Reconstruction of Human-Computer Interactive PE Classroom Instructional Quality Assessment System Based AI-powered CAD Technology

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Abstract. Improving the instructional quality of tertiary education has become the focus of current tertiary education. In the public physical education (PE) classes of universities, if the teaching process does not reflect the fitness function of PE, then the setting of PE classes in universities will not achieve the desired effect. Instructional assessment is a crucial measure to improve the quality of education and teaching, so it is essential to formulate a scientific and reasonable assessment system for classroom instructional quality in universities. To enhance the effectiveness and accuracy of instructional quality assessment in universities and reconstruct the assessment system of PE classroom instructional quality, this paper puts forward an assessment model of PE classroom instructional quality based on the Back propagation neural network (BPNN). AHP is used to construct the PE classroom instructional quality assessment index system. The comprehensive weights of each index are determined, and the initial weights and thresholds of the network are optimized by the improved particle swarm optimization (PSO) algorithm, which is one of the most popular AI-powered CAD technologies. The enhanced BPNN trains the BPNN model, the parameters of the BPNN are optimized by the genetic algorithm (GA) with adaptive mutation, and the assessment model of instructional quality is established. Whether the assessment model based on BPNN or LMBPNN is used to evaluate the quality of PE classroom teaching, it can improve the objectivity, rapidity, and accuracy of the assessment, realize the system reconstruction, and improve the instructional quality.

Keywords: BPNN; Instructional quality assessment; Physical education teaching; Physical healthcare.
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1 INTRODUCTION

With changes in people's sports consciousness, more and more college students are interested in sports, and the state attaches more importance to sports teaching. Improving the instructional quality is the eternal task of universities. At the same time, classroom teaching is the primary way to carry out education, and its quality reflects and determines the instructional quality of universities to a great extent. Classroom instructional quality assessment is a systematic project with a heavy workload and complicated statistics. The quality of teaching needs to be evaluated by a unique assessment system. Therefore, it is necessary to establish a school instructional quality assessment system. With the advent of the information age and the large number of online courses, teachers and students are now open to more than face-to-face offline courses. How to avoid the decline of instructional quality caused by online PE online courses as much as possible has become extremely urgent. BP (backpropagation), the assessment of instructional quality in Universities, is a fuzzy and complex nonlinear problem, mainly reflected in the wide range of assessment contents, many indicators, and so on. The nonlinear mapping ability of BPNN has apparent advantages, and it can be applied to the nonlinear mapping operation of complex causality. Traditional research methods generally use grey relational analysis, analytic hierarchy process, fuzzy comprehensive evaluation, and other techniques to evaluate learning levels. In this way, different evaluation factors are analyzed to some extent. Still, it is challenging to ignore subjectivity and randomness, and the analysis of nonlinear teaching levels needs to be improved. The neural network has certain advantages in solving nonlinear problems and autonomous learning. Its application in instructional quality assessment can enhance the accuracy of instructional quality assessment.

This paper focuses on the assessment of instructional quality in PE classrooms. First, the entropy method is used for the preliminary evaluation, and the assessment results are modified by the adaptive variation GA-BPNN. Then, the analytic hierarchy process (AHP) is used to construct the PE classroom instructional quality assessment index system. Determine the weight of each index, establish a BPNN for the assessment model of PE classroom instructional quality, and adopt the improved particle swarm algorithm to optimize the initial weight and threshold of the network. However, since the descending learning method adopted by the neural network (NN) is a local search, the NN quickly falls into the local minimum value, and the generalization ability is weak. On this basis, an improved algorithm LMBP model based on BPNN is constructed for instructional quality assessment, and the model is tested and trained using the Matlab NN toolbox. The results of the sample data test show that this model improves the accuracy and popularization of the assessment model structure, and it is feasible to reconstruct the assessment system of PE classroom quality. Its innovation lies in:

(1) This paper comprehensively introduces the knowledge of NN and the construction process of the BP network model, preliminarily evaluates it with the entropy method, puts forward the design of hierarchical optimization classroom instructional quality assessment index system, and studies the improved LMBP model in detail according to its limitations;

(3) The PE classroom instructional quality assessment system's NN assessment system is preliminarily reconstructed, including model design, network structure, learning parameters, and learning algorithm.

This paper studies the reconstruction of the PE classroom instructional quality assessment system based on BPNN. The structure is as follows:

The first chapter is the introduction. This part mainly expounds on the research background and significance of classroom instructional quality assessment based on BPNN and puts forward this paper's research purpose, method, and innovation. The second chapter summarizes the related literature, analyzing and summarizing the advantages and disadvantages and putting forward the research ideas of this paper. In chapter three, the knowledge of NN is comprehensively introduced from the related theories and technologies, and the principle, model construction, and learning algorithm of NN are emphatically discussed. Several methods to improve the shortcomings of the learning algorithm are put forward, and the algorithm is introduced in detail, which lays the foundation for the follow-up experimental work. The fourth chapter is the method part, which focuses on the improved method based on BPNN. The model is the overall method from the initial use of the entropy method to BPNN and then to the enhanced algorithm LMBP. The fifth chapter is the experimental analysis. Starting from the application of NN theory, a college classroom instructional quality assessment system based on NN is designed. This part is experimentally verified in the data set, and the model's performance is analyzed. Simulation software is used to verify the NN assessment system established by the experiment. Chapter VI, conclusions and prospects. This part reviews the study's main contents and results, summarizes the research conclusions, and points out the direction of further research.

2 RELATED WORK

The content of classroom instructional quality assessment is relatively extensive. Currently, there are four main methods of classroom instructional assessment: the traditional index weighted average method, the analytic hierarchy process, the fuzzy comprehensive assessment method, and the BPNN assessment method.

There are two representative index systems abroad: Michele's index system of teachers' instructional quality and the other is Babanski's assessment index of teachers' teaching. Both listed the quality assessment in detail and formulated the corresponding multi-level scoring standards, making the assessment indicators more operable. However, there is no strict definition of the assessment index system in China, which the school educational administration department generally formulates. Li Yingmei, etc., used the stage assessment model and various assessment methods to establish an assessment system of college teachers' classroom instructional quality based on the information platform to improve the quality of talent cultivation in universities. However, the assessment index constructed by this method has low coverage and limitations, leading to unsatisfactory assessment results. These traditional index-weighted average methods can not prove whether there is linear additivity between various assessment factors, nor can they prove the rationality of the weight obtained from experience: Xu Hui et al. Introduced the analytic hierarchy process in the assessment of the quality of information-based teaching in Universities, used this method to construct the quality assessment index in information-based teaching, and realized the practical assessment of instructional quality with the help of questionnaire survey and fuzzy comprehensive assessment model, However, when multiple assessment experts give different judgment matrices, analytic hierarchy process cannot get a practical ideal value structure: fuzzy comprehensive assessment method will get different judgment matrices due to the inconsistency of other experts, to get inconsistent assessment results. The above three methods all require a linear relationship between the assessment indexes. Therefore, this paper aims to solve the nonlinear BP model well.

This paper will explore and study its improved algorithm based on BPNN, such as the LMBP model, and construct a new classroom instructional quality assessment system for instructional quality assessment.

3 METHODOLOGY

3.1 BPNN

3.1.1 BP basic structure of NN

BPNN (Back Propagation) is a multi-layer feedforward NN composed of various neurons. As a feedback propagation network, similar to the human brain, it mainly comprises an input, hidden, and output layer. BPNN suits high-complexity problems and has good self-learning and self-organizing capabilities. There is no characteristic of feedback connectivity between layer neurons. The pioneering supplementary structure of BPNN is shown in Figure 1.

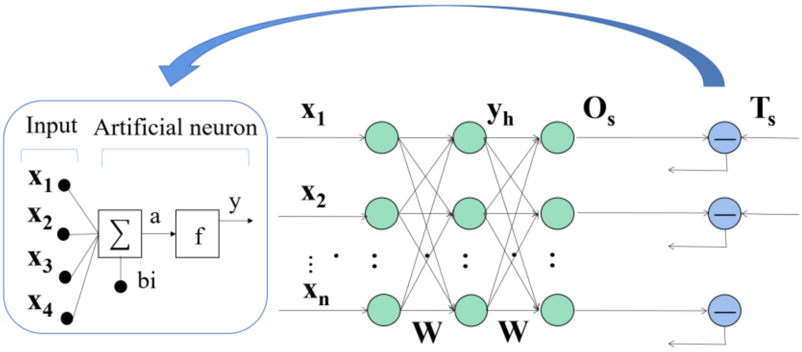

Figure 1: Topological structure of NN.

According to the structural analysis of the above figure, the input signal is represented by x_i, the node output of the hidden layer is mainly defined by h_y, the production of the output node is primarily represented by O_s, the expected output is T_s, and the given sample number is n, N1, N2, and N3, which are the number of input, hidden layer nodes, and output nodes, respectively. The function of nonlinear classification can be achieved by adjusting the connection weight and network scale in BPNN. BPNN can do nonlinear mapping and parallel distributed processing. Adjusting the connection weights and network scale in the BPNN can achieve the function of nonlinear classification. The BPNN has nonlinear mapping ability and parallel distributed processing ability. The nonlinear mapping ability refers to the ability of the NN to be arbitrarily accurate. The approximation of the nonlinear function, using the sample set to train it, that is, to learn and adjust the weights and thresholds of the network, so that the network can capture the input-output mapping relationship, the trained network, the parallel distribution processing capability refers to In the NN, the information distribution storage and processing are carried out at the same time, so that the BPNN has strong fault tolerance, and the processing speed is faster. From the point of view of function fitting, the generalization ability function shows that the network has an interpolation function. Colleague. The BPNN also functions as a multivariable system. The output and input data of the NN have the characteristics of being changeable, which can not only provide conditions for the univariate system but also provide a description method for the multivariate system.

3.1.2 BPNN calculation method

The primary calculation method of BPNN is based on the error correction principle. The gradient descent method reverses the network output error, and the network's connection weight is corrected and changed to minimize the error. Taking the three-layer NN as an example, the network has X1 inputs and X3 outputs, and the hidden layer has X2 neurons. The whole learning process can be divided into steps, as shown in Figure 2.

3.2 Improve GA-BPNN

Although the BP neural algorithm has high fault tolerance, its gradient descent algorithm makes it easy to make complex optimization objectives fall into the local minimum. The global search characteristic of GA is often used to optimize the weights and thresholds of NNs to overcome the shortcoming that NNs based on the gradient descent method are prone to fall into local optimization.

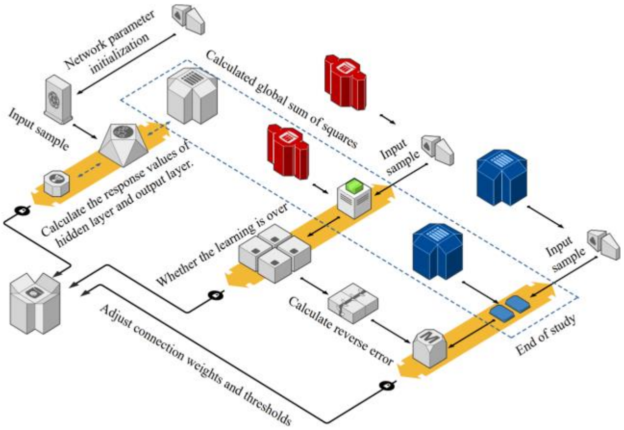

Figure 2: Neural network training flow chart.

This paper further studies its improved algorithm uses the entropy method for preliminary assessment and uses adaptive mutation GA-BPNN to modify the assessment results.

3.2.1 Entropy method

Using the entropy method to determine index weight based on data can overcome the randomness and subjectivity that the subjective weighting method can't avoid. The entropy method is first used to determine the index weight and make a preliminary assessment of instructional quality. The assessment result is taken as the target vector. Then, the improved GA is used to optimize the BPNN model for correction, and the learned and trained NN model is used for formal assessment.

Calculate the normalized data using the entropy method and get the initial assessment results. The calculation steps of the entropy method are as follows:

(1) Standardization of raw data:

$$x_{\mathrm{ij}} = \left(x_{\mathrm{ij}} - \overline{x}\right)/s_j \tag{1}$$

In the formula: x_{i_j} is the score of the i-th sample in the j-th index, $\overline{x}$ and s_j are the mean and standard deviation of the j-th index, respectively.

To meet the requirement of logarithm in the entropy method, the normalized numerical translation is:

$$\mathrm{Z_{ij}} = \mathrm{x_{ij}} + \mathrm{A} \tag{2}$$

Where: is the value after translation; A is the translation length.

(2) Calculate the entropy value of the jth index:

$$E_j = -k \sum_{i=1}^{10} p_{ij} \tag{3}$$

(3) Calculate the difference coefficient of the jth index as:

$$G_j = 1 - E_j \tag{4}$$

(4) Calculate the instructional quality Fi of the ith sample as:

$$F_i = \sum_{j=1}^{m} M_j p_{\mathrm{ij}} \tag{5}$$

3.2.2 GA optimization NN and its improvement

GA Optimization Neural Network and Its Improvement In this study, the mutation operation in GA is improved. The mutation operation helps to maintain the diversity of the GA population. The mutation probability is obtained through experience and continuous experiments [6]. The calculation method of the adaptive mutation probability P adopted is:

$$P = (P_1 + P_2)/2 = (P_0 - P_{\min}) \times F/\max_{x_i} F(x_h)/2 \tag{6}$$

Where: m is the most significant evolutionary algebra; M is the current evolutionary algebra; P_1 is inversely related to evolutionary algebra; P_2 is inversely proportional to the average fitness value; P_0 is the assumed initial mutation probability; $P_{\min}$ is the minimum value of the variation probability range; F is the average fitness value of the current population.

3.2.3 Intelligent instructional quality assessment model

The entropy method, the improved GA, and the NN are combined to establish an intelligent instructional quality assessment model, and the adaptive mutation probability is used in the genetic operation process, which not only improves the speed of NN convergence but also reduces the training process. Complexity. The model not only exerts the advantages of improving the global search of GA and BPNN in nonlinear mapping but also reduces the influence of unfavorable factors such as subjective randomness and uncertainty of thinking of traditional methods.

3.3 LMBPNN

LMBPNN, a deformation of Newton's method, is specially used to minimize the sum of squares of errors [15]. The most critical step in the algorithm is the calculation of the Jacobian matrix, which is realized by a deformation of the algorithm, so the whole algorithm is called an algorithm, which can approach the training speed of the matrix without calculating the matrix [2]. The performance of the algorithm is stable. Among all the algorithms, the training speed is the fastest, and the number of iteration steps is the lowest. It is very suitable for online learning on the network.

3.3.1 Iterative process of LMBPNN:

(1) all inputs are submitted to the network, and the following quantity formula calculates the corresponding network output and error,

$$a^0 = p$$

$$\mathrm{a}^{\mathrm{m}+1} = \mathrm{f}^{\mathrm{m}}(\mathrm{a}^{\mathrm{m}+1} + \mathrm{b}^{\mathrm{m}+1}\mathrm{w}^{\mathrm{m}}),\ \ \mathrm{m} = 0,\ \ 1,\ \ \cdots,\ \ \mathrm{m} - 1 \tag{7}$$

(2) Calculate Jacobian matrix

First, define the initial sensitivity with the following formula:

$$\overset{\lt M}{S_q} = -F^M \eta_M^q \tag{8}$$

Then, calculate the sensitivity recursively with the following formula:

$$\overset{\lt M}{S_q} = -F^M(\eta_q^m)(W^{m+1})^{\lt m+1} S_q \tag{9}$$

The matrix form given to the gradient is as follows:

$$\Delta F(x) = 2J^T(x^{m+1})v \tag{10}$$

(3) Repeat the calculation of the sum of squares of errors $x_k + \Delta x_k$. If the new sum is less than the sum calculated in the first step, divide μ by θ and set $x_{k+1} = x_k + \Delta x_k$; go to step 1. If the error sum does not decrease, multiply μ by θ, and go to step 3. The algorithm is considered to converge when the magnitude of the gradient is less than a given value or the sum of the squares of the errors is reduced to a specific target error.

3.3.2 Steps of LMBPNN

At the beginning of training, the learning rate η takes a smaller value: $\eta = 0.001$. If E cannot be reduced in a particular step, multiply η by 100 and repeat this step until the value of E decreases. If a specific step produces a minor E, multiply η by 0.01 and continue running. The execution steps of the algorithm are as follows:

(1) Initialize algorithm parameters and randomly initialize the particle swarm's initial position and speed. The number of neurons in that input layer, the middle layer, and the output layer of the LMBPNN is selected as N1, N2, and N3, which is the topological structure of the LMBPNN.

(2) Select the sample data (including training and testing) of PE classroom instructional quality assessment, normalize the sample data, calculate the fitness function value of each particle in the particle swarm, and use the NN output error E as the fitness function of the particle swarm algorithm:

$$E = \frac{1}{n}\sum_{j=1}^{n}\left(B_{jk} - A_{jk}\right)^2 \tag{11}$$

(3) For the fitness value of each particle, if its value is better than the particle fitness function value of the global best position, the particle position is the current international best position;

(4) The improved BPNN is adopted. The BPNN is trained according to formulas (1) and (2), and the connection weight and threshold of the BPNN are continuously adjusted until the set maximum training times or the network output reaches the minimum error accuracy requirements.

(5) Input the test samples into the trained LMBPNN to evaluate the quality of PE classroom teaching. The iterative process of the algorithm is shown in Figure 3.

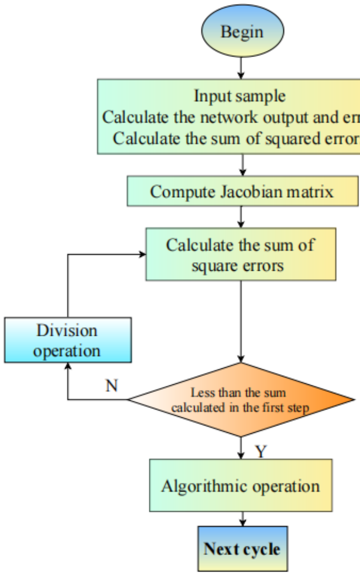

Figure 3: Iterative flow chart of LMBPNN.

4 RESULT ANALYSIS AND DISCUSSION

Therefore, compared with programs using C or Fortran for numerical calculation, it can save much programming time. The design process of this experiment is as follows: according to the entropy method mentioned before, the hierarchical assessment system of instructional quality is improved, and the quantitative assessment index scale of classroom instructional quality in universities is obtained. The sample data is obtained through an online assessment of students, and then the sample data is normalized [19]. Set the learning rate, learning times, and error precision, start the NN training, and stop the training when the obtained error meets the requirements or the training times reach the maximum. After the training, the corresponding NN model is generated, the test data is read in, and the test data is simulated and calculated.

After constructing the NN model, we analyze the instructional assessment results of 10 college teachers. The assessment result is that students grade each index according to the assessment index, and the maximum score of each index is 10 points. After evaluating the individual scores of each index, the sample of student scores can be seen in Table 1. Then, use the linear weighting method to calculate the final score of each teacher. To reduce the demand for the network for samples, the final score data for each teacher will be normalized. The normalized calculation formula is:

$$= \frac{x-\min}{\max-\min} \tag{12}$$

The scores after processing are shown in Table 1.

Sample	Assessment indicators									Comment target
	X1	X2	X3	X4	X5	X6	X7	X8	X9	
1	0.57	0.29	0.06	0.13	0.24	0.45	0.81	0	0.03	0.29
2	0.41	0.84	0.62	0.35	0.62	0.47	0.92	0.08	0.44	0.68
3	0.62	0.6	0.95	0.58	0.01	0.06	0.76	0.75	0.26	0.66
4	0.32	0.86	0.99	0.83	0.59	0.24	0.71	0.16	0.01	0.67
5	0.9	0.75	0.92	0.26	0.01	0	0.3	0.51	1	0.52
6	0.71	0.53	0.9	0.97	0.5	0.83	0.86	0.86	0.12	0.83
7	0.44	0.47	0.17	0.11	0.69	0.36	0.02	0	0.23	0.45
8	0.46	0.4	0.81	0.6	0.12	0.06	0.16	0.03	0.75	0.54
9	0.32	0.75	0.97	0.27	0.33	0.97	0.39	0.37	0.9	0.73
10	0.42	0.76	0.19	0.32	0.82	0.27	0.34	0.13	0.31	0.56
11	0.52	0.84	0.29	0.81	0.04	0.81	0.58	0.76	0.82	0.75
12	0.25	0.77	0.78	0.51	0.64	0.74	0.64	0.36	0.21	0.69

13	0.04	0.32	0.4	0.17	0.71	0.63	0.03	0.88	0.87	0.61
14	0.3	0.35	0.12	0.13	0.67	0.33	0.92	0.52	0.26	0.56
15	0.11	0.69	0.49	0.38	0.5	0.44	0.99	0.42	0.64	0.67

Table 1: Student assessment data.

In this paper, the first 10 data in Table 1 are taken as training data, and the last five are taken as test data. Trainlm [11] is selected as the learning algorithm. After ten training sessions, the NN error meets the requirements (See Figures 4 and 5).

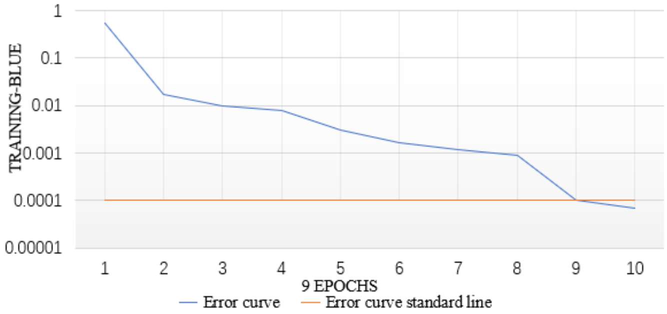

Figure 4: Training results (the training function is: train lm).

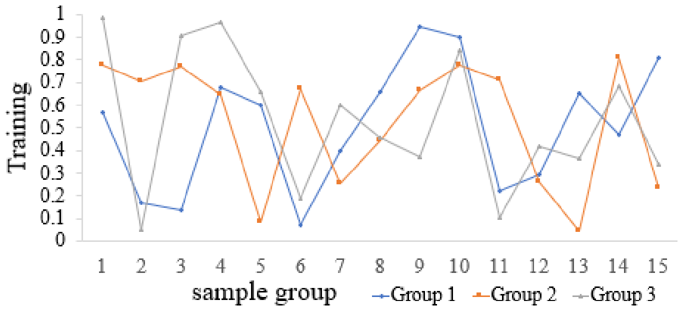

Figure 5: Error curve.

The binary nonlinear functions are fitted by comparing the traditional BPNN and the improved LMBPNN based on BP. Under the MATLAB platform, the input and output data are randomly 2000 pairs by the program. The first 1900 groups are used as training samples, and the last 100 data groups are tested. The prediction error curves of the two networks show that the optimized LMBP prediction error has been dramatically improved, so it is entirely feasible to use it in the assessment of classroom instructional quality.

From the data in Figure 6, the actual assessment curve of PE classroom instructional quality obtained by this paper's method is consistent compared with the ideal assessment curve. The curve begins to converge. It can be seen from Figure 7 that with the continuous increase in the number of iterations, the fitness value shows an increasing trend.

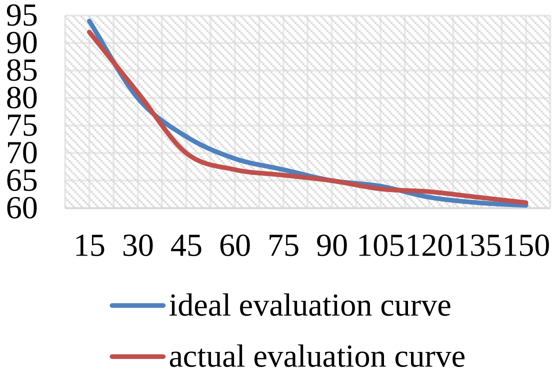

Figure 6: Mean square error and curve.

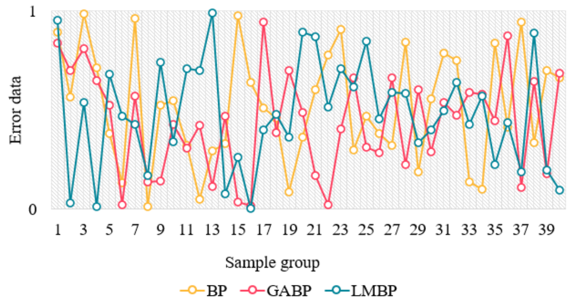

Figure 7: Error data of BP and improved algorithm.

The actual and ideal assessment curves show the same change trend, with a slight deviation. When the iteration is 95 times, the curve begins to stabilize. The experimental results show that the LMBPNN can effectively improve the assessment accuracy of PE classroom instructional quality. When iterating 95 times, the LMBPNN has the best performance.

Five classes were randomly selected in a university, and the instructional quality of each class was evaluated using this method. The accuracy of the assessment results was analyzed by comparing them with the actual assessment results. The experimental results are shown in Figure 7.

To realize the BPNN model, it is necessary to select high-performance numerical visualization MATLAB simulation software and establish a three-layer BPNN with 12 neurons in the input layer, one in the output layer, and eight hidden neurons. The number of training times is 1500, and the allowable error is 0.001. Five sample data and five test data are selected for verification. The results of the comparison between the two are satisfactory. The comparative analysis of the results of NN and expert assessments is shown in Table 2. It can be seen that the results of NN and expert assessment are close to each other. In addition, five groups of data prepared in advance are compared with the results of expert evaluation through simulation software to verify the experimental effect further, as shown in Figure 8.

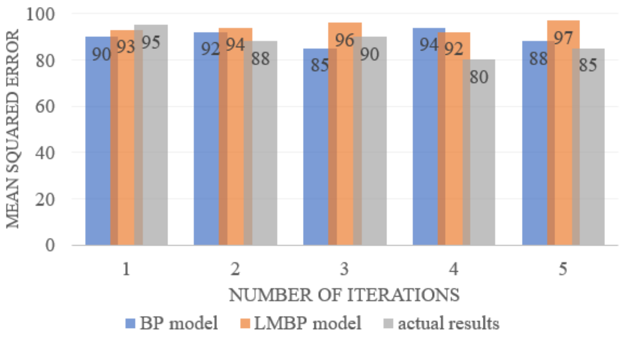

Figure 8: Analysis of the assessment results of PE classroom instructional quality.

The simulation results are similar to the assessment results given by experts, which shows that the application value of LMBPNN in the assessment of instructional quality is relatively high. It can replace manual evaluation and has a good assessment effect.

5 CONCLUSIONS

This paper proposes an assessment system for PE teaching in universities based on BPNN. The entropy method is used for preliminary assessment and adaptive mutation GA-BPNN modifies the assessment results. Then, the analytic hierarchy process (AHP) is used to construct the assessment index system of PE classroom instructional quality, determine the weight of each index, establish the assessment model of PE classroom instructional quality based on LMBPNN, and conduct simulation tests and analyses. Simulation results show that this algorithm has a sure accuracy of 9.34% higher than the previous GA. This result fully indicates that the proposed college PE instructional assessment system based on BPNN reconstruction has high accuracy and integrity, which can solve the relevant defects of BP relatively well, effectively reduce the time consumption of running programs, and improve fault tolerance. The application value of LMBPNN in instructional quality assessment is relatively high, which can replace manual assessment and has a good assessment effect. As more and more universities take the construction of PE instructional quality assessment system as the main starting point to promote PE teaching reform, it is also worth our further research and discussion to deeply understand the thinking and needs of college students and teachers on PE instructional quality assessment indicators, and further promote the construction and improvement of college PE instructional quality assessment system.

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