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PRESCHOOL TEACHERS TEACHING QUALITY EVALUATION BASED ON NEURAL NETWORK ALGORITHMS

HONGXIA CAI*

Abstract. Based on the current teaching situation of preschool teachers, in order to comprehensively evaluate the effectiveness of early childhood teaching, research have constructed a teaching quality evaluation model using fuzzy synthesis method and expert method. This model can handle the fuzzy relationship between evaluation indicators and achieve the evaluation of teaching quality. Considering that the teaching evaluation is influenced by many factors, the Genetic Algorithm back propagation (GA-BP) neural network algorithm is chosen for the solution model construction of the preschool teacher teaching quality. The entropy method chosen for the data calculation is to complete the preschool teaching quality evaluation. In the mean square error test for solving the model, the improved GA-BP model converged after 40 iterations with the model convergence speed increased by 34.65%. In the evaluation and prediction of preschool teacher indicators, the improved GA-BP model accurately evaluated the teacher classroom teaching indicators. In sample 3, sample 6, and sample 9, the improved GA-BP model scored 91, 89, and 88 points, respectively, close to the true scoring results. The improved model's accuracy was high as 90% in teacher skills, personality charm, and academic research evaluation. The improved model also effected better in the application of the preschool teaching quality evaluation. The application effect of this model in teaching effectiveness evaluation and teacher quality evaluation is good, providing valuable reference for the establishment of early childhood education evaluation system.

Key words: Preschool education; GA-BP algorithm; Teaching quality evaluation; Fuzzy comprehensive method; Entropy method

1. Introduction. China has established a complete educational and teaching evaluation system in primary and secondary education to improve the current educational and teaching effects and standardize the educational quality evaluation mechanism, meeting the requirements of educational and teaching development [1]. However, there is no relatively complete evaluation system in the current stage for the preschool teaching quality, which results in significant differences in the effectiveness of preschool education in different regions [2]. Preschool education received widespread attention from more and more parents and social figures. Improving the preschool education is crucial to ensuring the comprehensive physical and mental development of children [3]. Modern education focuses on the scientific implementation of teaching, teaching content, and teaching methods. Teachers' personal abilities and teaching concepts have an important impact on teaching development. Therefore, the expert method studying the present preschool education and the fuzzy theorem constructing a preschool teaching evaluation system are used for the preschool teaching effect. The preschool teaching evaluation is affected by environmental factors, teaching content, and the overall quality of teachers, etc., which can affect the final quality evaluation effect, the Genetic Algorithm back propagation (GA-BP) neural network algorithm is used for the preschool teaching evaluation. By adjusting the initial BP model parameters, using the GA algorithm, and introducing the entropy method to optimize sample parameters, a solution model for preschool teachers' teaching quality is constructed to achieve an effective evaluation of preschool teachers' teaching quality. The research carries referential value to promote a standardized and scientific development of modern early childhood education.

2. Related Work. Constructing a teaching evaluation system is important for the modern education, and it is a very complex nonlinear research issue. Effective teaching evaluation would directly present the preschool teaching situation, thereby achieving optimization of the educational process. Domestic and foreign experts have studied this issue. Qianna et al. found that intelligent educational evaluation methods were the key to the development of modern education. A classroom evaluating model was constructed with the neural algorithm

*Preschool Education Department, Zhumadian Preschool Education College, Zhumadian, 463000, China (Hongxia_Cai2023@outlook.com)

technology for evaluating the teaching quality, and an empirical modal method is used to improve the evaluation model. Through data testing, it was concluded that the proposed method had excellent application effects in classroom quality assessment [4]. Hou et al. analyzed the existing online education evaluation model and found that the model faced the problem of insufficient data. Neural learning models were introduced to participate in training and applied to the evaluation environment for the online teaching evaluation. After testing, this method can effectively evaluate the teaching effectiveness of universities and improve the overall evaluation effect of online education in universities [5]. Liu et al. conducted research on current English education and found that existing English education faced the problem of inaccurate evaluation in teaching quality evaluation. The existing educational content was researched, and a classroom evaluation system was constructed for college English teaching through the entropy method and clustering method. Applying this evaluation method to a college English teaching environment can effectively evaluate college English classrooms and provide an effective reference for improving college English teaching [6]. Bao et al. conducted research on existing college physical education (PE) and found that existing college physical education faces problems in online and offline quality testing. A composite PE evaluation model was constructed. The first was to clarify the objectives, influencing factors, and relevant standards of physical education, thus building a indicator system for PE. The second was to divide the importance of physical education factor indicators, simplify physical education evaluation indicators through clustering and fuzzy evaluation, and obtain the weight of each indicator. Finally, it was applied to the specific teaching. The test showed that this method can evaluate the online and offline PE and meet the PE teaching requirements of physical education and teaching [7].

Neural network algorithm technology is widely used in education with a positive impact. PoL et al. conducted research on existing neural network technology and found that neural network technology had good application value in the field of quality assessment. Therefore, neural network technology is applied to construct a classroom education evaluation system in the existing educational environment for evaluating teachers' teaching quality. Applying this method to specific teaching data samples can accurately evaluate classroom teaching effectiveness and meet the development requirements of education [8]. Pag et al. conducted research on the existing biological field. Bioinformatics is a complex and systematic engineering, and the existing evaluation system cannot effectively evaluate the effectiveness of biological education. A common method was to combine multiple research results and construct different output features based on experts in different fields. A protein model was proposed for the problem in evaluating, and a convolutional neural network was applied for the optimization. Finally, the method was applied to a specific database, and the results showed a good evaluation effect and met the requirements of teaching development [9]. Siyan et al. conducted research on existing teacher quality assessment methods and found that teachers' abilities cannot be quantitatively analyzed, resulting in an imbalance in final classroom teaching. A method of teacher competency assessment was proposed to solve the problems faced by current classroom education. This method was based on advanced digital twin technology and neural network technology, and it constructed a data fusion model through the data of teacher professional information. At the same time, a decision tree algorithm can analyze teacher competency data and build a competency mining model. Applying this evaluation method to the current educational environment, the results showed the accurate evaluation of teachers' abilities [10].

According to their research, teaching evaluation can effectively reflect teaching characteristics and provide an important basis for teaching optimization. The development of neural networks and other technologies used in the education evaluation significantly improved its shortcomings and improved the teaching evaluation, which has important research significance for modern education development.

3. Preschool teaching evaluation model construction based on the neural network algorithm.

3.1. Preschool teaching evaluation model construction. Preschool teachers' teaching level directly affects the effectiveness of education implementation, and it is particularly important to effectively evaluate the preschool teaching. Therefore, a survey is conducted in multiple preschool education institutions in a city, strictly implementing the principles of scientific, objectivity, and pertinence. Through fuzzy principal component analysis and expert methods. Among them, the expert evaluation method is a commonly used evaluation method, which invites experts from relevant fields to evaluate the teaching level of teachers, in order to obtain more accurate and objective evaluation results. In this paper, expert evaluation method is applied to determine the evaluation indicators of Preschool teacher 'teaching quality. the evaluation indicators are

Table 3.1: Teacher teaching evaluation index system

Evaluation target	Level 1	Level 2
Preschool evaluation target	Classroom teaching U1	Scientific teaching U11
		Teaching artistry U12
		Teaching effect U13
		Clear teaching objectives U14
	Teacher Skills U2	Practical ability training U21
		Innovation cultivation U22
		Philosophy Education U23
		Thinking Inspiration Cultivation U24
	Teacher personality U3	High character U31
		Responsibility attitude U32
		Professional enthusiasm U33
	Academic Research U4	Discipline cognition U41
		Teaching Practice U42
		Theoretical depth U43

identified for preschool teachers' teaching quality. The first level of indicators includes classroom teaching, academic research, teacher personality, and teaching skills. The first level indicator layer is further divided by expert method to obtain the second level indicator factors. According to the expert evaluation method, the first level indicators of Preschool teacher 'teaching quality are determined, including classroom teaching, academic research, teachers' personality and teaching skills. These indicators are obtained by inviting experts from relevant fields to evaluate the teaching level of teachers. Then, the first level indicators were further divided using expert methods to obtain the second level indicator factors. This includes various aspects of classroom teaching, such as science teaching, teaching art, and teaching effectiveness; Various aspects of teacher skills, such as practical ability training and innovation cultivation; Various aspects of a teacher's personality, such as high personality, responsible attitude, and professional enthusiasm; And various aspects of academic research, such as subject cognition, teaching internships, and theoretical depth.Table 3.1 shows the preschool teaching evaluation.

The set of factors for the preschool teaching evaluation constructed represents the factors set that affect teaching as $(U = \{U_1, U_2, U_3, U_4\})$. Based on the set of factors constructed, a corresponding evaluation set is constructed, as shown in Equation 3.1.

$$V = \{V_1, V_2, V_3, V_4\}) \tag{3.1}$$

In Equation 3.1, V_1 represents excellent, V_2 represents relatively excellent, V_3 represents qualified, and V_4 represents unqualified. Based on the established system, further analysis is needed for the factor weight [11]. Considering that evaluation factors directly affect the teaching, the impact of different evaluation factors on teaching is vague, and it is necessary to consider the educational objectives and the students' needs. Therefore, the expert method scores the relationship between teaching quality and evaluation factors, reflecting the impact of different evaluation factors on teaching quality through scoring, and assigning corresponding weights to evaluation indicators based on the scoring. The corresponding fuzzy weight of the first level indicator pair is defined as A , as shown in Equation 3.2.

$$(A = (0.3, 0.4, 0.1, 0.2)) \tag{3.2}$$

The corresponding fuzzy weights of the secondary indicators are shown in Equation 3.3.

$$\begin{cases} A_1 = (0.2, 0.35, 0.2, 0.25) \\ A_2 = (0.28, 0.32, 0.25, 0.15) \\ A_3 = (0.3, 0.4, 0.3) \\ A_4 = (0.35, 0.4, 0.25) \end{cases} \tag{3.3}$$

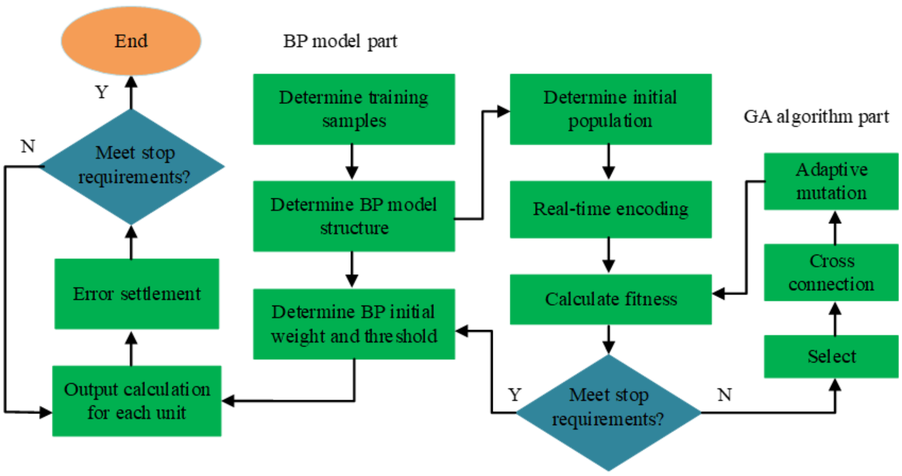


Fig. 3.1: Results of GA-BP Model Operation Process

After obtaining the fuzzy expression relationship of evaluation factors, it is also necessary to determine the fuzzy matrix relationship between evaluation factors and teaching quality. The relationship between evaluation set U and scoring set V is referred by R , the fuzzy matrix, and its relationship is shown below [12].

$$R = (r_{nm}) \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{3.4}$$

In Equation 3.4, r_{nm} is the evaluation vector, indicating the degree of the $n-$th evaluation factor subordination to the m grade. According to the fuzzy matrix relationship, the fuzzy evaluation matrix is calculated, and its calculation expression is shown in Equation 3.5.

$$B_i = A_i \times R_i \tag{3.5}$$

The expression relationship is calculated from the fuzzy matrix, and B is defined as the set of fuzzy relationship matrices for teacher teaching evaluation in Equation 3.6.

$$B = \{B_1, B_2, B_3, \ldots, B_n\}, \quad n > 1 \tag{3.6}$$

By calculating the fuzzy relational matrix of evaluation factors, a comprehensive evaluation of teachers' teaching quality can be achieved. Table 3.2 shows the final teacher index weights.

3.2. Teacher's teaching quality solving model construction based on GA-BP. In early childhood teaching, the early childhood teaching is influenced by many factors, and the traditional fuzzy evaluation method cannot effectively reflect teachers' comprehensive abilities and quality Considering that the teaching evaluation problem is non-linear, GA-BP is introduced to solve the problem. The GA algorithm optimizes the traditional BP's initialization parameters and improves its training accuracy [13]. The GA-BP model running process is shown in Figure 3.1.

Figure 3.1 is an optimization diagram of the GA-BP model, although the BP model has good solving ability in solving nonlinear problems. However, traditional BP models highly rely on initial thresholds and weights during initial training, and BP is prone to falling into local optimal solution problems during the

Table 3.2: The final teacher index weights

Evaluation target	Level 1	Level 2	Weight	Comprehensive weight
Evaluation target system of teaching quality for preschool teachers U	Classroom teaching U1	Scientific teaching U11	0.20	0.035
		Teaching artistry U12	0.35	0.045
		Teaching effect U13	0.20	0.035
		Clear teaching objectives U14	0.25	0.040
	Teacher Skills U2	Practical ability training U21	0.28	0.041
		Innovation cultivation U22	0.32	0.043
		Philosophy Education U23	0.25	0.040
		Thinking Inspiration Cultivation U24	0.15	0.025
	Teacher personality U3	High character U31	0.30	0.042
		Responsibility attitude U32	0.40	0.068
		Professional enthusiasm U33	0.30	0.042
	Academic Research U4	Discipline cognition U41	0.35	0.047
		Teaching Practice U42	0.40	0.067
		Theoretical depth U43	0.25	0.046

training process [14]. In practical optimization, the GA model is introduced to optimize the parameters of the BP model, obtaining the best fitness value through selection, crossover, and other behaviors, and using the optimization results as the training parameters of the BP model. Firstly, the rounding method determines the number of BP hidden layers, as shown in equation 3.7.

$$m = \sqrt{n + l} + a \tag{3.7}$$

In Equation 3.7, l is the total of output layer nodes, n is that of input layer nodes, and a is an arbitrary constant within 1 to 10. The number of BP model nodes has direct impact on the target variable dimensions and is represented by a hyperbolic function, as shown in Equation 3.8 [15].

$$f(x) = \frac{1}{1 + e^{x}} \tag{3.8}$$

In BP model training, the more sample data of teacher teaching quality indicators constructed, the more accurate the model training effect will be. However, there is a certain limit to the number of model training samples. If the size of the parameter setting is exceeded, the model training accuracy will decrease [16]. Therefore, in actual model training, it is necessary to reasonably select effective initial parameters and select a reasonable hidden layer model as the training model. Generally, the initial weight selection is based on the minimum initial weight, but the selected initial weight is not accurate. Therefore, genetic algorithms optimize BP's initial parameters and build a GA-BP solution model [18].

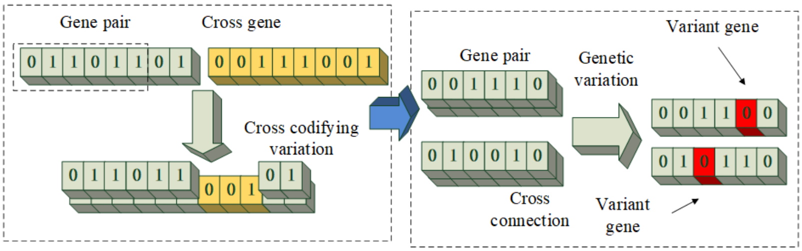


Fig. 3.2: Flow chart of gene crossover and gene mutation of GA algorithm

GA models do not directly search for feasible solutions when solving parametric problems, and require the first step of coding the feasible solutions. Effective coding will improve the global search ability of the GA model. Then, optimal gene selection is achieved through gene selection, gene crossover, and gene mutation. The crossover and mutation of genes are shown in Figure 3.2.

The training goal of GA models is to search for the initial parameter values of the minimum sum of errors in evolutionary iterations. GA models typically evolve in the direction of higher fitness. Choosing an appropriate fitness directly affects the search performance of GA models for initial parameters. Therefore, the individual error reciprocal is taken for the actual training as the fitness value, and the learning error is shown in Equation 3.9.

$$E = \frac{\sum_{k=1}^{P}\sum_{j=1}^{I}(y_j^k - o_j^k)^2}{2} \tag{3.9}$$

In Equation 3.9, $(y_j^k - o_j^k)$ represents the sample k's output error to the node j . k is P's sample number, and l is the total output nodes. According to the learning error, the fitness function of the GA model can be obtained, as shown in Equation 3.10.

$$\text{fitness} = \frac{1}{E} \tag{3.10}$$

In the research, roulette is selected as the method of selecting the GA model. The roulette method is selected based on the individual's fitness. The higher the fitness, the higher the probability of being selected, while the lower the fitness, the lower the probability of being selected. This selection method can maintain a proportional relationship of fitness, making individuals with high fitness more likely to be selected, thereby increasing the probability of retaining excellent individuals. First, the BP's initial parameters fitness value is calculated for individual genetic individuals, and the proportion of this value in the overall fitness value is calculated as the probability of individual selection. Then, the optimal individual value is obtained through crossover and mutation and chosen as BP's initial threshold and weight parameters [17].

When training sample data in the GA-BP model, the normalized data is processed through the entropy method for model's training effect. Equation 3.11 shows the standardized indicators of teaching evaluation.

$$x'_{ij} = \frac{x_{ij} - \bar{x}}{s_j} \tag{3.11}$$

In Equation 3.11, x_{ij} is the $i-$th evaluation indicator sample score on the $j-$th indicator factor, x'_{ij} represents the standardized value, $\bar{x}$ represents indicators' mean value, and s_j represents the standard deviation. Sample data also requires translation operations to meet training requirements on standardized data, as shown in Equation 3.12 [19].

$$Z_{ij} = x'_{ij} + A \tag{3.12}$$

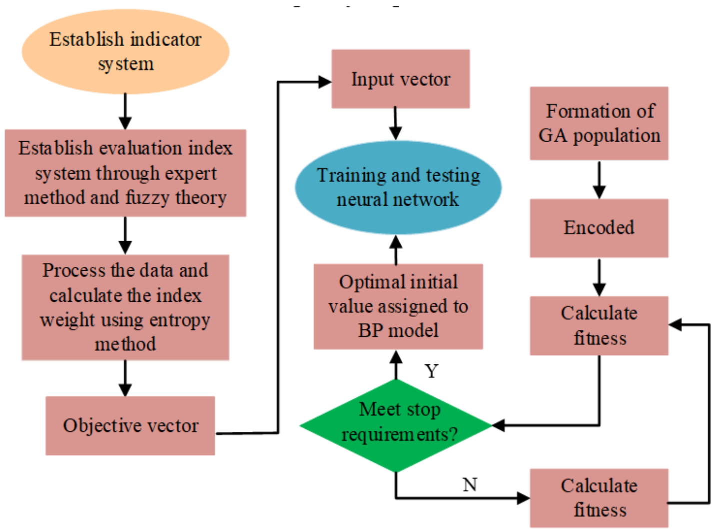


Fig. 3.3: Flow chart of preschool teaching quality evaluation model

In Equation 3.12, Z_{ij} represents the value after the translation operation, and A represents the translation length. Due to the differences among the preschool teaching evaluation indicators, it is also necessary to conduct a quantitative operation of indicator similarity, as shown in Equation 3.13 [19].

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{m} Z_{ij}} \tag{3.13}$$

In Equation 3.13, p_{ij} represents the proportion of the j index factor in the $i-$th evaluation index. The abnormal index coefficient of item j represents G_j , and if the abnormal index coefficient is normalized, the index weight of item j is as shown in Equation 3.14.

$$w_j = \frac{G_j}{\sum_{j=1}^{n} G_j} \tag{3.14}$$

According to the index weight in Equation 3.14, the $i-$th index sample can be calculated, as shown in Equation 3.15.

$$F_i = \sum_{j=1}^{n} w_j p_{ij} \tag{3.15}$$

The GA-BP model is used to construct a solution model for evaluating the preschool teaching. The teaching evaluation flowchart for the quality of preschool teachers is shown in Figure 3.3.

Due to the initial parameterization problem affecting the training accuracy faced by the BP model during training in the GA-BP model, the GA algorithm optimizes the BP's parameters for its training effect. Considering the interference of value differences on quality evaluation, the entropy method is adopted for the index deviation reduction, thereby improving the GA-BP's training.

4. Algorithm model simulation test. In the constructed preschool teaching evaluation, the number of primary indicators was 4, and that of secondary was 14. The indicators needed to be distributed to parents of young children and experts in the field of early childhood for scoring, with a total of 500 samples. The collected sample data needed to be standardized to obtain experimental training data, with a total of 1200 experimental sample data, The collected sample data needs to be standardized in order to obtain experimental training data, including 800 training sets and 400 testing sets. Table 4.1 shows some sample data information.

Table 4.1: Sample data after GA-BP standardization

Sample No	Classroom teaching	Teacher Skills	Teacher personality	Academic Research
1	0.86	0.78	0.86	0.82
2	0.86	0.65	0.56	0.75
3	0.84	0.87	0.68	0.68
4	0.71	0.45	0.78	0.82
5	0.68	0.74	0.68	0.71
6	0.68	0.82	0.75	0.68
7	0.85	0.74	0.82	0.71
8	0.65	0.67	0.75	0.82
9	0.72	0.68	0.82	0.83
10	0.75	0.68	0.72	0.72
11	0.85	0.75	0.62	0.48
12	0.71	0.72	0.81	0.75
13	0.82	0.80	0.75	0.82
14	0.75	0.82	0.82	0.75
15	0.72	0.68	0.72	0.81

Table 4.2: Parameters of improved GA-BP model training model

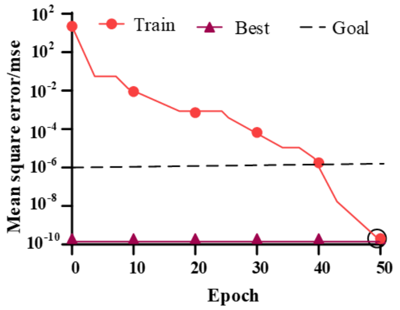
Model training parameters	Parameter value
BP model input layer node	15
Output layer node	1
Number of hidden layers	5
Maximum Iterations	100
GA model encoding length	80
GA model size	20
Cross probability	0.66

To verify the improved GA-BP's application in the evaluation of preschool teachers' teaching quality, the data in Table 4.1 were selected for model training. The test platform was Windows 10, with 64G of memory, an I7 64 core processor, and a graphics card NVIDIA RTX3080. Table 4.2 shows the training parameters.

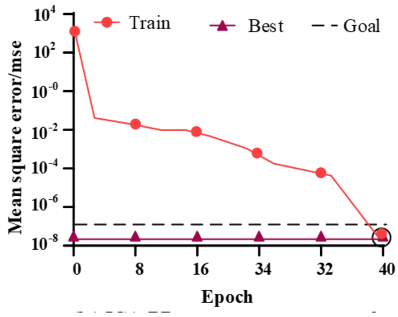
The simulation training of the preschool teaching evaluation was completed on the Matlab 2016 platform, and the mean square error training effects of the improved GA-BP model and the GA-BP model were compared. If the mean square error is smaller, the training accuracy will be higher. The training effect will be closer to the actual evaluation results of preschool teachers, as shown in Figure 4.1.

Figure 4.1a shows GA-BP's mean square error test results. From training curve changes, the GA-BP model converged after 50 iterations, and the model iteration speed was slower during the 10th to 40th iterations. After 40 iterations, the GA-BP model reached a training target position. The use of genetic algorithms to optimize BP's initial parameter performance significantly improved its accuracy. Thus, the GA-BP model accelerated its training speed after 40 iterations, converged after 50 iterations, and obtained the optimal training value. At this moment, the MSE value was 10-10. Figure 4.1b shows improved GA-BP's mean square error results. Using the entropy method to optimize training data during model training can improve the GA-BP model to converge faster and achieve higher accuracy values. The improved GA-BP model tended to converge after iteration 40. At this moment, the optimal MSE value was 10-8. The improved GA-BP model improved the convergence speed by 34.65%. Figure 4.2 shows the fitness training results of the two models.

Figure 4.2a shows the fitness value training results of the GA-BP model. According to the trend of training curve changes, the GA-BP model had a faster training speed during the first 40 iterations and gradually tended to a stable state after 40 iterations. After 80 iterations, the GA-BP optimal fitness curve tended to converge, and the average fitness curve coincided with the optimal fitness curve. At this moment, the optimal fitness

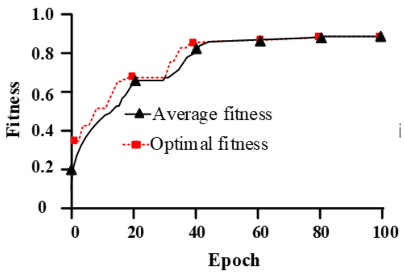


(a) GA-BP mean square error result

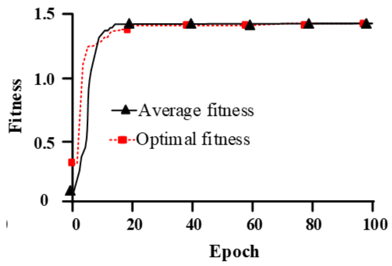


(b) IGA-BP mean square error result

Fig. 4.1: Main Figure Caption



(a) GA-BP model fitness



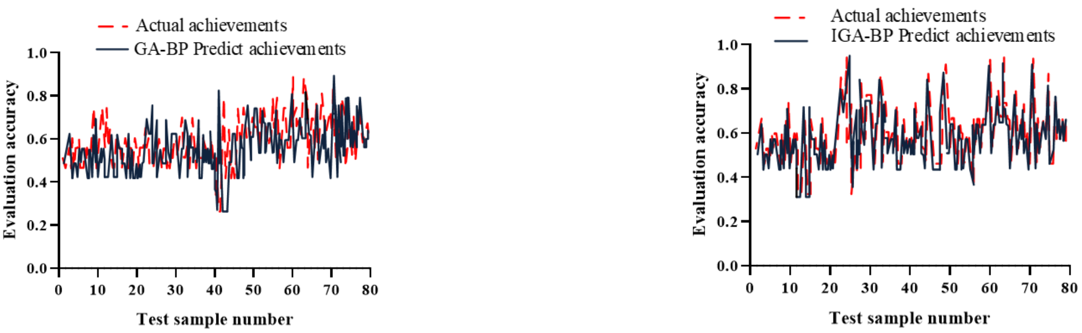
(b) IGA-BPmodel fitness

Fig. 4.2: Fitness training results of two solving models

value was 0.856. Figure 4.2b shows the fitness value training results. The improved GA-BP model tended to converge after 20 iterations, and the optimal fitness value was 1.452 at this moment. The improved GA-BP model can obtain the optimal fitness value faster, while the fitness value was higher, which showed its better individual optimization ability. In Figure 4.3, the preschool teaching evaluation prediction are shown.

Figure 4.3a and Figure 4.3b show the evaluation and prediction results of both. Among them, the red dotted line is the actual result of sample evaluation, and the black solid line is the model training prediction result. In eighty training sets, the results of the GA-BP model had a significant deviation from the actual results. In samples 43 and 70, the prediction accuracy was less than 60%, and the average prediction accuracy was 73.85%. The improved GA-BP's average prediction accuracy in 80 groups of samples was 92.65%, while in sample 43 and sample 70, the prediction accuracy was 91.61% and 90.35%. The improved GA-BP's sample training accuracy increased by 39.65%. The prediction results of preschool teacher evaluation index scores are shown in Fig. 4.4.

Four types of primary indicator data for preschool teachers were selected for testing, and the number of model iterations was 100 to test the predictive effect of the two models on teacher performance scores. In Figure 4.4, the green line represents the actual grading results of preschool teachers, the red line represents the GA-BP's grading results of preschool teachers, and the blue line represents the improved GA-BP's grading results of preschool teachers predicted. Figure 4.4a shows the predicted scoring results of classroom teaching ability indicators. According to the curve changes in the figure, the actual teacher scores were 92, 90, and 89, respectively in sample 3, sample 6, and sample 9. There was a significant difference between the GA-BP model and the actual scoring results of preschool teachers. Its scores in samples 3, 6, and 9 were 70, 70,



(a) GA-BP Prediction

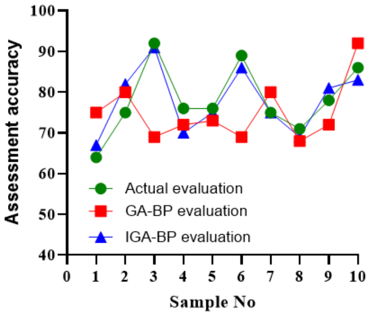
(b) IGA-BPmodel Prediction

Fig. 4.3: Preschool teaching evaluation prediction

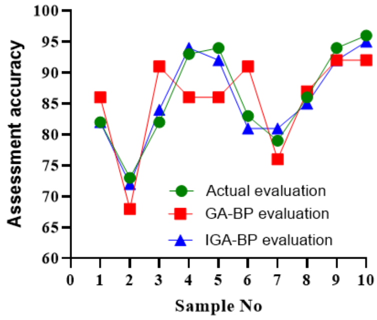
and 72, respectively. The improved GA-BP's scores were 91, 89, and 88, respectively, indicating that it was more accurate in scoring teacher teaching indicators. Figure 4.4b shows the predicted results of teacher skill index scores. According to the scoring results, the GA-BP model scored 91 points, 86 points, and 86 points, respectively in sample 3, sample 4, and sample 5, while the improved GA-BP model scored 72 points, 93 points, and 94 points, respectively. Compared with the actual scoring results, the GA-BP's accuracy rate is 82.65%, while the improved GA-BP's accuracy rate is 94.65%. The predicted results of teacher personality charm index scores are shown in Figure 4.4c. The personality charm index is influenced by many factors, including teacher affinity, emotional state, and moral quality, which further tests the training and analysis ability. Based on the change results of the curve, the GA-BP model had a significant error in evaluating teachers' personality charm indicators, with a scoring accuracy of 76.65%, while the improved GA-BP model had a scoring accuracy of 90.35% for teachers' personality charm indicators. For example, there was a significant difference between the GA-BP model and the actual scoring results of teachers in Sample 2, 4, 5, 6, and 8 with the accuracy rate of the evaluation results being less than 70%, which cannot meet the quality evaluation requirements. The prediction results of teacher academic research index scores are shown in Figure 4.4d. In sample 4, 5, and 7, the GA-BP model scored 75, 81, and 70 points, respectively, while the improved GA-BP model scored 85, 90, and 80 points, respectively. The improved GA-BP model training curve results were closer to the actual teacher scoring results, with a scoring accuracy of 94.65%, while the GA-BP model scoring accuracy rate was 82.65%. Table 4.3 shows the final scoring results of some preschool teachers' teaching quality.

In Table 4.3, the GA-BP model performed the worst in the preschool teaching evaluation. For example, the overall scoring accuracy of the GB-BP model was lower than 80% in sample 2, sample 7, and sample 11 of classroom teaching indicators, and the overall scoring results were poor, unable to meet the requirements of preschool teachers' teaching quality evaluation. However, the improved GA-BP model had an accuracy rate of more than 90% for evaluating teachers' classroom teaching indicators except for sample 9, meeting teaching requirements. At the same time, in the evaluation of teacher skills, teacher charm, and academic research indicators, the improved GA-BP model had a scoring accuracy of more than 89%, while the traditional GA-BP model had a scoring accuracy of less than 80% in individual sample tests, which cannot accurately evaluate the comprehensive personal abilities of teachers. The improved GA-BP model met the evaluation requirements for the preschool teaching and had better effects in evaluation.

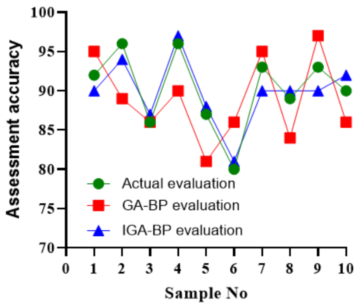
5. Conclusion. Preschool education is an important component of modern education, focusing on the cultivation of children's physical, mental, and creative abilities. The comprehensive quality level of teachers will directly affect the effectiveness of preschool education. Fuzzy theorem, analytic hierarchy, and expert method are used to analyze the current situation of preschool education, and constructs an evaluation system to improve the preschool teaching evaluation. Considering that the preschool teaching evaluation is a nonlinear problem that affects the effectiveness of quality evaluation, a genetic algorithm-optimized BP model is used to



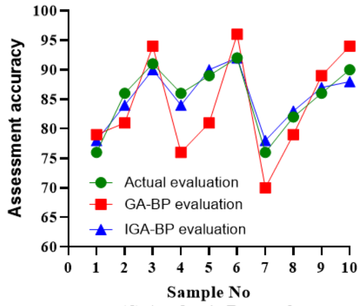
(a) Classroom teaching



(b) Teacher Skills



(c) Teacher Personality



(d) Academic research

Fig. 4.4: Predicted results of preschool teachers' index scores

Table 4.3: Final preschool teaching evaluation results

Sample No	Classroom teaching		Teacher Skills		Teacher personality		Academic Research	
	GA-BP	IGA-BP	GA-BP	IGA-BP	GA-BP	IGA-BP	GA-BP	IGA-BP
1	0.82	0.95	0.75	0.93	0.80	0.97	0.82	0.95
2	0.76	0.91	0.72	0.93	0.74	0.90	0.71	0.96
3	0.86	0.93	0.82	0.94	0.86	0.93	0.86	0.93
4	0.89	0.94	0.84	0.96	0.76	0.94	0.89	0.94
5	0.84	0.96	0.83	0.96	0.86	0.95	0.79	0.96
6	0.81	0.95	0.81	0.97	0.86	0.95	0.81	0.93
7	0.69	0.93	0.83	0.93	0.84	0.96	0.72	0.91
8	0.89	0.91	0.84	0.91	0.92	0.90	0.87	0.91
9	0.83	0.89	0.83	0.90	0.83	0.89	0.83	0.93
10	0.88	0.93	0.89	0.94	0.71	0.93	0.82	0.93
11	0.72	0.94	0.83	0.97	0.87	0.96	0.87	0.95
12	0.84	0.93	0.84	0.93	0.84	0.93	0.84	0.93
13	0.87	0.98	0.84	0.94	0.87	0.96	0.84	0.94
14	0.86	0.93	0.81	0.93	0.89	0.92	0.88	0.93
15	0.81	0.94	0.79	0.93	0.81	0.94	0.89	0.96

train indicator data and construct a GA-BP solution model. The entropy method is used for index data to optimize the training effect. When solving the fitness value, the improved GA-BP model tends to converge after 20 iterations, with an optimal fitness value of 1.452 and a fitness value of 0.856 for the traditional GA-BP model. Compared with the traditional GA-BP model, the improved GA-BP model has faster iteration efficiency and higher fitness values, proving that the improved GA-BP has better individual optimization ability. In preschool teaching evaluation, the overall prediction accuracy of traditional GA-BP is less than 80%, and the accuracy of teaching evaluation is relatively low. Except for sample 9, the improved GA-BP model has an accuracy rate of over 90% in all four primary indicators, which is superior to the traditional GA-BP model. The proposed model can accurately reflect the overall quality level of teachers. The proposed improvement GA-BP has good teaching evaluation results and meets the requirements of early childhood education development. However, there are also shortcomings in the research content. The effectiveness of preschool education is influenced by various factors, including teachers' teaching methods, students' family backgrounds, etc. Future research can comprehensively consider these factors and construct a more comprehensive evaluation system.

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