

An Evaluation Model for the Innovation and Entrepreneurship Thinking Ability of College Students Based on Neural Network

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Abstract—Mass innovation and entrepreneurship (I&E) is a national campaign in China. In this context, it is important to encourage college students to engage in I&E activities, and this calls for accurate and comprehensive evaluation of their I&E thinking ability. Therefore, this paper proposes an evaluation model for the I&E thinking ability of college students based on neural network (NN). Firstly, a reasonable evaluation index system was created for the I&E thinking ability of college students, and the evaluation indices were preprocessed through fuzzy analytic hierarchy process (AHP). Then, a fuzzy neural network (FNN) was constructed based on GA rule optimization and the specific steps of the algorithm were given. Moreover, a few representative rules were selected by GA based on uncertain fuzzy knowledge rules, a 4-layer NN model with fuzzy inputs and outputs was established, and the evaluation flow of the I&E thinking ability of college students was proposed. Finally, the effectiveness of the proposed model was verified through experiments. The research results of this paper provide a reference for the application of NN in the field of ability evaluation.

Keywords—Fuzzy neural network (FNN), college students, innovation and entrepreneurship (I&E) thinking ability, ability evaluation, genetic algorithm (GA)

1 Introduction

In the context of mass innovation and entrepreneurship (I&E) in China, the country has vigorously promoted I&E education for college students and listed it as a key education plan for colleges and universities in China. At present, higher educational schools have actively carried out related educational reform programs and taken them as the primary task of their teaching management works [1-4]. Contemporary college students are the main force of I&E in Chinese society, and a comprehensive evaluation system of college students' I&E thinking ability will play a positive guiding and encouraging role in their I&E activities [5-9]. However, judging from the status quo of the cultivation of college students' I&E thinking ability, the constructed evaluation systems are not perfect enough [10-14]. As a result, it is a very necessary work to

scientifically evaluate college students' I&E thinking ability so as to provide references for formulating I&E talent cultivation strategies for the I&E education in colleges and universities, and help college students make reasonable carrier plans based on the evaluation of their I&E thinking ability in the meantime.

Domestic and foreign scholars have carried out relevant researches on college students' I&E thinking ability, and the research results mainly focused on three aspects: the connotation and assessment of I&E ability, the evaluation system of I&E ability, and the evaluation of college students' I&E ability [14-16]. In terms of the connotation and assessment of college students' I&E ability, literature [17] defined college students' I&E ability from an overall conceptual perspective and pointed out that this ability is a comprehensive ability to evaluate the I&E methods, the knowledge and skill transformation ability, and the I&E value orientation. Literature [18] researched from the perspective of management and psychology, and proposed that I&E ability is the ability to utilize one's resources and personal features to create economic values innovatively and practically. Literature [19] believes that college students' I&E ability is a simple combination of entrepreneurial ability and innovation ability; the innovation ability refers to the transformation and application ability of innovation consciousness and innovative thinking; and the entrepreneurial ability is a collection of various abilities such as the human resource management ability, the interpersonal communication ability, and the ability to grasp opportunities, etc. In terms of evaluation system of I&E ability, literature [20] applied the grey relational model and the entropy weight method (EWM) to empirically analyze and evaluate college students' I&E thinking ability. Literature [21] used questionnaires to survey the status quo of college students' I&E ability cultivation and adopted AHP to construct an evaluation system for I&E education in higher educational schools from the three aspects of the student, the school, and the society. In terms of the evaluation of college students' I&E ability, literature [22] took engineering college students as the subjects and proposed that their I&E ability can be evaluated from a few aspects of I&E knowledge, I&E realization and mastery, practical experience, innovation motivation, desire to innovate, entrepreneurial risk tolerance, and innovative thinking, etc. Literature [23] believes that the evaluation of college students' I&E ability can be conducted from four aspects: the mastery of I&E knowledge and skills, practical experience, optimistic and firm I&E psychology, and the ability to lead, organize and coordinate. With the development of statistics and fuzzy mathematics, modern mathematical statistical methods such as multiple linear regression, factor analysis, fuzzy comprehensive evaluation, and AHP have achieved good application effects in comprehensive ability evaluation, but the evaluation results are greatly influenced by subjective factors, causing large deviations between the actual situations and the evaluation results.

Since most of the evaluation indices are non-linear data, existing researches have generally focused on the improvement of neural network structure or the complementation of optimization algorithms, and their research purposes are to improve the network efficiency and the accuracy of comprehensive ability evaluation. In order to obtain more accurate evaluation results of college students' I&E thinking ability, with relevant influencing factors and the cultivation modes of innovative talents taking into consideration, this paper proposes a novel model for the evaluation of college students' I&E

thinking ability based on neural network. The main content of this paper includes the following aspects: chapter 2 constructs a reasonable evaluation index system for college students' I&E thinking ability, and preprocesses the evaluation indexes using fuzzy AHP; chapter 3 constructs a FNN model based on GA rules, and gives the flow of the algorithm; chapter 4 constructs a comprehensive evaluation model of college students' I&E thinking ability and gives the evaluation process; at last, this paper uses experimental results to verify the effectiveness of the constructed model.

2 Construction of the Evaluation Index System

To obtain an accurate evaluation model, a reasonable evaluation index system for college students' I&E thinking ability is the prerequisite, besides, the constituent elements and evaluation emphases of college students' I&E thinking ability need to be taken into consideration, and the evaluation goals of college students' I&E thinking ability should be determined based on current society's requirements for college students' I&E ability; moreover, the structure of traditional evaluation index systems needs to be optimized. Based on existing studies of domestic and foreign scholars concerning college students' I&E thinking ability, this paper follows the principles of scientific, systematic, feasible, objective, and uniform to minimize the influence of subjective factors, and comprehensively and objectively evaluate college students' I&E thinking ability from multiple angles and dimensions. The constructed ladder-shaped system structure includes an evaluation target layer (level A), a primary index layer (level B) and a secondary index layer (level C). The primary index layer includes 4 primary indices of knowledge ability, practical ability, conscious thinking, and personal quality; and there're a total of 35 secondary indices under these primary indices.

The first layer (level-A indices): $B = \{\text{college students' I\&E thinking ability}\}$

The second layer (Level-B indices):

$B = \{B_1, B_2, B_3, B_4\} = \{\text{knowledge ability, practical ability, conscious thinking, personal quality}\};$

The third layer (Level-C indices):

$B = \{B_{11}, B_{12}, B_{13}, B_{14}, B_{15}, B_{16}, B_{17}, B_{18}, B_{19}, B_{110}, B_{111}\} = \{\text{Social practice participation, skill competition participation, mastery of technical skills, skill certificate acquisition, intellectual property acquisition, scientific research product acquisition, team building, theory transformation, network technology application, entrepreneurial practice, internship participation}\};$

$B_2 = \{B_{21}, B_{22}, B_{23}, B_{24}, B_{25}\} = \{\text{Academic performance, professional knowledge, policy understanding, interdisciplinary knowledge, basic theory}\};$

$B_3 = \{B_{31}, B_{32}, B_{33}, B_{34}, B_{35}, B_{36}, B_{37}\} = \{\text{Interest in I\&E, definite motivation, time input, cost input, innovation awareness, entrepreneurship awareness, training participation}\};$

$B_4 = \{B_{41}, B_{42}, B_{43}, B_{44}, B_{45}, B_{46}, B_{47}, B_{48}, B_{49}, B_{410}, B_{411}, B_{412}\} = \{\text{knowledge learning ability, time planning ability, learning planning ability, interpersonal communication ability, psychological quality, organizing and planning ability, divergent thinking}\};$

ability, market insight ability, teamwork ability, problem-discovering ability, problem-summarizing ability, creative thinking ability};

Aiming at the above evaluation indices, this paper adopted a fuzzy AHP method that integrated the fuzzy comprehensive evaluation method and the connotations of AHP to preprocess the evaluation indices, the specific steps are as follows:

1. First, in the evaluation process of college students' I&E thinking ability, the domain $I = \{I_1, I_2, \dots, I_n\}$ of the evaluation indices of the comprehensive evaluation schemes of higher education schools and relevant educational departments was determined, and then the domain of the related index comment level $C = \{C_1, C_2, \dots, C_m\}$ was determined as well. Wherein, I_i is basic level evaluation index in the evaluation index domain, $i=1, 2, \dots, n$. C_j is the comment level of the evaluation index, $j=1, 2, \dots, m$. Suppose the number of comment levels of college students' I&E thinking ability is m , and each fuzzy subset corresponds to a level.
2. Second, in the evaluation process of college students' I&E thinking ability, the weight vector matrix of higher education schools and relevant educational departments is $W = [\omega_1, \omega_2, \dots, \omega_n]^T$. In the formula, ω_k is the weight coefficient of the k -th index, $k=1, 2, \dots, n$. For indices of a same level in the AHP, the logarithmic least square method was adopted to calculate the weight coefficients.

$$A = \sum_{s=1}^n \sum_{t=1}^n \left[\ln a_{st} - \ln \left(\frac{\omega_s}{\omega_t} \right) \right]^2 \tag{1}$$

Each ω_k value can be obtained by solving the minimum value of A , where $s, t \in k$ and $s \neq t$; and the weight vector matrix W can be obtained after ω_k is normalized. In the evaluation process of college students' I&E thinking ability, if a comprehensive evaluation scheme of higher education schools and relevant educational departments is reviewed by a certain number of experts, namely element a_{st} in the judgment matrix has multiple values that represent different opinions, then Formula 1 can be altered to Formula 2:

$$A = \sum_{s=1}^n \sum_{t=1}^n \sum_{r=1}^N (\ln a_{str} - \ln \omega_s + \ln \omega_t) \tag{2}$$

where, a_{str} is the revised value of a_{st} , by the r -th expert, $r=1, 2, \dots, N$, and N is the number of expert reviewers. To obtain the minimum value of A , calculate the partial derivative for each weight coefficient in Formula 2, and make the sum of the partial derivative equal to zero.

3. Third, each evaluation scheme of higher education schools and relevant educational departments is subject to comprehensive evaluation, and a corresponding fuzzy relationship matrix H is established. Then, the basic-level evaluation indices $I_i (i=1, 2, \dots, n)$ of the evaluation schemes are quantified one by one, thereby, from the perspective of each single evaluation index, the membership degrees ($H_i|I_i$) of the

evaluation scheme to the fuzzy subsets of each level were examined, and the expression of fuzzy relationship matrix H is:

$$H = \left[\begin{array}{c|c} H_1 & I_1 \\ H_2 & I_2 \\ \vdots & \vdots \\ H_n & I_n \end{array} \right] = \begin{bmatrix} h_{11} & \cdots & h_{1m} \\ \vdots & & \vdots \\ h_{n1} & \cdots & h_{nm} \end{bmatrix} \quad (3)$$

where, h_{ij} is the degree of membership of an evaluation scheme to the C_j -level fuzzy subset from the perspective of evaluation index I_i .

4. Fourth, the evaluation result vector R of each evaluation scheme of the higher education schools and relevant educational departments was calculated:

$$R = W \circ H = [\omega_1, \omega_2, \dots, \omega_n]^T \circ \begin{bmatrix} h_{11} & \cdots & h_{1m} \\ \vdots & & \vdots \\ h_{n1} & \cdots & h_{nm} \end{bmatrix} = [r_1, r_2, \dots, r_m] \quad (4)$$

where, r_l reflects the degree of membership of the evaluation scheme to each fuzzy subset in evaluation index comment domain C . " \circ " is the fuzzy composition operator between matrices W and H , r_l can be expressed as:

$$r_l = (\omega_1 \cdot h_{1l}) \oplus (\omega_2 \cdot h_{2l}) \oplus \cdots \oplus (\omega_n \cdot h_{nl}) = \min \left(1, \sum_{k=1}^n \omega_k h_{kj} \right) \quad (5)$$

5. At last, the comprehensive evaluation result of each evaluation scheme was subject to weighted average processing using Formula 6:

$$CER = \frac{\sum_{l=1}^m r_l \cdot l}{\sum_{l=1}^m r_l} \quad (6)$$

where, CER is the quantified final result of the evaluation scheme of higher education schools and relevant educational departments, it represents the relative position of the evaluation scheme in the evaluation index comment domain C . The smaller the value of CER , the more ideal the position of the evaluation scheme in domain C , and this indicates that the evaluation effect of the evaluation scheme is better.

3 Construction of FNN Model Based on GA Optimization

After processed by fuzzy AHP, for evaluation index sample data with same fuzzy variable partition number, this paper constructed a FNN model based on rule optimization, Figure 1 gives the structure diagram.

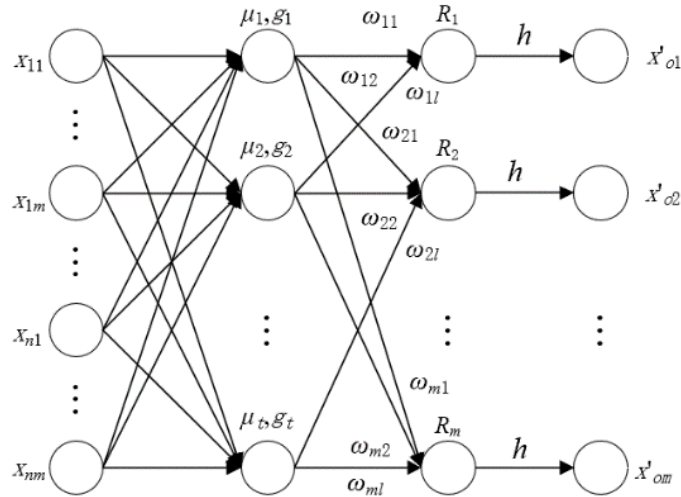


Fig. 1. FNN model based on GA optimization

The specific steps of the algorithm are as follows:

1. Determine the input nodes $(x_{11}, x_{12}, \dots, x_{1m}, \dots, x_{n1}, x_{n2}, \dots, x_{nm})$ and output nodes (x_{o1}, \dots, x_{om}) of the neural network, where n is the number of fuzzy variables, and the number of output variables m is the number of fuzzy subsets corresponding to each fuzzy variable;
2. The i -th fuzzy learning sample S can be expressed by Formula 7:

$$S = (x_{i11}, \dots, x_{i1m}, x_{i21}, \dots, x_{i2m}, \dots, x_{ijm}, x_{i1m}, \dots, x_{io1}, \dots, x_{iom}) \tag{7}$$

where, $(x_{i11}, \dots, x_{i1m}, x_{i21}, \dots, x_{i2m}, \dots, x_{io1}, x_{iom})$ is an evaluation index data sample input to the network, $(x_{io1}, \dots, x_{iom})$ is the expected evaluation result output by the network.

3. Through GA, l optimal rules (g_1, g_2, \dots, g_l) are obtained, and the distance $D=(D_1, D_2, \dots, D_l)$ between an evaluation index data sample and the l rules that represent the cluster center can be calculated:

$$D_t = \sqrt{\sum_{j=1}^n \sum_{i=1}^m (x_{ijs} - x_{rjs})} \tag{8}$$

where, D_t is the distance from an evaluation index data sample to the t -th rule, by combining with the comprehensive membership degree represented by D , the antecedents of each rule can be obtained. Suppose the maximum value of the l distance values is $\max D$, then INF_t is the influence degree of the t -th rule on the evaluation index data sample, and there is:

$$INF_t = \frac{\max D}{D_t} \tag{9}$$

Since INF_t is greater than or equal to 1, suppose $\max INF$ is maximum value among the l influence degrees, then the fuzzy membership degree μ_t of the evaluation index data sample belonging to the t -th rule (corresponding cluster center) is:

$$\mu_t = \frac{INF_t}{\max INF} \tag{10}$$

Then for the evaluation index data sample, the output comprehensive membership degree $\lambda(t)$ of the fuzzy category applying the t -th rule is:

$$\lambda(t) = (\lambda_{t1}, \lambda_{t2}, \dots, \lambda_{tm}) = (x_{t01}, x_{t02}, \dots, x_{t0m}) \cdot \mu_t \tag{11}$$

where, " \cdot " in the formula represents the multiplication operation, then λ , the sum of the comprehensive membership degrees of l rules, can be expressed by Formula 12:

$$\lambda = \sum_{t=1}^l \sum_{q=1}^m \lambda_{tq} \tag{12}$$

4. Then $\lambda(t)$, threshold θ_u and connection weight ω_{ut} are subject to network output calculation shown as Formulas 13 and 14:

$$R_u = \sum_{t=1}^l \omega_{ut} \cdot \lambda_{tu} - \theta_u \tag{13}$$

$$x'_{ou} = \frac{1}{1 + e^{-R_u}} \tag{14}$$

where, $u = 1, 2, \dots, m$. The values of threshold value θ_u and connection weight ω_{ut} can be obtained via the following two steps:

- A) If the number of iterations ε is equal to 0, the values of $\theta_u(0)$ and $\omega_{ut}(0)$ can be set randomly;
- B) If the number of iterations ε is greater than 0, the values of $\theta_u(0)$ and $\omega_{ut}(0)$ should be set according to the error correction formulas shown as Formulas 15 and 16:

$$\omega_{ut}(\varepsilon + 1) = \omega_{ut}(\varepsilon) + \Delta\omega_{ut} \tag{15}$$

$$\theta_u(\varepsilon + 1) = \theta_u(\varepsilon) + \Delta\theta_u \tag{16}$$

5. The error between the actual output (x'_{o1}, \dots, x'_{om}) and the expected output (x_{o1}, \dots, x_{om}) of the FNN is calculated by Formula 17:

$$\Delta e = \sum_{u=1}^m (x'_{ou} - x_{ou}) \tag{17}$$

After the learning of evaluation index data samples is completed, if the total error obtained by Formula17 is less than the preset error, the learning of the network model is stopped, and the values of $\theta_u(0)$ and $\omega_{ut}(0)$ should be corrected using the error correction formulas in the previous steps, and then return to step 2 to continue the next-round learning of the training samples. Table 1 shows the setting of part of the thresholds and connection weights.

Table 1. Setting of some thresholds and connection weights

Net-work parameter	Threshold θ	Connection weight ω									
		Value	0.242	0.451	0.534	0.950	0.546	0.569	0.876	0.719	0.498
0.160	0.775		0.812	0.683	0.724	0.651	0.612	0.656	0.655	0.679	0.961
0.013	0.832		0.765	0.874	0.412	0.632	0.611	0.960	0.953	0.446	0.834
0.121	0.910		0.668	0.932	0.587	0.541	0.846	0.609	0.615	0.827	0.653
0.233	0.575		0.911	0.628	0.590	0.592	0.741	0.793	0.713	0.904	0.542

6. After the learning of all evaluation index data samples is completed, the global error E of the network model is calculated:

$$E = \frac{\sum_{i=1}^M E_i}{M} = \frac{\sum_{i=1}^M \sum_{u=1}^m (x'_{ou} - x_{ou})^2}{2M} \tag{18}$$

7. Then, the global error E of the network and the number of iterations ϵ are judged; if E is less than the preset error or ϵ is greater than the preset maximum number of iterations, stop the network learning, and return to step 2 to enter the next-round learning of training samples. Repeat steps 2 to 7 until the network model learning terminates.

The correction formulas of $\Delta\omega_{ut}$ and $\Delta\theta_u$ can be expressed by Formulas 19 and 20:

$$\Delta\omega_{ut} = -\eta \frac{\partial(x'_{ou} - x_{ou})}{\partial\omega_{ut}} = -\eta \cdot e \cdot \lambda_{tu}^* \tag{19}$$

$$\Delta\theta_u = -\eta \frac{\partial(x'_{ou} - x_{ou})}{\partial\theta_u} = -\eta \cdot e \cdot R_u^* \tag{20}$$

where, λ_{tu}^* is the expression of λ_{tu} after it is normalized, and R_u^* is the expression of R_u after it is normalized. Therefore, after the constructed neural network is optimized

by GA, the fuzzy membership degree corresponding to the premise and conclusion of the p-th rule can be expressed by Formula 21:

$$g_p = (x_{p11}, \dots, x_{p1m}, x_{p21}, \dots, x_{p2m}, \dots, x_{pjl}, \dots, x_{pjm}, \dots, x_{p01}, \dots, x_{p0m}) \quad (21)$$

If there is a fuzzy input evaluation index sample $(x_{11}, x_{12}, \dots, x_{1m}, \dots, x_{n1}, x_{n2}, \dots, x_{nm})$ processed by fuzzy AHP, the corresponding fuzzy classification membership degree is (x_{o1}, \dots, x_{om}) , the comprehensive membership degree of the fuzzy category g_t of the t-th rule is $\lambda(t) = (\lambda_{t1}, \lambda_{t2}, \dots, \lambda_{tm})$, after the input evaluation index data sample is processed by the GA-optimized network model, its fuzzy output is $(x'_{o1}, \dots, x'_{om})$, then the proposed GA-optimized neural network model can be expressed by Formula 22 as follows:

$$x'_{ou} = h\left(\sum_{t=1}^l \omega_{ut} \lambda_{tu} - \theta_u\right) = h\left(\sum_{t=1}^l \omega_{ut} x_{tou} \mu_t - \theta_u\right) \quad (22)$$

4 Construction of the Comprehensive Evaluation Model

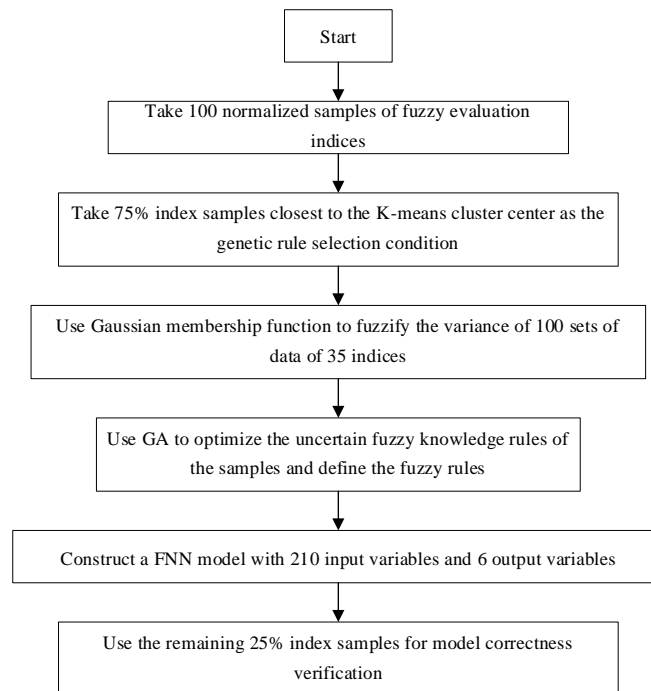


Fig. 2. Evaluation flow of college students' I&E thinking ability

Figure 2 shows the evaluation flow of college students' I&E thinking ability using the GA-optimized FNN model. Since the number of the optimal rules of GA will be extremely large if the data of 35 secondary indices are taken as the high-dimensional

input, and it's not easy to construct such a huge FNN, this paper selected a few representative rules using GA based on uncertain fuzzy knowledge rules, and constructed a four-layer neural network model with fuzzy input and output data.

Because the data types of the 35 secondary indices are quite complicated. The K-S test showed that, except for indices of knowledge learning ability, time planning ability, learning planning ability, interpersonal communication ability, entrepreneurial awareness, training participation, social practice participation, skill competition participation, mastery of technical skills, and skill certificate acquisition, the K-S test probability values of other indices were all less than 0.06, therefore, it's determined that the evaluation indices of college students' I&E thinking ability did not obey the normal distribution, and this study divided all indices into 4 types, and the division of the 4 types fuzzy subsets is shown in Table 2.

Table 2. Classification of fuzzy subsets of evaluation indices

Fuzzy subsets	Level-A (poor)	Level-B (Pass)	Level- C (Average)	Level- D (Good)	Level- E (Excellent)
Fuzzy subset 1	[40,50)	[50,60)	[60,80)	[80,90)	[90,100]
	45	55	70	85	95
Fuzzy subset 2	[0,20)	[20,40)	[40,60)	[60,80)	[80, max]
	15	35	50	75	85
Fuzzy subset 3	[20,30)	[30,50)	[50,70)	[70,80)	[80,100]
	24	40	56	72	88
Fuzzy subset 4	[min,30)	[30,40)	[40,60)	[60,70)	[70, max]
	15	28	46	64	82

After that, different discrete methods were adopted to discrete different-type indices, and the Gaussian membership function was adopted to fuzzify the variance of 100 sets of data of the 35 indices. Each index variable corresponded to 6 fuzzy subsets, and the j-th fuzzy subset of the i-th variable was denoted as F_{ij} , then the degree of membership of the i-th variable x_i to F_{ij} can be expressed by Formula 23:

$$\lambda_{ij\sigma} = \lambda_{ij}(x_i^\sigma) = \exp \left(-\frac{x_i^\sigma - \tau(j)}{2\sigma^2} \right) \tag{23}$$

where, $i=1, 2, \dots, 35, j=1, 2, 3, 4, 5, 6$, and $\sigma=1, 2, \dots, 100$. Figure 3 shows the Gaussian membership function curve.

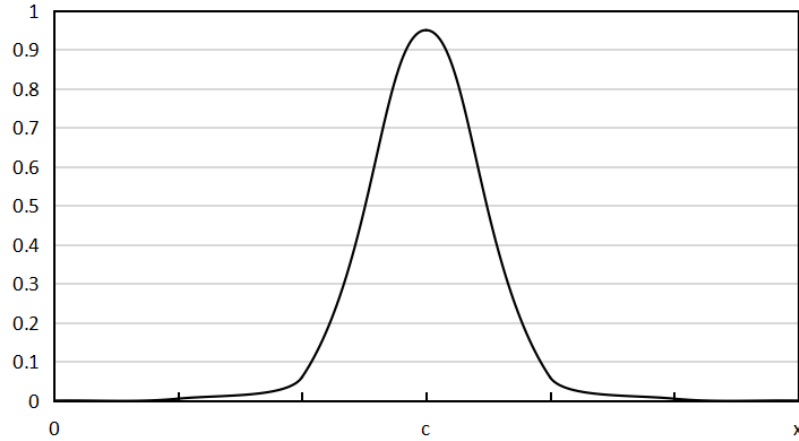


Fig. 3. Curve of Gaussian membership function

For the 100 fuzzy evaluation index samples (B^1, B^2, \dots, B^{100}), each sample $B^\sigma = (x_{\sigma 11}, \dots, x_{\sigma 16}, x_{\sigma 21}, \dots, x_{\sigma 26}, \dots, x_{\sigma \sigma 1}, \dots, x_{\sigma \sigma 6})$. The K-means clustering method was used to select 75% of the index samples that were closest to each cluster center, which were taken the rule optimization conditions of GA in turn, and the remaining 25% index samples were used to test the correctness of the rule categories. At last, a total of 65 index samples were selected for model construction, and the remaining 35 index samples were used to test the correctness of the model. As for the rule layer of the FNN model, 10 rules were selected based on GA for the model construction. The number of fuzzy input variables was $35 \times 6 = 210$, and the number of fuzzy output variables was 6.

5 Experimental Results and Analysis

To verify the effectiveness of applying the proposed GA-optimized FNN model on the evaluation of college students' I&E thinking ability, the proposed method was used to conduct simulation analysis on the evaluation of the I&E thinking ability of 4562 college students. The simulation program was compiled using the MATLAB simulation software, and the parameters of the 4-layer FNN model were set as shown in the table. Figure 4 gives the change of network training error with the increase of the number of training times, it can be seen that the network built after about 200 iterations can converge well.

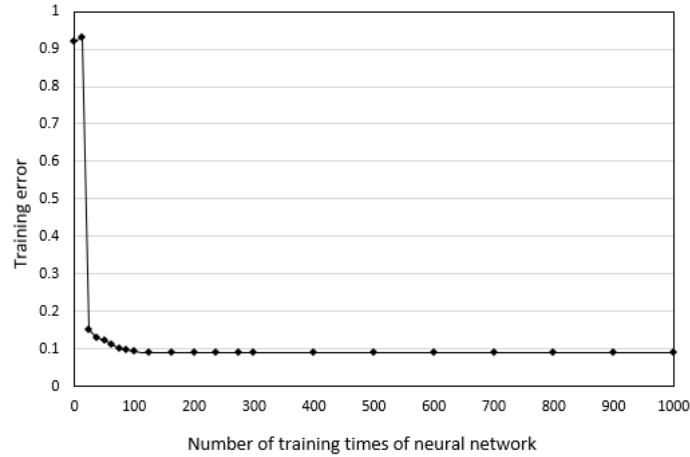


Fig. 4. Change of network training error with the number of training times

The neural network model proposed in this paper was constructed with 35 secondary index samples as high-dimensional input. Figure 5 shows the error curve of the correctness of the neural network under high-dimensional input condition, it can be seen from the figure that, in case of high-dimensional input variables, the evaluation error of the FNN constructed in this paper did not fluctuate much, indicating that it is more stable than other neural network algorithms.

Table 3 shows the evaluation accuracy corresponding to different optimal rule numbers selected by GA, it can be seen from the table that, it's proper to determine the number of clusters of the 35 secondary indices to be 9, when the value of l takes 9, the correct rate of the rules for the test index data samples was the highest value 79.57%. Since there're too many rules and they are quite long, Table 4 only gives a few simplified representative rules. There are 532 fuzzy rules in the classic fuzzy neural network, and this paper only selected 9 representative rules, the number was reduced by 97%, but the correct rate was remained at 100%, indicating that the selected rules are of good representativeness.

In order to verify the performance of the constructed neural network in evaluating college students' I&E thinking ability, this paper conducted regression analysis on the expected output results and the actual output results of the network. Figure 6 shows the analysis results under different correlation coefficients. It can be seen from the figure that the correlation coefficients were large, all greater than 0.99. Therefore, the expected output of the neural network was basically consistent with the training output value, it has good correlation and generalization ability.

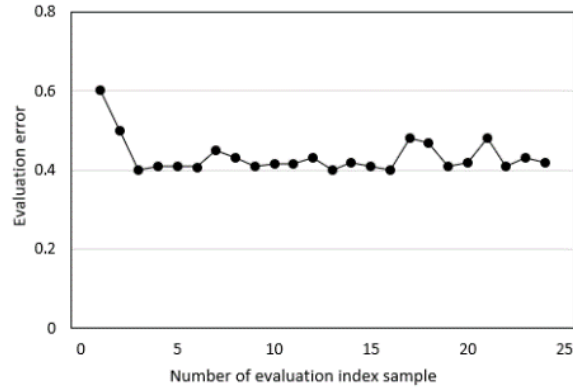


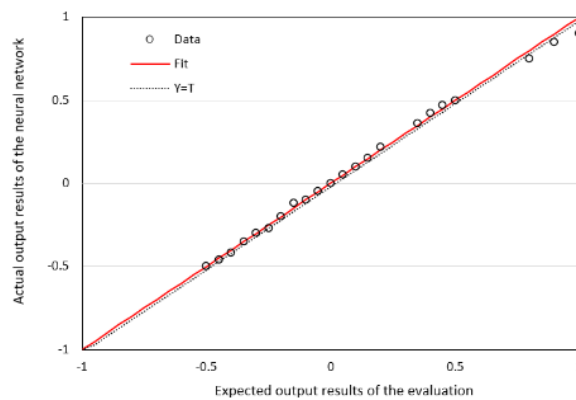
Fig. 5. Error curve of the neural network under high-dimensional input condition

Table 3. Evaluation accuracy corresponding to different rule numbers

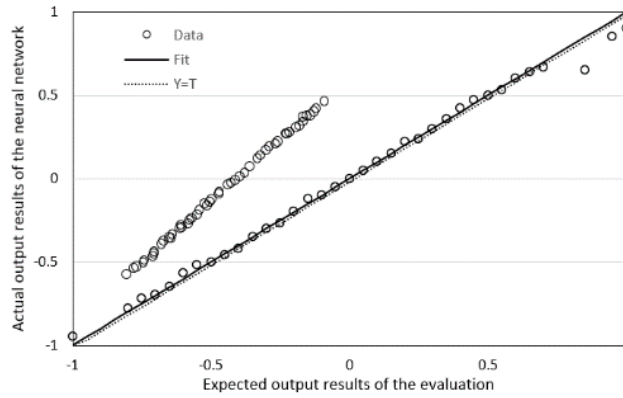
l value	6	7	8	9	10	11	12	13
Accuracy	61.87%	65.37%	72.17%	79.57%	73.91%	69.57%	65.22%	61.33%

Table 4. GA rules of some fuzzy evaluation index data

Rule No.	1	2	3	4	5	6	7	8	9
Fuzzy index antecedent 1 B_1	6	5	6	4	5	5	6	5	4
	0.925	0.944	0.996	0.984	0.983	0.988	0.988	0.982	0.990
Fuzzy index antecedent 2 B_2	6	5	6	4	2	3	2	4	6
	1.021	1.011	1.001	1.004	1.006	1.006	1.005	1.004	1.002
Fuzzy index antecedent 3 B_3	6	2	2	3	1	4	6	4	4
	1.004	0.987	1.021	1.011	0.996	0.984	1.020	0.982	0.991
Fuzzy index antecedent 4 B_4	5	5	6	4	3	3	5	6	3
	0.982	1.021	1.011	1.014	1.005	0.998	0.984	0.999	0.981
Fuzzy index antecedent 5 B_5	6	4	4	5	6	4	3	2	3
	0.996	1.021	1.011	1.010	0.994	1.007	1.004	1.004	0.987



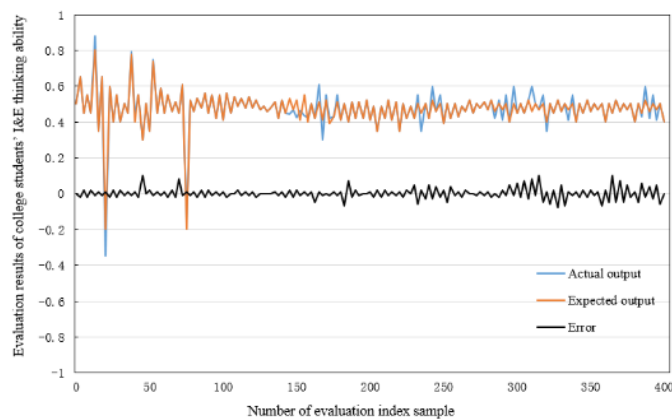
(a)



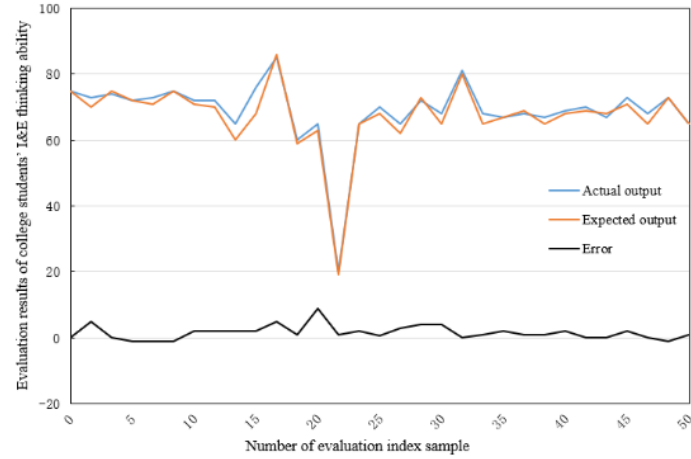
(b)

Fig. 6. Regression analysis of expected and actual output results of the network

Figure 7 shows the output of the training and testing index samples of the neural network and the error curves. Figure 7(a) is the output of 100 index samples. The output of the neural network is the score value after defuzzification, which is the comprehensive evaluation of the I&E thinking ability of each college student. In the test process, in order to further test the generalization ability of the neural network, two sets of scoring interference items were introduced into the input. It can be seen from Figure 7(a) that the constructed neural network had good prediction evaluation effects on both the normal testing index samples and the interference items, and the output of all testing index samples was highly consistent with the evaluation results given by expert reviewers, indicating that the proposed model can objectively and comprehensively evaluate the I&E thinking ability of college students. Figure 7(b) shows the comparison between the predicted evaluation index sample output and the actual value given by expert reviewers, which had verified the feasibility and effectiveness of the constructed model.



(a)



(b)

Fig. 7. Output of training and testing index samples and the error curves

6 Conclusion

This paper proposed an evaluation model for college students' I&E thinking ability based on neural network. First, it constructed a reasonable evaluation index system for college students' I&E thinking ability, and preprocessed the evaluation indices based on fuzzy AHP. Then, the paper gave construction steps of the FNN model based on GA rule optimization. At last, according to uncertain fuzzy knowledge rules, a few representative rules were determined by GA, and a neural network model with fuzzy data as both the input and output of the model was constructed for the evaluation of college students' I&E thinking ability. Using experimental results, the paper proved that the proposed FNN model is more stable than other neural network algorithms, and the optimal rules selected by GA are highly representative. For the evaluation of college students' I&E thinking ability, the expected output value of the network was basically consistent with the training output value, therefore it has good correlation and generalization ability.

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