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Optimization path analysis of education legal system based on Markov chain model

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Abstract The development of the times calls for the need to further strengthen the construction of the education legal system and promote the deep development of the education legal system. In order to realize the effective evaluation of the quality of education legal system, the article designs an evaluation model (PSO-BPNN model) for the quality of education legal system based on heuristic algorithm. The model uses the PSO algorithm with sinusoidally adjusted inertia weights to optimize the initial values of the weights and thresholds of the BPNN to improve the convergence efficiency of the model. Subsequently, the assessment was completed in conjunction with the established educational legal system. In order to verify the performance of the model, the model is compared, and the relative error between the predicted value and the real value of PSO-BPNN on the quality of the educational legal system is between 1.36 and 22.34, with a difference of 20.98, and the fit between the network output of the model and the target value is high, and the trend of the predicted value and the real value is in agreement, and the model predicts with a high degree of accuracy. The intelligent decision-making path can be carried out at three levels: the collection of information, the identification of decision-critical issues and the proposal of decision-making solutions.

Index Terms PSO-BPNN, heuristic algorithm, educational legal system, intelligent decision paths

I. Introduction

Education is the cornerstone of national revitalization and social progress, as well as the fundamental way to improve the national quality and promote the comprehensive development of human beings [1], [2]. With the development of the times and social progress, China's education legal system faces a series of challenges and problems, and how to optimize the education legal system has become a hot topic [3]-[5]. Optimizing the education legal system means improving and perfecting the existing education model and system from many aspects to meet the needs of students, improve the quality of education, and cultivate more comprehensively developed talents [6]-[8].

Heuristic optimization algorithm is a class of optimization algorithms based on the idea of natural evolution or based on heuristic methods, which is a kind of algorithm to find the optimal solution or near-optimal solution of a problem through iteration, compared with traditional deterministic optimization algorithms, heuristic optimization algorithms are more suitable for high-dimensional, nonlinear, non-smooth and other complex problems, and have shown great potential in practical applications [9]-[12]. Heuristic optimization algorithms are a powerful class of optimization tools that can effectively solve complex optimization problems [13]. In practical applications, we can choose suitable heuristic optimization algorithms according to the nature and needs of the problem, and perform parameter tuning and optimization to achieve better optimization results [14]-[16]. In the optimization of the educational legal system, the heuristic teaching method can carry out appropriate optimization of this system according to the students' learning interest and initiative to meet the students' individual needs [17]-[19]. The optimization of the educational legal system under the heuristic algorithm can develop towards students' creativity and critical thinking ability in order to cultivate students' ability of independent thinking and innovation [20], [21].

The article firstly designs and builds a PSO-BPNN model based on the improved PSO, adjusts the inertia weight value sinusoidally to improve the optimization seeking effect of the PSO algorithm, and optimizes the weight and threshold initial value of the BPNN with the improved PSO algorithm to improve the convergence speed and efficiency of the BPNN. Subsequently, the evaluation index system of education legal system is established, and the PSO-BPNN algorithm is applied to the evaluation of education legal system. In order to verify the feasibility of the improved PSO-BPNN-based model, the performance test experiments of the model were conducted, and the model was also compared with five methods, namely, AHP, LR, BPNN, BP and PSO-BP. Finally, according to the experimental results, intelligent decision paths are mined from three levels of decision information accuracy, capturing key issues and issuing decision solutions.

II. Improvement and optimization based on heuristic algorithms

II. A.Improved PSO algorithm with BPNN

II. A. 1) PSO algorithm improvement

(1) PSO algorithm

PSO algorithm is a population intelligent global optimization algorithm, which simulates the natural mechanism of nature, generates a specific number of particles, and abstracts all the problems related to optimization into the feeding behavior of birds for research. It is characterized by fewer parameters to be regulated, shorter computing time consumption and higher search quality.PSO is a global dynamic optimization searching computational method based on particle iteration to find the optimal solution in the target solution space, which seeks the global optimum and the individual extremes by continuously adjusting its own position and speed during each iteration [22]. Its ultimate goal is to find the optimal candidate solution. The particle velocity update of the particle swarm optimization algorithm is shown in equation (1) and the particle position update is shown in equation (2). The particle position update is shown in Fig. 1.

$$v_{ij}(t+1)=wv_{ij}(t)+C_1r_1[p_{ij}(t)-x_{ij}(t)]+C_2r_2[p_{gj}(t)-x_{ij}(t)] \tag{1}$$

where, $v_i(t+1)$ --Velocity of the i st particle at $t+1$ iterations, t --Number of iterations, w --Inertia weights, $v_{ij}(t)$ --Velocity of the i rd particle at t iterations, C_1, C_2 --Acceleration constant, r_1, r_2 --Stochastic constant, $p_{ij}(t)$ --Optimal position of the i th particle at t iterations, $p_{gj}(t)$ --Optimal position of the particle swarm at t iterations, $x_{ij}(t)$ --Position of the i th particle at t iterations. I.e.:

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

where, $x_i(t+1)$ - the position of the i th particle at the $t+1$ th iteration.

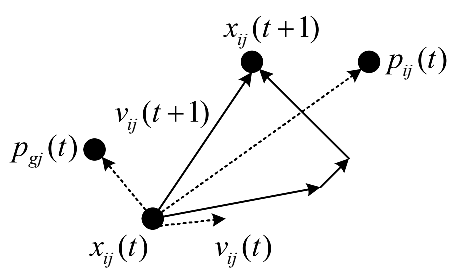


Figure 1: Particle position update

From the combination of Eq. (1) and Eq. (2), the position update of the particle can be expressed as:

$$x_{ij}(t+1)=x_{ij}(t)+wv_{ij}(t)+C_1r_1[p_{ij}(t)-x_{ij}(t)]+C_2r_2[p_{ij}(t)-x_{ij}(t)] \tag{3}$$

During the iterative optimization search of the particle, different restrictions are placed on the position and velocity of the particle as shown in Eq. (4) and Eq. (5), respectively. So that they change within the set interval respectively, preventing the blind search of the particles. Namely:

$$x_{ij}=\begin{cases}-x_{\max} & x_{ij}<-x_{\max}\\ x_{\max} & x_{ij}>x_{\max}\end{cases} \tag{4}$$

$$v_{ij}=\begin{cases}-v_{\max} & v_{ij}<-v_{\max}\\ v_{\max} & v_{ij}>v_{\max}\end{cases} \tag{5}$$

where, $x_{\max}$ - the position maximum of the particle, $v_{\max}$ - particle velocity maximum.

(2) PSO algorithm improvement

In the standard PSO algorithm, the inertia weight w is a random value between [0.5, 1.5]. When w is set too small, the original speed cannot be retained, making the local convergence ability strong and the global convergence ability weak. The opposite is true when w is set too large. In order to make the PSO algorithm have strong global search ability in the early iteration period and achieve local optimization effect in the later period, an improved PSO algorithm based on the sinusoidal adjustment of inertia weights is proposed, i.e., the inertia weights are adjusted sinusoidally according to the current iteration step number and the maximum iteration step number in the optimization process of the particle swarm. The sinusoidally adjusted inertia weights are calculated as shown in equation (6):

$$w(t) = w_{\max} - (w_{\max} - w_{\min}) \cdot \sin(\frac{t}{t_{\max}})^2 \tag{6}$$

where, $w_{\max}$ - maximum inertia weights, $w_{\min}$ - minimum inertia weight, t_m - set maximum number of iteration steps.

II. A. 2) BPNN Optimization

(1) Theory of BPNN

BPNN is a kind of multilayer feed-forward neural network trained according to the error back propagation algorithm, which consists of three parts: input layer, hidden layer and output layer. For different influence factors, BP neural network can get the influence of changes on the analyzed target.The basic idea of BPNN is to divide the network learning process into two processes: information forward transmission and error backward feedback. It is built based on the multilayer perceptron of BP algorithm, so its topology is the same as that of the multilayer perceptron, and the BPNN topology is shown in Fig. 2.

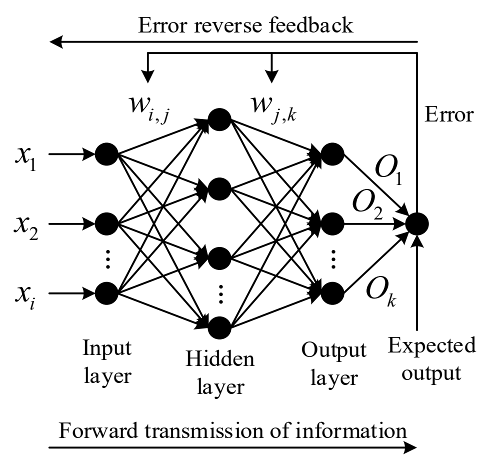


Figure 2: BPNN topology

In the forward information transfer process, information is passed from the input layer to the output layer through the implicit layer and the output value of each layer, the error between the actual output and the desired output of the output layer is calculated.

The implicit layer output value is calculated as shown in equation (7). The output layer output value is calculated as shown in equation (8). The error between output layer output result and actual value is shown in equation (9):

$$z_j = f_1\left(\sum_{i=1}^{m} w_{1ij} x_i + b_{1j}\right) \tag{7}$$

$$o_k = f_2\left(\sum_{i=1}^{n} w_{2jk} z_j + b_{2k}\right) \tag{8}$$

$$E = \frac{1}{2}\sum_{i=1}^{\infty}\left[(o_k - O_k)^2\right] \tag{9}$$

where, z_j - implicit layer node output, f_1 - implicit layer activation function, w_{1ij} - weights between input and implied layers, x_i - network input, b_{1j} - Implicit layer threshold, o_k - output node output, f_2 - output layer activation function, w_{2jk} - weights between implicit and output layers, b_{2k} - output layer threshold, E - error value.

m - number of iterations, O_k - network desired output.

If the error E is not within the set range, the BPNN starts the error information from the output layer and adjusts the thresholds of each layer and the weights between the layers inversely according to the gradient descent method, and the output weights change as shown in Equation (10), and the implicit layer weights change as shown in Equation (11):

$$\Delta w_{2jk} = -\eta \frac{\partial E}{\partial w_{2jk}} = \eta (o_k - O_k) f_2' z_j \tag{10}$$

$$\Delta w_{1jk} = -\eta \frac{\partial E}{\partial w_{1jk}} = \eta \sqrt{E} f_2' w_{2jk} f_1' x_i \tag{11}$$

where, η - learning rate.

BPNN after information forward transfer and error reverse feedback two processes of repeated learning and training, and finally make the error E in the set range or until the set number of learning.

(2) Improve PSO algorithm to optimize BPNN

The introduction of PSO algorithm with faster running speed and better global optimization ability can effectively solve the BPNN problem, and the improvement of PSO algorithm can further improve the global search ability and iteration efficiency. Using the improved PSO algorithm to optimize the initial parameters of the BPNN network can better solve the shortcomings of the BPNN and improve the effect of BPNN optimization search. The flow of the improved PSO algorithm to optimize BPNN is shown in Figure 3.

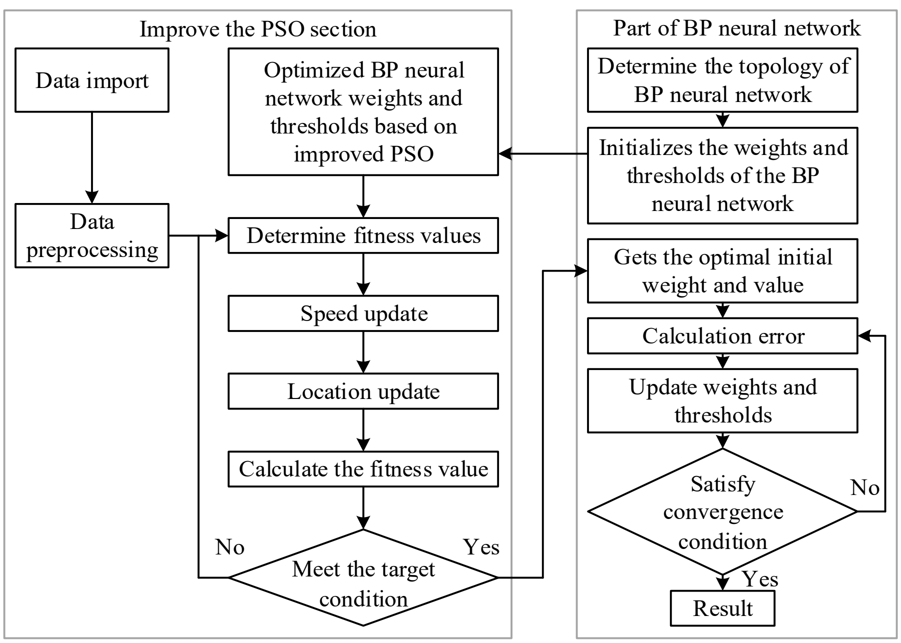


Figure 3: Optimizing BPNN process based on improved PSO algorithm

Before using the improved PSO algorithm to optimize the BPNN, the mapping relationship between the particle dimension j and the initial weights w_{1ij}, w_{2jk} of the BPNN and the thresholds b_{1j}, b_{2k} is established first. The mapping relation is represented as follows:

$$\left[\overbrace{123 \cdots I \times H}^{w_0}, \overbrace{123 \cdots H \times O}^{w_0}, \overbrace{123 \cdots H}^{b_0}, \overbrace{123 \cdots O}^{b_0} \right] \tag{12}$$

The matrix length L, i.e., the dimension j of the particle, can be expressed by Eq:

$$L = j = I \times H + H \times O + H \times O \tag{13}$$

where, I - number of input layer nodes, H - number of implicit layer nodes, O - number of output layer nodes.

II. B.PSO-BPNN algorithm model construction

II. B. 1) PSO-BPNN algorithm model structure design

BPNN algorithm is based on biological brain neurons, multiple neurons composed of parallel distributed network structure, it consists of 3 parts, the first part is the input layer. Used to receive information: the second part is the hidden layer. Used to process the received information: the last part is the output layer. It is used to summarize and output the processing results.PSO-BPNN algorithm is an algorithm that combines particle swarm and BP neural network, and adds a feedback mechanism on the basis of BP neural network, which has adaptive learning ability, and it can give feedback according to the output results, and constantly adjust the corresponding parameter weights, so as to make the output vector reach the ideal error with the desired vector.The PSO-BPNN structural model is shown in Fig. 4. The PSO-BPNN structure model is shown in Figure 4, where the input layer is the evaluation index of the education legal system, the output layer is the evaluation result of the education legal system, and the arrows indicate the training feedback process, and the model will adjust the parameter weights and thresholds through the feedback during the training, which will improve the fitting effect and convergence speed.

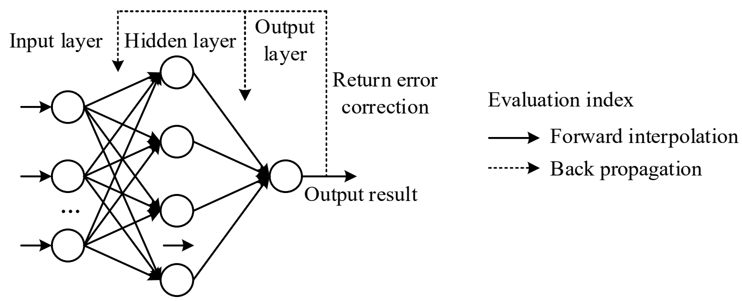


Figure 4: PSO-BPNN structure model

II. B. 2) PSO-BPNN algorithm steps

The amount of information in the evaluation of the education legal system is relatively large, and there are many influencing factors in the comprehensive evaluation, if the data are directly input into the PSO-BPNN model, some special data will increase the algorithmic error and slow down the convergence speed, so the data must be processed before training and learning [23]. First, the optimized particle swarm algorithm model is established. Take the sample teaching quality evaluation index as the output vector, design a fitness function associated with the error function, calculate the fitness and optimal position of the particles, and then select the particles with strong fitness as inputs, and use the data obtained from repeated iterations as the weights and thresholds of the optimized particle swarm, and the specific process is as follows:

(1) Establish PSO-BPNN model with training sample indicators as input and T as output vector.

(2) Randomly generate a set of individuals, each individual represents the initial threshold of the neural network, and the length of the individual is equal to the sum of the number of individuals and the threshold of the neural network, which is calculated as follows:

$$n = R \times S_1 + S_1 \times S_2 + S_1 + S_2 \tag{14}$$

where n is the coding length of the neural network, S_1 is the number of hidden layer node quanta, S_2 is the length of the output vector, and R is the length of the input vector.

(3) Design a fitness function related to the error function with the following formula:

$$f = \frac{1}{E+1} E = \frac{1}{2}\sum_{k=1}^{n}(d_k - o_k)^2 \tag{15}$$

where d_k and o_k are the desired and actual outputs of k sets of data, respectively, and the individuals are evaluated based on the RMS values.

(4) Update particle velocity and position. According to the particle adaptation value and the current optimal solution, update the particle velocity and position. The velocity update can be realized by the particle swarm algorithm formula, and the position update is calculated according to the velocity. By constantly updating the particle velocity and position, the particles can gradually approach the optimal solution.

$$V_{id}^{k+1} = w \times v_{id}^{k+1} + c_1 r_1 (p_{id,pbest}^{k} - x_{id}^{k}) + c_2 r_2 (p_{id,gbest}^{k} - x_{id}^{k}) \tag{16}$$

$$X_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{17}$$

where V_{id} is the i th particle velocity, X_{id} is the i th particle position, c_1 and c_2 denote the acceleration factors, c_1 regulates the particle to fly to the optimal position of itself, and c_2 regulates the particle to fly to the optimal position of the whole world, and typically One can take $c_1 = c_2 = 2$. The r_1, r_2 are uniformly distributed random numbers in [0, 1], which are intended to increase the randomness of the particle search. $p_{id,gbest}^{k}$ is the d -dimensional historical optimal position, i.e., the overall particle swarm optimal solution, in the k th iteration of the population. $p_{id,pbest}^{k}$ is the d -dimensional historical optimal position of particle i in the k th iteration, i.e., the optimal solution of i -particle search.

(5) Improve the inertia weights. In the BPNN algorithm, ω is a fixed constant, which leads to the algorithm's weak local search ability and easy to fall into the local optimum. In order to solve the problem of particles easily falling into local optimization, this paper introduces inertia weights to adjust the particle search ability, so as to avoid falling into local optimization [24]. The optimized inertia weights are shown in equation (18):

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \frac{iter}{iter_{\max}} \tag{18}$$

where ω is the inertia coefficient, which represents the effect of the particle's historical velocity on the current velocity, $\omega_{\max}$ is the maximum inertia weight, and $\omega_{\min}$ is the minimum inertia weight. $iter$ is the current number of selected generations and $iter_{\max}$ is the maximum number of iterations. When ω is relatively large, its global and local optimization seeking ability is strong. When ω is smaller, its global optimization seeking ability is weak and local optimization seeking ability is strong.

(6) Select the adaptable particles and keep the current optimal solution in each step until the accuracy requirement is satisfied or the maximum number of iterations is 100, and then select and crossover according to the law to produce the next generation.

(7) Use the adaptive maximum individual obtained after repeated iterations as the BP neural network threshold.

(8)Train the PSO-BP neural network using information and error backpropagation so that the error converges to the specified accuracy range.

(9) After the above computational steps, the samples were evaluated using the trained PSO-BPNN algorithm model.

III. Evaluation index system of education legal system based on PSO-BPNN algorithm

Quality evaluation of educational legal system is an important measure to improve the quality of legal education. In this section, the constructed PSO-BPNN algorithm model is applied to the evaluation index system of education legal system.

III. A. Construction of the education legal system

The construction of the evaluation index system for the legal system of education is designed to objectively, comprehensively and accurately evaluate the quality of legal education and provide teachers with a basis for improvement. When constructing the evaluation system, in order to ensure that the evaluation indicators are scientific and operable, it is necessary to follow the principles of comprehensiveness, operability and practicality. The evaluation index system of education legal system is designed to measure, analyze and evaluate the quality of legal education, so the attitude of the evaluation subject must be objective to ensure that the evaluation results are true and reliable. The educational legal system constructed is shown in Table 1.

Table 1: Educational law system

Primary indicator	Secondary indicator	Explain
Education legislation(x1)	Improve the lateral coverage of the education law(x11)	We will accelerate the development of important education laws and regulations in the practice of education
	Improve the longitudinal structure of the education law(x12)	The system of education law, education administrative law, local education law, departmental education regulations and local education regulations
	Improved legislative technology(x13)	Try to avoid the language of the law of education law, and make specific explanations for the principle of principle to enhance its operability

Educational division(x2)	Science properly set up a major(x21)	Set up the education planning, training mode and talent specification according to the market demand, and set up the course system according to the ability of the position
	We will strengthen the basic construction of teaching(x22)	Teaching teachers' degree promotion, training and other work increases the cultivation of teachers and the cooperation with enterprises to promote the construction of training bases
	Strengthen the design of the practice(x23)	The school ADAPTS to the job market including the "promotion of graduates" as an important link in running a school.
	The need to establish and improve the employment guidance committee(x24)	Measures to strengthen employment education and help graduates succeed in market
Strengthen higher vocational students' thought education(x3)	Cultivate your own job consciousness(x31)	Students can take advantage of their holidays to participate in social practice activities, seek opportunities to socialize more, and actively understand the current employment policies of graduates
	To introduce the development trend and culture goals of higher vocational education(x32)	Let students know the actual higher theoretical quality and knowledge level of higher vocational training
	Emancipate the mind and change the idea(x33)	Actively adapt to the market needs, improve the students' comprehensive quality, and survive the quality

III. B. Application of PSO-BPNN algorithm in the evaluation of educational legal system

The BPNN algorithm model consists of three main layers: input layer, implicit layer and output layer. Among them, the evaluation indexes are used as optimization particles. The current common method to determine the nodes of the hidden layer is the test method, which is calculated as follows:

$$m = \sqrt{n+l} + a \tag{19}$$

$$m = \log_2 n \tag{20}$$

$$m = \sqrt{nl} \tag{21}$$

where the number of nodes in the input, hidden, and output layers are set to m, n and l, a are constants between 0 and 10, respectively, and the hidden layer nodes are calculated to be 6 to 16 according to the above formula, and the optimal hidden layer nodes are 8.

Tansig hyperbolic tangent function is used as the activation function of the hidden layer unit, after processing in the sample data training, the output value of the evaluation result falls in the interval of 0 to 1, so the functions on the output layer unit are all Sigmoid functions with the following expressions:

$$f(x) = \frac{1}{1+e^{-x}} \tag{22}$$

In this network model construction, the input vector is $x = (x_1, x_2, x_3, \cdots, x_{26})^T$. The weights from input layer cells to hidden layer cells h are $W = (w_1, w_2, w_3, \cdots, w_{26})^T$. Hidden layer output $Y = (y_1, y_2, y_3, \cdots, y_8)^T$. Hidden layer output weights $W = (w_1, w_2, w_3, w_8)$. The actual output of the model $O = net(Y)$ and $T = (T)$ denotes the output before the training samples [25]. The formula is calculated as follows:

$$y_h^k = f\left(\sum_{i=1}^{12} w_{ih} x_i^k + z_h\right) \tag{23}$$

$$O_h^k = g\left(\sum_{h=1}^{7} w_h y_h^k + z\right) \tag{24}$$

IV. Quality assessment of the education legal system

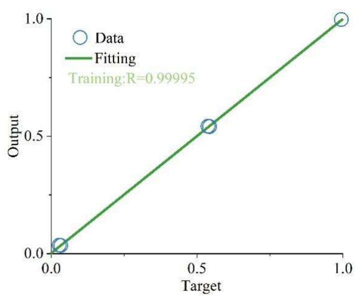
IV. A. Comparison of PSO-BPNN Predicted and True Values

In this section of the experiment, 60 sets of sample data that meet the experimental conditions are selected from the legal and regulatory education library, and the data are randomly disrupted, and then the first 50 sets of data are used as training samples, while the last 10 sets of data are used as prediction samples. The input layers are x1, x2 and x3, and the output layer is the quality of education and legal system assessment.

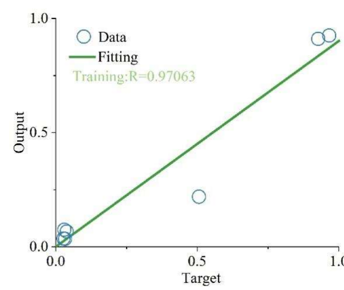
The comparison of PSO-BPNN predicted and real values is shown in Table 2. As can be seen from the table, the relative and absolute errors between the predicted values and the true values are between 1.36 and 22.34 and 0.019 and 0.6576, respectively, with a difference of 20.98 and 0.6386, and the average relative and absolute errors are 11.81 and 0.23742, respectively.The curve of the PSO-BPNN training regression state is shown in Fig. 5 (Figs. a~b are the four times of PSO-BPNN training regression state) is shown in Fig. 5 (Fig. a~b are four times of training regression state respectively), through the figure can be obtained, the network output of the model and the target value of the fit between the network and the target value of the high degree of goodness of fit, indicating that the training results of the valid. PSO-BPNN prediction results curve is shown in Fig. 6, PSO-BPNN prediction and the real value of the trend of the change of the trend of the PSO-BPNN prediction and the real value of the change of the trend of the PSO-BPNN prediction and the two do not have a small difference between the two, indicating that the prediction of the accuracy of the higher.

Table 2: The PNN prediction is compared to the real value

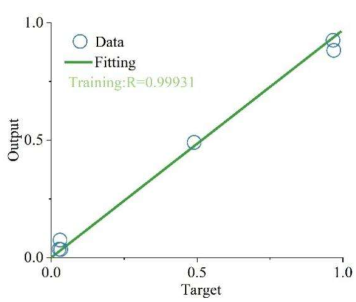
Serial number	True value	Predictive value	Absolute error	Relative error
1	4	2.8109	0.1943	4.86
2	2	2.9576	0.0272	1.36
3	2	1.909	0.048	2.40
4	1	0.8094	0.2017	20.17
5	3	2.5981	0.6576	21.92
6	1	1.0054	0.019	1.90
7	1	1.1908	0.2234	22.34
8	3	2.543	0.4221	14.07
9	2	1.6241	0.4171	20.86
10	2	1.191	0.1638	8.19



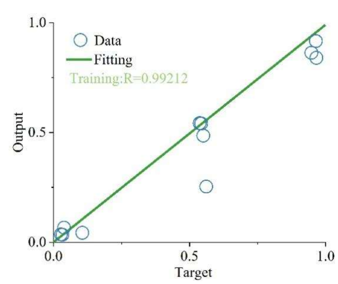
(a) First training



(b) Second training



(c) Third training



(d) Fourth training

Figure 5: PNN training regression state curve

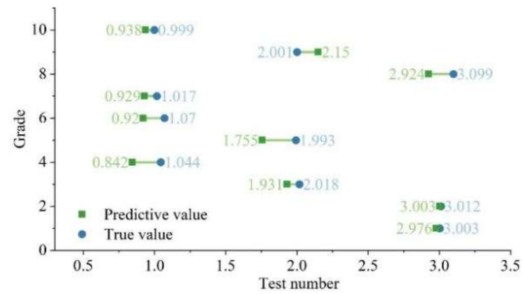


Figure 6: PSO-BPNN prediction curve

IV. B. Model validation and comparison

IV. B. 1) Confusion matrix

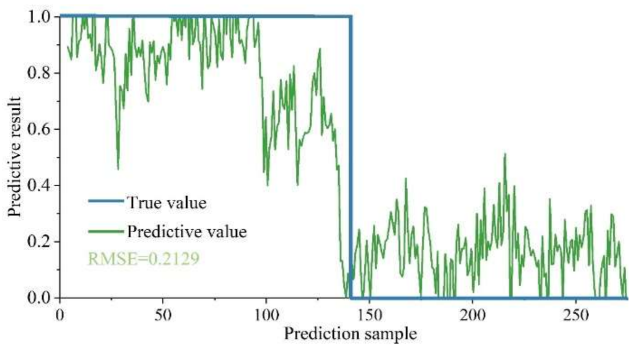
The AHP, LR, BPNN, BP, PSO-BPNN, and PSO-BP models were validated using the training dataset and test dataset, respectively, and the validation results are shown in Table 3. The results show that the BPNN and BP models show a better fit, and the standard error SE is less than 0.3. Compared with a single algorithm, the PSO-BPNN model with the introduction of the meta-heuristic algorithm is able to more accurately assess the quality of the educational legal system, and the F1 value of the test set of the PSO-BPNN model reaches 0.899.

Table 3: Results of validation

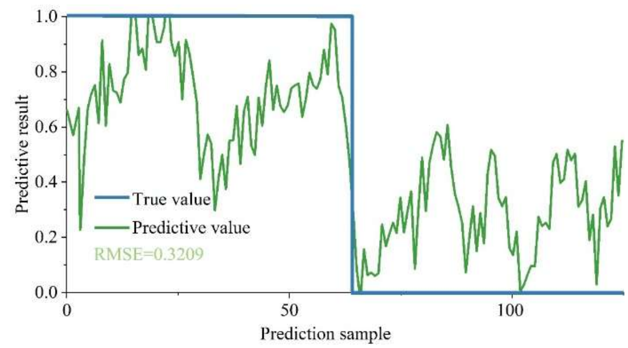
Index	Training set					
	AHP	LR	BPNN	BP	PSO-BPNN	PSO-BP
TP	114	105	123	135	120	137
TN	80	107	125	132	124	139
FP	59	31	8	4	10	0
FN	20	35	16	6	21	0
sensitiveness	0.858	0.738	0.956	0.935	0.92	1
specificity	0.643	0.6	0.802	0.73	1.022	1
Accuracy rate	0.631	0.644	0.977	0.953	0.998	1
correctness	0.886	0.619	0.914	0.961	0.94	1
F1	0.674	0.778	0.996	0.948	0.809	1
Standard error	0.021	0.016	0.015	0.003	0.011	0
95% confidence interval(CI)	0.732-0.851	0.857-0.935	0.923-0.977	0.991-0.999	0.926-0.983	1
Index	Test set					
	AHP	LR	BPNN	BP	PSO-BPNN	PSO-BP
TP	56	50	53	51	50	54
TN	34	41	50	53	51	51
FP	26	16	10	9	8	9
FN	2	10	7	8	6	4
sensitiveness	0.878	0.83	0.856	0.86	0.89	0.871
specificity	0.492	0.736	0.891	0.904	0.882	0.871
Accuracy rate	0.655	0.767	0.924	0.88	0.91	0.852
correctness	0.738	0.771	0.901	0.883	0.867	0.864
F1	0.81	0.815	0.805	0.843	0.899	0.879
Standard error	0.038	0.031	0.025	0.019	0.024	0.01
95% confidence interval(CI)	0.741-0.892	0.793-0.933	0.865-0.973	0.905-0.981	0.901-0.993	0.932-0.996

IV. B. 2) Analysis of assessment results

This section further measures the effectiveness of the BPNN and PSO-BPNN models by the root mean square error RMSE, and the test results of the BPNN and PSO-BPNN models are shown in Fig. 7 and Fig. 8, respectively (Fig. a is the training set, and Fig. b is the test set). The RMSE is extremely sensitive to the maximum and minimum errors, which can effectively reflect the accuracy of the results, and the smaller the value of the RMSE indicates the better model performance. The RMSE of PSO-BPNN model is 0.2882 (training set), 0.3122 (test set), and the RMSE of BPNN model is 0.3375 (training set), 0.2931 (test set), which proves that the optimized model of PSO algorithm has a better performance in the evaluation of educational legal system, and can accurately and correctly assess the risk level.

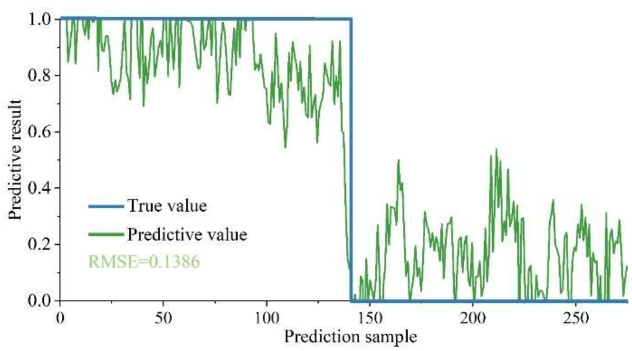


(a) The BPNN training set

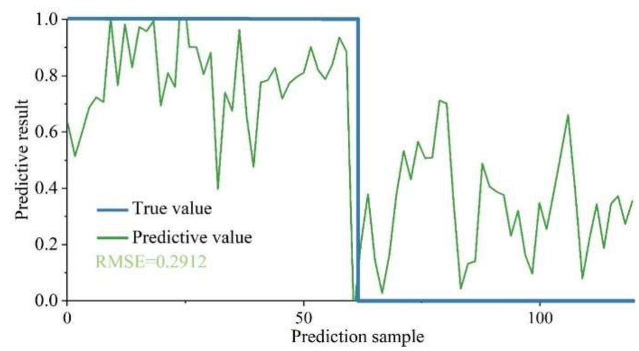


(b) Test set of BPNN

Figure 7: Test results of the BPNN model



(a) The POS-BPNN training set



(b) Test set of POS-BPNN

Figure 8: Test results of the POS-BPNN model

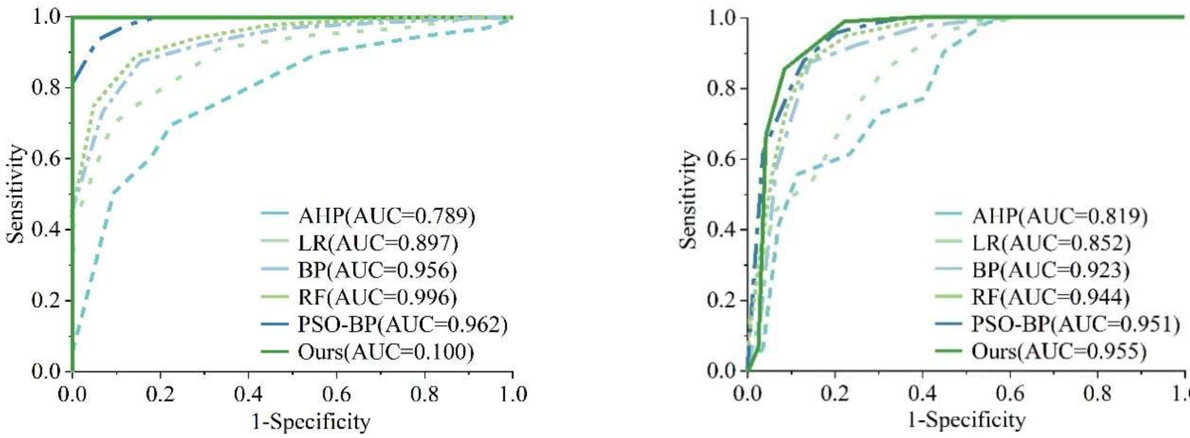
IV. B. 3) Subject operating characteristic curves

The subject operating characteristic curve (ROC) was used to determine the ability of the models to assess the educational legal system, with the x-axis indicating 1-specificity and the y-axis indicating sensitivity. The area under the curve (AUC) values indicate the overall performance of each model in assessing sensitivity, ranging from 0.5-1, with the following numerical and qualitative categories: 0.5-0.6 (poor), 0.6-0.7 (fair), 0.7-0.8 (good), 0.8-0.9 (very good) and 0.9-1 (excellent).

The evaluation performance of the six models was assessed using success rate curves and prediction rate curves based on the training and test sets, respectively, and the analysis of ROC curves based on the different methods (Fig. a for the training dataset and Fig. b for c) is shown in Fig. 9. The results show that the PSO-BPNN model has the highest AUC value (1.000) in the training set, followed by the BP, PSO-BP, BP, LR and AHP models. In the test set data, PSO-BPNN still has better evaluation with AUC values of 0.962 and 0.939, respectively.Taken together, machine learning based on meta-heuristic algorithms exhibits higher AUC values, lower RMSE values, and better overall performance.

IV. B. 4) Quality assessment of the education legal system

The numerical assessment of the risk of the education legal system is shown in Table 4. The PSO-BPNN model calculations indicate that the very low, low, medium, high and very high quality are 31.44%, 22.31%, 19.95%, 17.79% and 10.51% respectively, and overall, the model evaluation results are reasonable.



(a) Training data set (b) Test data set

Figure 9: ROC curve analysis based on different methods

Table 4: Evaluation of risk of education system system

	AHP	LR	BP	RF	PSO-BPNN	PSOBP
Very low	9.88	16.84	11.91	21.07	31.44	13
Low	21.76	22.63	20.43	27.45	22.31	30.44
Medium	31.48	23.78	25.6	22.04	19.95	21.32
Height	25.85	19.87	27.06	17.33	17.79	20.91
Very high	11.03	17.03	14.41	13.42	10.51	14.68

V. Intelligent decision paths are proposed

The quality evaluation model of educational legal system is an important step to improve the quality of legal education, on the basis of which the article further explores the intelligent decision-making path.

V. A. Ensure accurate and comprehensive information for decision-making

The collection of information can be said to be the first stage of decision-making, this stage can also be regarded as the core and premise of scientific decision-making, only through the collection of decision-making information, can provide sufficient and effective information for the development of decision-making, so as to provide a realistic basis for the finalization of decision-making programs. Therefore, the development of decision-making first needs to be supported by information, and large and effective information is a prerequisite for ensuring correct and scientific decision-making.

V. B. Key Issues in Capture Decision Making

The capture of key issues in decision-making is an important part of the decision-making programme, which is mainly carried out by the organization that provides consulting services for decision-making, which must be composed of professionals who use specialized knowledge to analyse and judge the specific issues of decision-making and to make predictions.

V. C. Producing optimal solutions for decision-making

Determination of the optimal solution for decision-making is the most critical link in the entire decision-making system, which not only involves coordination of the whole process of decision-making, but also determines the core issues and objectives of decision-making based on the collected decision-making information and the opinions of experts, on the basis of which decision-making solutions are formed and the optimal solution is determined among the various solutions. Therefore, the determination and introduction of decision-making options require an examination of the entire decision-making process, the issues and objectives of decision-making, and a scientific evaluation of the different options.

VI. Conclusion

In this paper, PSO-BPNN model is proposed, and the machine learning model of coupled meta-heuristic algorithm is applied to the optimization of education legal system and a comparative analysis of model performance is carried out:

In the ROC curve analysis of different methods, the PSO-BPNN model in the training set has the highest AUC value of 1.000, followed by BP, PSO-BP, BP, LR and AHP models. In the test set data, the AUC values of PSO-BPNN are 0.962 and 0.939, respectively. This shows that the model in this paper has better overall performance.

The intelligent decision-making path can be carried out in three aspects: ensuring the decision-making information is accurate and comprehensive, capturing the key issues of decision-making and producing the optimal solution for decision-making.

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