evaluation based on experts' scores. Single-index and multi-index evaluations of teaching quality are achieved through empirical analysis. As shown in the experimental result, the evaluation result of teaching quality by using the FOA-BP neural network is better than that of BP; meanwhile, with a quick convergence rate, the BP neural network optimized by FOA is superior to the BP algorithm, so the validity and reliability of teaching quality evaluation by using FOA-BP are verified and thus FOA-BP can be popularized in other fields and engineering applications.

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