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Web-based optimization algorithm for web-based platform course design in teaching reform of university mathematics

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ABSTRACT

In this paper, we first constructed a mathematics network course goal achievement index system with 5 primary indicators, 16 secondary indicators and 70 evaluation points to provide a scientific basis for course design. After that, based on the radial basis function (RBF) neural network structure, the fruit fly optimization algorithm (FOA) is introduced to dynamically optimize the parameters of the RBF model, and the dynamic FOA-optimized RBF neural network model is put forward to predict the degree of achievement of the course objectives. The results show that the model in this paper has good convergence and prediction accuracy, and its error on the four course math network goal attainment is only about 0.4%, with excellent model accuracy and simulation effect. Combined with the prediction results, considering the shortcomings of the current teaching, a blended teaching model based on mathematics majors is constructed, and the advantages of the teaching scheme in this paper are elaborated, which provides support for the teaching reform of mathematics courses.

Keywords: Radial Basis Function, Drosophila Optimization Algorithm, Goal Attainment, Online Platform Course

1. Introduction

In recent years, the continuous progress of computer technology has brought great impact on education, but also injected new life into the modernization of education, and the field of education will be one of the most valuable and promising application fields among the many application fields of computers [1-4]. The organic combination of modern education concepts and advanced computer technology provides a wider development space for education [5-6].

Network teaching platform is born in this big background, different from the traditional teaching methods, network teaching platform is based on the network to realize the function of the course [7-8]. Through online learning and creating a digital learning environment, it can promote the reform of educational concepts, teaching content and methods [9]. University mathematics as a basic course of

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education, in the context of the era of network teaching platform, the curriculum design of mathematics on the network platform is of great significance for the development of mathematics teaching [10-12]. The curriculum design of university mathematics network teaching platform can promote the sharing and exchange of educational resources, improve the efficiency and quality of teaching, and explore and summarize the quality network teaching resources and teaching methods through practice, which can help to optimize the teaching content and methods and promote the reform of education and teaching [13-16]. The construction of university mathematics network teaching platform can also expand the scope of dissemination of education and promote the internationalization and modernization of education [17-18].

Literature [19] examines the issue of online training of master's degree students in mathematics and preparing them for teaching at universities, outlining the structure and design of an open access online course on a mathematics education platform by analyzing research papers and resources on online training of undergraduate mathematics majors for their professional dispositions. Literature [20] emphasizes the integration of education with the Internet, which will be at the forefront of educational innovations, and analyzes the computer networked teaching platform (TCNTP) for Higher Mathematics (HM), showing that this will change the traditional teaching and learning process. Literature [21] presents a study aimed at analyzing the support and limitations of digital educational platforms for mathematics teachers, and the results highlight the differences between these platforms, which are closely related to the existence of national educational policies and national perceptions of teachers' work. Literature [22] introduces and describes the MathE platform for mathematics learning, which is divided into three sections: student assessment, library and community of practice, and describes the impact that the platform has had on students and teachers in eight countries, featuring a good organization, the number and diversity of questions. Literature [23] outlines an educational experiment in the use of social platforms in the teaching of mathematics, aiming to emphasize the role played by teachers in online discussions and revisiting their role as knowledge transmitters, stressing its importance in the acquisition of skills. Literature [24] emphasizes the impact that information technology has had on mathematics education and shares insights gained from the period of distance education, examining the potential application of digital technology in other areas, aiming to demonstrate the opportunities offered by these platforms.

In this paper, we first constructed a multi-dimensional mathematics online course goal achievement index system including teaching preparation, teaching design, etc., which provides a quantitative basis for optimizing course teaching. Afterwards, for the defects of traditional RBF network that converges slowly and easily falls into local optimization, the FOA algorithm based on dynamic adaptive weights and population grouping is proposed to realize the global optimization of the central parameters and weights of RBF network. Through the model performance test and prediction effect analysis, it proves the superiority of the method in this paper in the prediction of students' academic performance. Then combined with the advantages of the network platform, the classroom teaching mode of university mathematics based on blended teaching is designed, which provides technical support and practical solutions for the reform of university mathematics teaching.

2. A model for assessing the degree of achievement of the teaching objectives of university mathematics online platform courses

2.1. *Construction of Teaching Quality Evaluation Indicator System for Online Courses*

The evaluation indicators of this evaluation indicator system are set at three levels: five “first-level indicators”, 16 “second-level indicators” and 70 “evaluation points”.

Level 1 indicators: set up according to the general requirement standards of the course as five parts: teaching preparation, teaching design, teaching content, teaching process and teaching effect. The evaluation mainly involves the reserve of teaching materials, the selection of teaching platforms, the use of teaching methods, the design of teaching organization, the selection of teaching content, the implementation of the teaching process, the achievement of the teaching objectives and the manifestation of the teaching effect and other elements.

Secondary indicators: Based on the connotation of the first-level indicators under the various aspects of the content. It is mainly based on the essential connotation that network course teaching breaks through the traditional teacher-centered to student-centered, and the basic characteristics of network course education and teaching objectives such as personalized stratification, remote separation of teaching subjects, rich sharing of teaching resources, two-way interaction of the teaching process, flexible and open teaching time and space, and tracking and recording of teaching process. Under teaching preparation, three secondary indicators are set, namely, "positioning objectives, learning situation analysis and resource integration". Under teaching design, three secondary indicators are set: "teaching concept, design features, and method utilization". Under teaching content, three secondary indicators are set up, namely, "course ideology, content organization, and teaching innovation". Under the teaching process, there are four secondary indicators: teaching attitude, class preparation, classroom management, and teaching implementation. Under the teaching effect, there are three secondary indicators: teaching effectiveness, evaluation of effect, and reflection on teaching.

Evaluation points: Setting up specific evaluation contents and scoring points reflecting the secondary indicators, and scoring the indicators as accurately as possible.

2.2. Radial Basis Function Neural Networks

2.2.1. Radial basis function neural network structure. Feedforward Neural Networks [25-26] RBFNN is a three-layer neural network consisting of an input layer, a hidden layer, and an output layer.The distinguishing feature of RBF neural networks is that the distance is negatively correlated with the response, i.e., the further the distance from the center, the smaller the effect on the results, and vice versa.

RBF supports discrete data interpolation; it has very high accuracy and often gives exponential error convergence; the theoretical support and applications are not limited to one, two and three dimensions, and it is very simple to extend to higher dimensional spaces. Therefore, RBF can also be used as an interpolation basis function for solving correlation problems such as missing data interpolation and time series prediction at spatial points.

The kernel function from the hidden layer to the output layer and substituting in the hidden layer is to map the input vector from linearly non-separable low dimensions to linearly separable high dimensions, thus solving the problem more intuitively. The mathematical formula realizes the process as:

$$r = \| I_i - c_j \| = \sqrt{(x_1 - c_1)^2 + (x_2 - c_2)^2 + \cdots (x_j - c_j)^2} \tag{1}$$

$$D(r) = e(-\frac{r^2}{c^2}) \tag{2}$$

The neural network output is obtained by calculating a linearly weighted sum of the hidden layer outputs according to the following equation, where k is the number of neurons in the hidden layer. I.e:

$$net_1 = G(\| I_i - c_j \|) = e(-\frac{\| I_i - c_j \|^2}{c^2}) \tag{3}$$

$$out_i = \sum_{j=1}^{k} w_j net_j = \sum_{j=1}^{k} w_j G(\| I_i - c_j \|) \tag{4}$$

2.2.2. Parameter update method for radial basis function neural networks. The radial basis function [27] has four main parameters, which are the number of nodes k in the hidden layer of the neural network, the center of the radial basis function C, the width of the radial basis function σ and the connection weights w, etc., and all of them affect the accuracy of the RBF neural network. The σ affects the network accuracy and generalization performance; k determines whether the neural network is overfitting or underfitting; the center c determines the convergence speed of the network; and w reflects the input response.There are two methods for updating the parameters of RBF neural network: gradient descent method and self-organized selection of centers method. Below I explain the two methods, and their mathematical processes, respectively.

1) Gradient descent method. The computational objective function E of the gradient descent method is:

$$E = \frac{1}{2}\sum_{i=1}^{m} e^2 = \frac{1}{2}\sum_{i=1}^{m}(y_i - out_i)^2 \tag{5}$$

where y_i is the expected output of the neural network and m is the number of input data samples.

The w,c and σ parameters are updated by choosing a certain step size from the negative gradient direction, respectively:

$$w_j(t+1) = w_j(t) + \Delta w_j(t) = w_j(t) - \eta\frac{\partial E}{\partial w_j} \tag{6}$$

$$c_j(t+1) = c_j(t) + \Delta c_j(t) = c_j(t) - \eta\frac{\partial E}{\partial c_j} \tag{7}$$

$$\sigma_j(t+1) = \sigma_j(t) + \Delta \sigma_j(t) = \sigma_j(t) - \eta\frac{\partial E}{\partial \sigma_j} \tag{8}$$

Obtain each parameter correction to be updated according to the chain derivation rule and update the following equation:

$$\Delta c_j = \eta\frac{w_j}{\sigma_j^2}\sum_{i=1}^{m} e_i G(\| I_i - c_j \|)\| I_i - c_j \| \tag{9}$$

$$\Delta \sigma_j = \eta\frac{w_j}{\sigma_j^3}\sum_{i=1}^{m} e_i G(\| I_i - c_j \|).(\| I_i - c_j \|)^2 \tag{10}$$

$$\Delta w_j = \eta\sum_{i=1}^{m} e_i G\| I_i - c_j \| \tag{11}$$

2) Self-organized center selection method. First, the k-means clustering algorithm is used to determine the hidden layer centroids c_j, and the same width σ is used for each center of the RBF neural network:

$$\sigma = \frac{c_{\max}}{\sqrt{2k}} \tag{12}$$

where. c_{max} and k are the maximum distance between centroids and the number of neurons in the hidden layer, respectively.

Solving the linear equation directly calculates the following equation to connect the weight matrix from the hidden layer to the output layer:

$$\begin{cases} w_1G_1(\| I_1 - c_1 \|) + w_2G_2(\| I_1 - c_2 \|) + \cdots + w_kG_k(\| I_1 - c_k \|) = y_1 \\ w_1G_1(\| I_2 - c_1 \|) + w_2G_2(\| I_2 - c_2 \|) + \cdots + w_kG_k(\| I_2 - c_k \|) = y_2 \\ \vdots \\ w_1G_1(\| I_m - c_1 \|) + w_2G_2(\| I_m - c_2 \|) + \cdots + w_kG_k(\| I_m - c_k \|) = y_m \end{cases} \tag{13}$$

Written in matrix form, it is equivalent to the following equation:

$$W.\phi = Y \tag{14}$$

In order to avoid the effects of matrix invertibility, the concept of matrix pseudo-invertibility is introduced, i.e., the

$$\phi^{+1} = (\phi^T\phi)^{-1}\phi^T \tag{15}$$

Combining Eq. (13) with Eq. (14), Eq. (15) is rewritten as the following equation:

$$W = Y.\phi^{+1} \tag{16}$$

2.2.3. Improvement of RBF Neural Networks. There are roughly three ideas and methods for improving RBF neural networks:

The first one is to start the research in how to use various types of evolutionary algorithms in order to obtain the optimal parameters of neural networks.

The second idea is to improve on the clustering algorithm of the centroids of the hidden layer of the RBF neural network in order to improve the generalization performance of the RBF neural network.

The third idea is to improve and optimize around the structure of RBF neural network. One of them is to construct a relatively complex neural network structure first, and then streamline the neural network structure with relevant algorithms; the other is to construct a streamlined neural network structure first, and then add nodes until it meets the neural network training accuracy requirements.

It is reasonable to improve the radial basis function neural network through these above, which can improve the radial basis function neural network model performance and accuracy. However, in the process of using the above methods, it is a key to reasonably determine the shape parameter c, and the value of c has a positive correlation with the convergence speed of the RBF neural network, and in the process of constructing the RBF neural network, it is generally chosen a reasonable c value by the experience or control variable method. Aiming at the above problems, this paper introduces the concept of effective condition number to select a reasonable c value directionally.

The effective condition number (k_{eff}) is a concept to study the interpolation stability of the interpolation matrix, which has the advantage of being more informative than the standard condition number, which is reflected in the fact that k_{eff} is considered as the interpolation matrix as well as the interpolation function. In summary, a bridge between maximizing k_{eff} and a reasonable c-value can be built to establish the correlation between the two. Determine the interval of validity of c-value and use c-value as the independent variable, k_{eff} as the dependent variable, and k_{eff} changes with the change of c-value. Smaller errors in RBF neural networks are obtained by maximizing the shape parameter c corresponding to k_{eff}. The k_{eff} is defined as follows:

$$A\alpha = f \in R^n \tag{17}$$

$$k_{eff} = \frac{\| f \|}{\sigma_n \| \alpha \|} \tag{18}$$

where A is the interpolation matrix, α is the weights, and f is the known dependent variable. where n is the number of centroids and σ_n is the rank n singular value. $\| \cdot \|$ is the 2-parameter.

2.3. Optimizing RBF neural network based on dynamic FOA

2.3.1. FOA algorithm. Fruit Fly Optimization Algorithm [28-29] (FOA) an emerging population intelligent optimization algorithm. Although it has not appeared for a long time, FOA has the advantages of plasticity, easy programming, faster search speed, etc., and can realize the iterative search of the population in the solution space.The computational steps of the FOA algorithm are as follows:

1) Let the initialized Drosophila population location be [X, Y], then the random direction K in which Drosophila use their sense of smell to search for food is at a distance from A:

$$K = X + r \tag{19}$$

$$A = Y + r \tag{20}$$

where: r is a random variable.

2) Calculate the distance D between the individual Drosophila and the origin as:

$$D = \sqrt{K^2 + A^2} \tag{21}$$

3) Calculate the flavor concentration determination value S as:

$$S = 1 / D \tag{22}$$

4) Take the flavor concentration value and bring it into the flavor determination function, which is shown in the following equation, to find the flavor concentration at the location of the fruit fly, and from that, find the flavor concentration of each fruit fly:

$$S_m = Fitness(S) \tag{23}$$

5) Find the Drosophila with the largest one-generation flavor concentration in the population with coordinates $[X', Y']$. Use this coordinate as the new Drosophila population location, add the random variable again, and repeat steps 1-5 until the Drosophila with the largest flavor concentration in the population is found.

2.3.2. Dynamic FOA optimized RBF neural network. The traditional FOA algorithm will have the problem of falling into the local optimal solution, in the early stage of FOA iteration, a long iteration step size is needed to carry out the global optimization successfully, but in the late stage of iteration, the step size is too long and leads to the decrease of local optimization ability. In order to improve this problem, the proposed FOA algorithm with dynamic search radius and optimized radial basis function (RBF) algorithm can reduce the search radius generation by generation and effectively solve the problem of falling into the local optimal solution. Optimize the RBF neural network using dynamic FOA with the following steps:

1) Initialize the RBF neural network according to the dataset, and determine the number of neurons in the input layer, hidden unit layer, and output layer of the RBF.

The activation function is a radial basis function, which is a monotonic function of the Euclidean distance between any - point in space to a center point.RBF neural network often uses Gaussian function as the activation function of radial basis neural network, which can be expressed as:

$$R(x_p - c) = \exp\left(-\frac{1}{2\sigma^2} \| x_p - c \|^2\right) \tag{24}$$

where: $\| x_p - c \|$ is the Euclidean paradigm; c is the center of the Gaussian function; σ is the variance of the Gaussian function; ρ is the number of samples.

2) According to the number of neurons in the hidden unit layer, initialize the Drosophila population position as [X, Y] and set the maximum search radius $Q_{\max}$ so that the search radius decreases with the number of iterative steps generation by generation. Namely:

$$Q_w = Q_{\max}(1 - \frac{w-1}{g}) \tag{25}$$

where: w is the current iteration step; Q_w is the search of the wth selected generation; g is the total arrival step.
3) The mean square error metric of the RBF neural network is chosen as the fitness function:

$$E = \frac{1}{M}\sum_{i=1}^{M}(y_i^{'} - y_i)^2 \tag{26}$$

where: M is the number of samples in the dataset; $y_i^{'}$ is the predicted output of the network; y is the true output of the network.
4) Follow the steps of FOA algorithm to calculate the distance, flavor concentration, and optimal concentration sequentially, and find the fruit fly with the best flavor concentration in the current population at the minimum of the fitness function.
5) Cycle steps 2-4 and keep adjusting the position of the fruit flies until the pre-set number of iterations is satisfied to find the optimal solution with the smallest fitness function, thus constructing the RBF neural network.

3. Prediction and design of course objective attainment for the university mathematics web platform

3.1. Experimental data preparation

The construction of neural network model can not be separated from the learning and training of samples, the input samples in the FOA-RBF neural network are the experimental scores of 320 students in 10 classes of mathematics in the class of 2023. And for the output samples of the model, i.e., the degree of achievement of math network course objectives. Since the college currently adopts a qualitative method to define the relationship between the experimental program and the math network course goal attainment, in order to reduce the impact of a single subjective factor or calculation method on the training of the neural network model, two ways are used to carry out the comprehensive calculation of the math network course goal attainment value in the sample data. The specific steps are as follows.
1) Standardize the 320 samples and reduce their values to between [0, 1], the specific formula is:

$$G^* = \frac{1}{100}G \tag{27}$$

where: $G = \begin{bmatrix} g_{11} & \cdots & g_{1m} \\ \vdots & \vdots & \vdots \\ g_{n1} & \cdots & g_{nm} \end{bmatrix}$ is the original set of achievement samples of 320 students; $n = 1, 2, \cdots, 320$, denotes the nth student; $m = 1, 2, \cdots, 12$, denotes the m th experimental achievement of the student; G^* is the standardized set of achievement samples.

2) The Delphi method is used to determine the weight of the experimental item scores on the degree of achievement of the objectives of the mathematics online course, $W_1 = \begin{bmatrix} w_{11} & \cdots & w_{14} \\ \vdots & \vdots & \vdots \\ w_{i1} & \cdots & w_{i4} \end{bmatrix}, i = 1, 2, \cdots, 12$, then the degree of goal attainment of this math online course $T_i = G^* \times W_i$.

3) The scoring method of professional teachers is used for calculation. There are 13 senior professional teachers in the Experimental Teaching Center of the college, and based on the long-term professional experience of the teachers, the scoring of the mathematics online course goal attainment is directly carried out with reference to the students' total experimental scores, and the course goal attainment value of another group of 320 students, T_2, is obtained.

4) Summing and averaging the above two groups of data to obtain the final math online course goal attainment value for a total of 320 sets of sample data:

$$T = \frac{T_1 + T_2}{2} \tag{28}$$

The degree of achievement of mathematics online course objectives of mathematics majors under the weighted sum method, the professional teacher scoring method and the final data are shown in Figures 1 to 3, respectively. The results show that the calculation of the degree of achievement of the objectives of the four mathematics online courses of mathematics majors under the three methods found that the results of the professional teacher scoring method were the most concentrated, and the final scores combined the weighted sum method and the professional teacher scoring method, and the results were in line with the actual specifications.

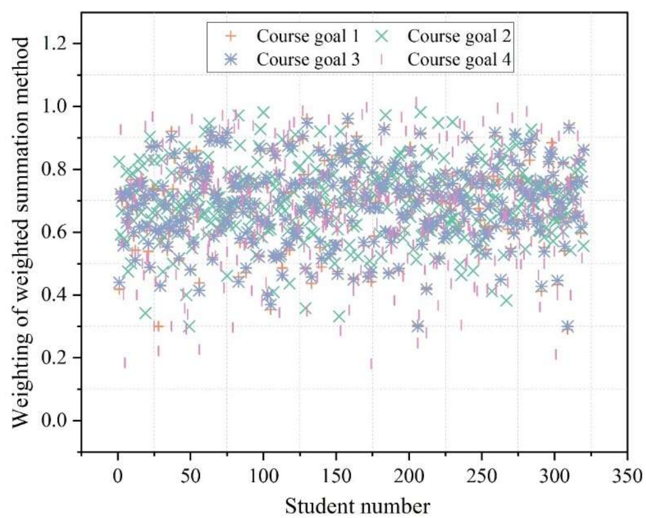


Fig. 1. The experimental course goal of the weighted sum method is achieved

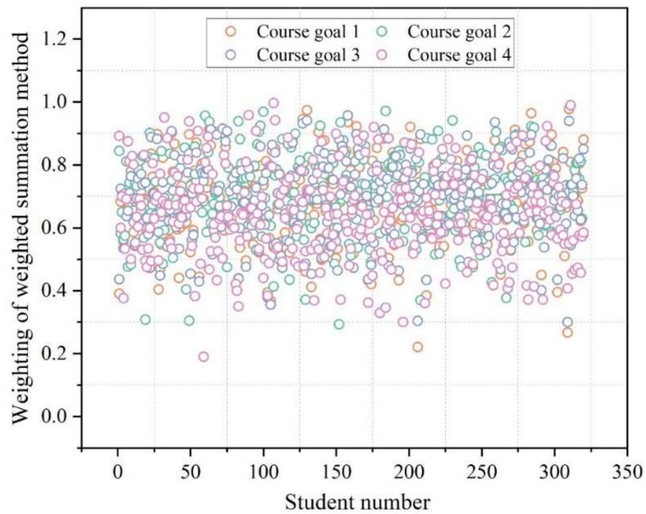


Fig. 2. The experimental course goal of the teacher's grading method

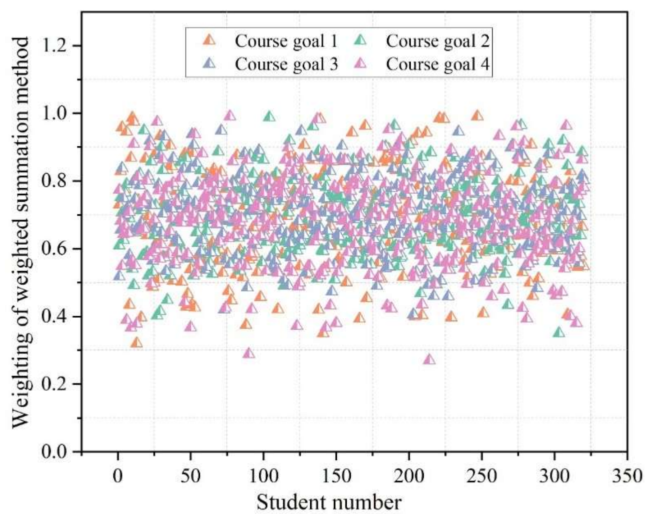


Fig. 3. The achievement of the experimental course goal of the final data

3.2. Comparative analysis of FOA-RBF model performance

In the experiment, the maximum number of iterations of the Drosophila algorithm initialization was set to maxgen=445 times, and the population size was size pop=45. The optimization process of the model parameters is shown in Fig. 4, and the root-mean-square error (RMSE) was used as the evaluation parameter, and the Drosophila population began to converge from the 75th generation with the RMSE value of 0.00605, and the smaller the value of the RMSE was, the better it was, and after 227 iterations, the final determination of the the best parameter value was 0.9034.

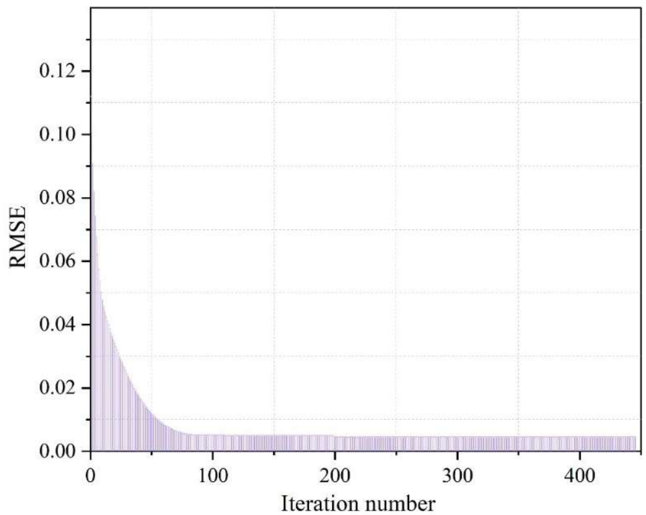
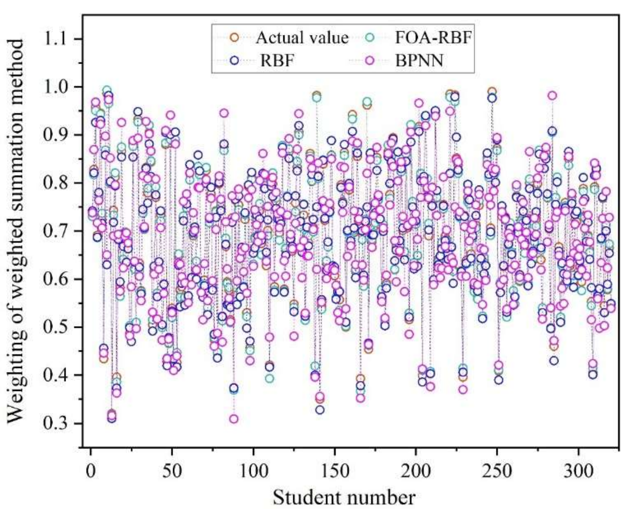
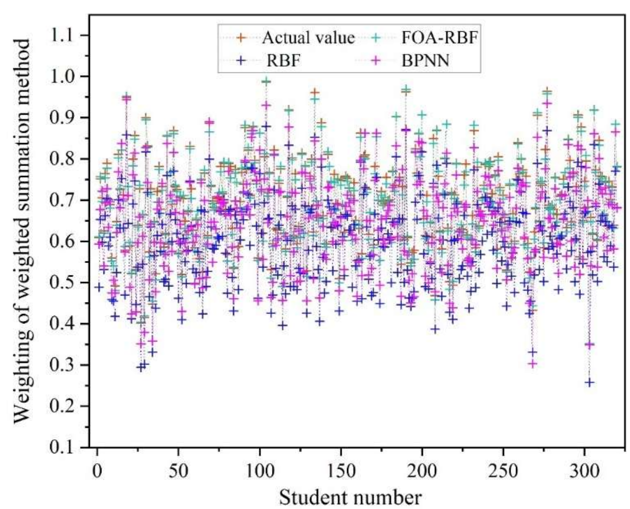


Fig. 4. Model parameter optimization process

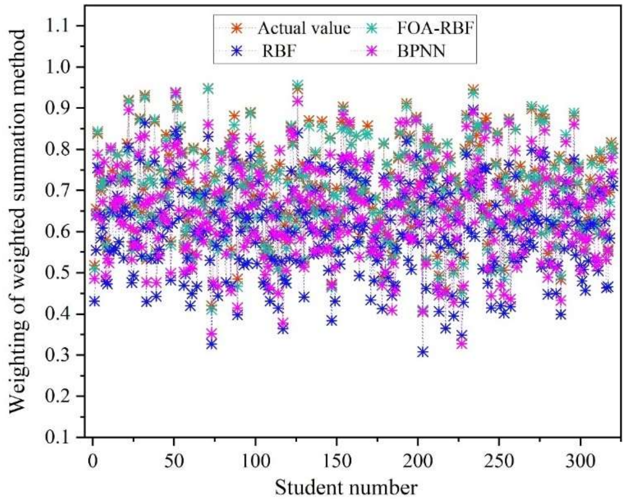
Apply the best Spread parameters for RBF neural network modeling and complete the FOA-RBF model design. The training samples were input into the model for learning and training, and then the classical BPNN neural network and RBF neural network were applied for modeling, and then the test samples were used to predict the results of the three models, and the results of the comparison of the test data of the three neural networks are shown in Fig. 5, with (a) to (d) representing the mathematical network course objectives 1, 2, 3, and 4, respectively.The results show that the FOA-RBF's prediction of the four mathematical network course goal attainment the error between the mean network prediction accuracy and the original data is around 0.4% overall; while the error between the comparison model and the four math network course goal attainment is greater than 1%. In contrast, the FOA-RBF network prediction accuracy performed the best and was better modeled compared to the other two networks.



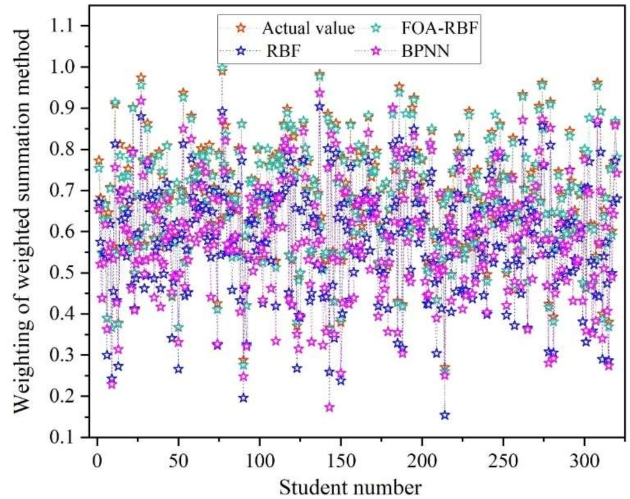
(a)Target course 1



(b)Target course 2



(c)Target course 3



(d)Target course 4

Fig. 5. Three neural network test data comparison results

The computational results of the three neural network models are shown in Table 1, with mean error, mean squared error and maximum relative error as the determination parameters. In the table, the course objective 1, course objective 2... are referred to as 1, 2, 3, 4. The results show that the model in this paper has the smallest mean error and the shortest running time (74.18s), compared to the best performance of the model.

Table 1. The calculation results of the three neural network models

Model	Implicit number	Running time/s	Target course	Mean error	Mean variance	Relative error(%)
BPNN	15	110.74	1	0.1394	0.02949	1.0149
			2	0.151	0.02997	1.2636
			3	0.1984	0.03082	1.201
			4	0.1012	0.03007	1.5426
RBF	18	99.36	1	0.1083	0.02969	1.1709
			2	0.0998	0.03171	1.4299
			3	0.0992	0.031	1.3251
			4	0.1002	0.03041	1.4539
FOA-RBF	21	74.18	1	0.00016	0.01938	0.9129
			2	0.0048	0.01029	0.8456
			3	0.00488	0.02099	1.0579
			4	0.0041	0.01085	0.9042

3.3. FOA-RBF model prediction effect analysis

The Mackey-Glass time series is one of the benchmark problems for evaluating the comprehensive performance of the algorithm with the equation:

$$x(t+1) = (1-a)x(t) + \frac{bx(t-\tau)}{1+x^{10}(t-\tau)} \tag{29}$$

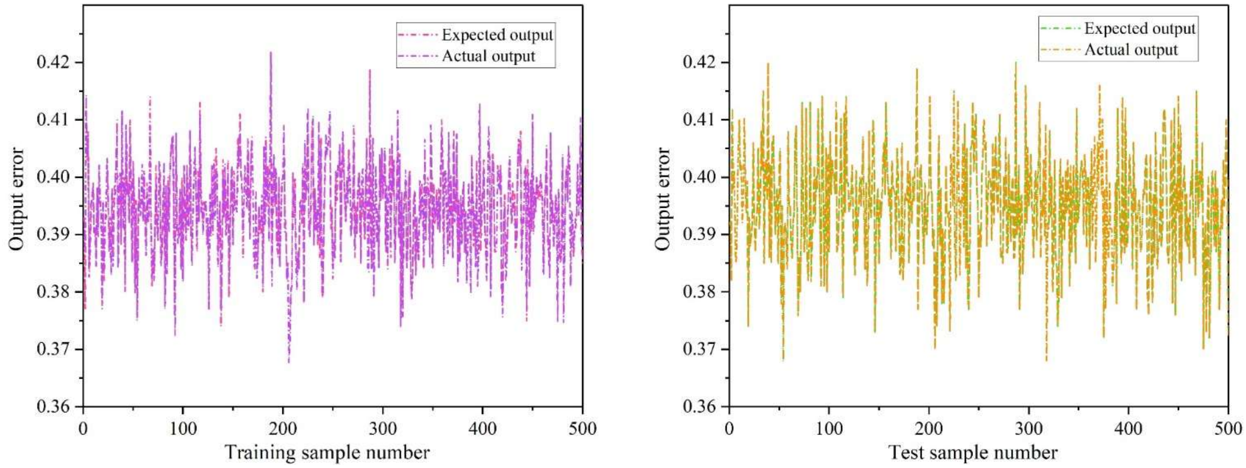
where $a = 0.1; b = 0.2; \tau = 17$. In a time series forecasting model, the input variables can be represented as $\{x(t), x(t-\Delta t), \ldots, x(t-(m-1)\Delta t)\}$, and the output variable can be expressed as $x(t+\Delta t)$. In this paper, the initial value $x(0) = 1.2, n = 4, \Delta t = 6$ is chosen and the above model can be described as:

$$x(t+6) = f\left[x(t), x(t-6), x(t-12), x(t-18)\right] \tag{30}$$

From the data generated in the above equation, the first 50% of the data is selected for FOA-RBF model training and the second 50% of the data is used for FOA-RBF model testing.

To verify the effectiveness of the proposed method, Mackley-Glass time series prediction simulation experiments are conducted. The basic parameters in the experiment are set as follows: the inertia weights are used in a linearly decreasing strategy, and the initial and final values are set as $w_i = 0.9, w_f = 0.4$; the learning factor is set as $c_1 = c_2 = 1.49$; the number of elite knowledge is set as $l = 0.1 \times I$; and the number of elite particles for reverse learning quantity is: $\varphi = 0.1 \times I$; learning rate is: $\lambda = 0.5$. The experimental results are all statistical results of 25 independent runs of each algorithm on the same test problem.

The results of the FOA-RBF algorithm for Mackley-Glass time series prediction are shown in Fig. 6, where (a) and (b) represent the training and test samples, respectively. As can be seen from the training output curves and test output curves, both are able to track the desired output with high accuracy, which indicates that the FOA-RBF neural network has good prediction accuracy.



(a)Training sample (b)Test sample

Fig. 6. The FOA-RBF algorithm predicts the Mackley-Glass time series

The output errors of the FOA-RBF algorithm for Mackley-Glass time series prediction results are shown in Figure 7. From the training error and testing error of FOA-RBF algorithm in Mackley-Glass time series prediction experiments, it can be seen that both errors fluctuate stably between [-0.0046,0.0053], which indicates that the proposed FOA-RBF algorithm not only has small testing error, but also possesses a good generalization ability.

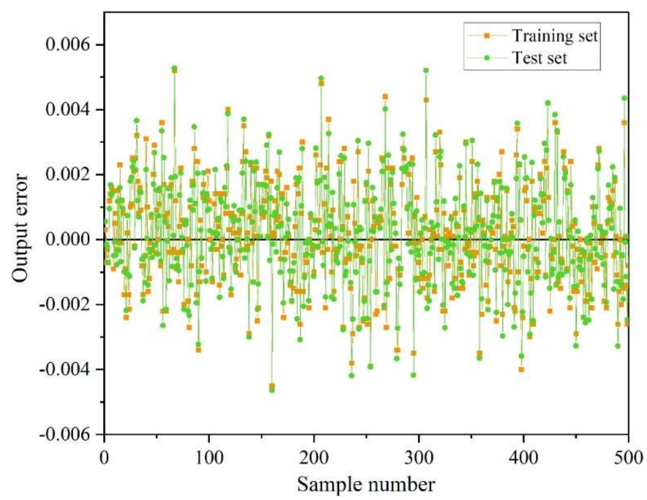


Fig. 7. The output error of the FOA-RBF algorithm for the prediction results

3.4. Instructional Program Model Design for Mathematics Programs

The design model of blended learning synthesizes online learning and classroom instruction. It mainly includes the design of learning environment, interactive classroom teaching, online Q&A teaching and developmental learning assessment. The specific clues of the teaching program are "teacher introduction - students' pre-course discussion - classroom communication - teacher summary - online Q&A - teaching evaluation". The design scheme of the blended teaching mode is shown in Figure 8. Teachers provide courseware according to the teaching content and teaching objectives of each chapter, and students understand the content of the course in advance and get in touch with the actual problem model. The content shared online before the class is mostly presented in a vivid and visual way, such as Flash, pictures, graphs and charts, to arouse the interest and attention of learning, and guide students to think and explore from shallow to deep.

Groups can also choose other topics related to the course, divide the work to collect information, group discussion and summarize the problems. In the classroom, the teacher guidedly analyzes mathematical models, explains and deduces mathematical theorems and formulas in depth, then asks interactive questions, and finally the teacher comments and summarizes. After class students complete the exercises online, and can put the problems on the line to discuss, the teacher answer questions, analyze and comment.

Blended teaching based on the web platform can design teaching programs with different weights according to the characteristics of specific learning contents, and flexibly allocate teaching time and arrange teaching progress. For example, lectures focusing on theoretical derivation can be based on classroom lectures and boards, while computational and independent learning topics are considered to be based on online teaching, which not only enhances students' motivation to learn, but also improves teaching efficiency.

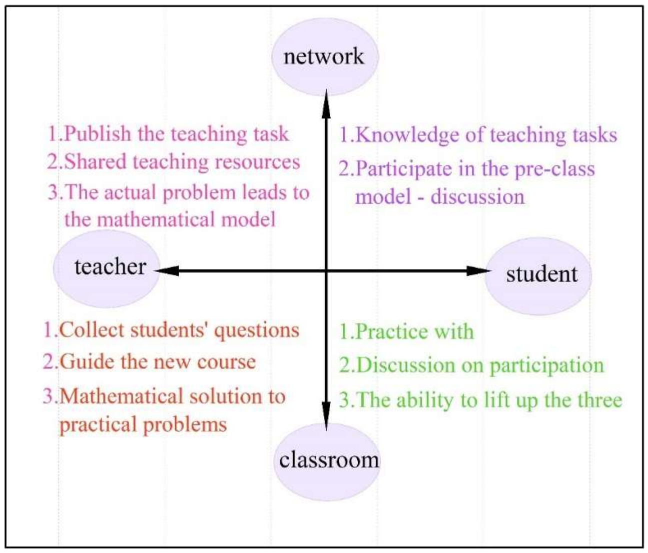


Fig. 8. The hybrid teaching mode design party case

4. Conclusion

With the wide application of network technology in the field of education, the teaching mode of university mathematics is gradually developing in the direction of networkization and intelligence. This study aims to improve the course design of university mathematics network platform through network optimization algorithm to enhance the quality of teaching. The mean error of network prediction accuracy of this paper's model on the achievement of the four course objectives of the mathematics teaching network platform is controlled between 0.00016-0.00488, and it has the shortest running time (74.18s), which is the best performance of the network prediction accuracy of this paper's model and the best simulation effect compared with the comparison model. This paper's model FOA-RBF has good prediction accuracy, and the Mackley-Glass time series prediction experiments also show that the prediction of this paper's model is extremely small, only fluctuating between -0.0046-0.0053, which can be seen that it has a good generalization ability. In view of the shortcomings of the current network teaching platform, this paper constructs a hybrid teaching mode based on the network platform, so as to enhance the enthusiasm of college students to learn mathematics and improve teaching efficiency.

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