

Application Big Data and Intelligent Optimization Algorithms on Teaching Evaluation Method for Higher Vocational Institutions

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Abstract

INTRODUCTION: The optimization of the teaching evaluation system, as an essential part of teaching reform in higher vocational colleges and universities, is conducive to the development of higher vocational colleges and universities' disciplines, making the existing teaching more standardized.

OBJECTIVES: Aiming at the problems of inefficiency, incomplete index system, and low assessment accuracy in evaluation methods of higher vocational colleges and universities.

METHODS: Proposes a teaching evaluation method for higher vocational colleges and universities with a big data mining algorithm and an intelligent optimization algorithm. Firstly, the teaching evaluation index system of higher vocational colleges and universities is downgraded and analyzed by using principal component analysis; then, the random forest hyperparameters are optimized by the grey wolf optimization algorithm, and the teaching evaluation model of higher vocational colleges and universities is constructed; finally, the validity and stability of the proposed method is verified by simulation experimental analysis.

RESULTS: The results show that the proposed method improves the accuracy of the evaluation model.

CONCLUSION: Solves the problems of low evaluation accuracy, incomplete system, and low efficiency of teaching evaluation methods in higher vocational colleges.

Keywords: teaching evaluation in higher education institutions, random forest, gray wolf optimization algorithm, principal component analysis approach

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1 Introduction

With the deepening of educational reform, the traditional teaching mode is no longer adapted to the current concept of social development, and the demand for talent training is no longer satisfied. With the development and application of big data technology and artificial intelligence methods, teaching in colleges and universities based on big data and artificial intelligence has become a new research hotspot and idea in the development of

teaching reform. However, it still faces many problems [1]. Higher vocational education, as an essential part of higher education, focuses on cultivating students' "vocational education" and has a high degree of vocational and technical application. The optimization of the teaching evaluation system is an essential part of teaching reform in higher vocational colleges and universities, which is conducive to the development of higher vocational colleges and universities and makes the existing teaching more standardized. Therefore, studying the teaching evaluation systems in higher vocational

colleges and universities is an urgent and essential research topic [2].

As a vital part of the teaching evaluation system, the teaching evaluation method of higher vocational colleges and universities is not only related to the teaching quality of teachers in higher vocational colleges and colleges and students' post-course feedback but also related to the judgment standards of experts in the teaching field [3]. Currently, teaching evaluation methods in higher vocational colleges are mainly studied and analyzed from three aspects: the connotation of teaching evaluation in higher vocational colleges, the main body of teaching evaluation in higher vocational colleges, and the problems of teaching in higher vocational colleges [4]. Literature [5] defines the connotation of teaching evaluation in higher vocational colleges and universities from six aspects of teaching objectives, conditions, processes, effects, outputs, and social feedback; literature [6] summarizes the content of practical teaching through literature surveys and other methods, and gives that the practical teaching in vocational colleges and universities should include basic experiments, functional training, modular internships and productive internships; literature [7] researches the main body of teaching evaluation in vocational colleges and universities from the multidimensional teaching structure to the main body of teaching evaluation, and analyzes the problems of teaching in higher vocational colleges and universities. Research from the teaching structure of multidimensional analysis and literature [8] for the characteristics of higher vocational education put forward the construction of a higher vocational teaching quality evaluation model from the school evaluation, outside the school evaluation of the quality of higher vocational education; Literature [9] from the connotation of the flipped classroom, put forward the flipped classroom teaching quality assessment method; Literature [10] through the analysis of the current status of the assessment of the quality of teaching from the teaching attitude, approach, content, ability and quality of teaching. Five aspects of teaching philosophy, method, content, knowledge, and design to construct the teaching quality evaluation system. The problems of teaching evaluation methods in higher vocational colleges and universities are analyzed through the way of a literature survey, and the current evaluation methods in higher vocational colleges and universities have the problems of inefficiency, incomplete index system, insufficiently objective distribution of weights of various indexes, and low utilization rate of data analysis [11]. With the development of data mining technology and artificial intelligence methods, the research on teaching evaluation methods of higher vocational colleges and universities based on big data technology and intelligent algorithms has become a hotspot of professional attention in the field. Currently, teaching quality evaluation methods in higher education institutions include the questionnaire survey method [12], fuzzy comprehensive evaluation method [13], expert scoring method [14], support vector machine [15], neural network algorithm [16], and deep learning

method [17]. Existing approaches have the following shortcomings: 1) poor objectivity and parameter setting by experience; 2) the design of the teaching evaluation system needs to be more comprehensive and objective.

Aiming at the above problems of teaching evaluation methods in higher vocational colleges and universities, this paper proposes a teaching evaluation method for higher vocational colleges and universities based on random forest and intelligent optimization algorithms. The main contributions of this paper are (1) extracting the teaching evaluation indexes of higher vocational colleges by using principal component analysis, (2) optimizing the random forest by using the grey wolf optimization algorithm, and at the same time, proposing a teaching evaluation method for higher vocational colleges based on grey wolf optimization of the random forest, and (3) verifying the method of this paper has a higher evaluation accuracy through investigation and simulation.

2 Construction of Teaching Evaluation System in Higher Vocational Colleges and Universities

This paper analyzes the construction principles to build an objective teaching evaluation system for higher vocational colleges and universities. It makes a higher vocational teaching evaluation index system from six aspects.

2.1 Principles of Construction

To promote the high efficiency of cultivating talents in higher vocational colleges and improve the rationality of teaching management in higher vocational colleges, the construction of a teaching evaluation index system of higher vocational colleges should follow the following principles [18]:

(1) Systemic

The principle of systematicity requires the evaluation system to evaluate the teaching process of teachers in higher vocational colleges and universities from the overall consideration. It is not limited to details but comprehensively evaluates the quality of teachers in higher vocational colleges and universities and fully grasps the internal and external evaluation factors to obtain complete evaluation results.

(2) Objectivity

The principle of objectivity requires that the evaluation system be constructed to carry out teaching evaluation from the perspective of fairness, impartiality, and openness and to establish evaluation indexes linking the evaluator and the evaluated to ensure that the evaluation indexes are objective.

(3) Orientation

The orientation principle requires that the teaching evaluation system constructed in higher vocational colleges and universities is conducive to teachers actively

improving their teaching level, optimizing the teaching process, and improving the quality of teaching.

(4) Reasonableness

The principle of rationality requires that the teaching evaluation system constructed in higher vocational colleges and universities needs to be combined with quantitative and qualitative evaluation, and the evaluation results of the two evaluation methods have a slight error to ensure that the evaluation system constructed can effectively solve the problem of teaching quality.

(5) Feedback

The principle of feedback requires that the evaluation system constructed can promote teaching, utilize the input of the evaluation results to find out the deficiencies and defects in education, and put forward feasible methods to improve the quality of teaching to help the managers of higher vocational colleges and universities in their management and decision-making level.

(6) Feasibility

The feasibility principle indicates that the teaching evaluation system constructed in higher vocational colleges and universities can respond to the overall quality improvement of teaching and make the teaching evaluation index system concise and moderate to ensure that the establishment and implementation of the teaching evaluation model is feasible.

2.2 System of Evaluation Indicators

According to the above principles of evaluation index construction, this section describes the characteristics of the indicators of higher vocational colleges and universities from six aspects. It constructs a complete system composed of a series of related indicators. The teaching evaluation index system proposed in this paper includes six factors, including teaching objectives, teaching content, teaching methods, teaching methodology, teaching attitude, teaching effect, and business level [19], and the specific indicators of each aspect are detailed in Figure 1.

Teaching objectives should include whether teaching teachers in higher vocational colleges and universities align with the curriculum standards and whether the goals have knowledge, ability, and emotional indicators that align with the actual situation of students and are operable. Teachers of higher vocational colleges and universities should have systematic, scientific, advanced content, teaching knowledge points highlighting the key issues and difficulties, information is relatively affluent, theories and practical combination, and the content arrangement is reasonable and appropriate. Teaching methods should include five evaluation indexes: multi-method combined teaching, thought development, teaching organization, homework, tutoring, and question-answering. Teaching attitude should consist of three evaluation indexes: enthusiasm for teaching, observing teaching discipline, and teaching rigor. The teaching effect should include three evaluation indexes: ability

quality cultivation, students' learning interest cultivation effect, and learning achievement. The business level should have three evaluation indicators: strong self-learning ability, flexible and innovative teaching methods, and scientific research ability.

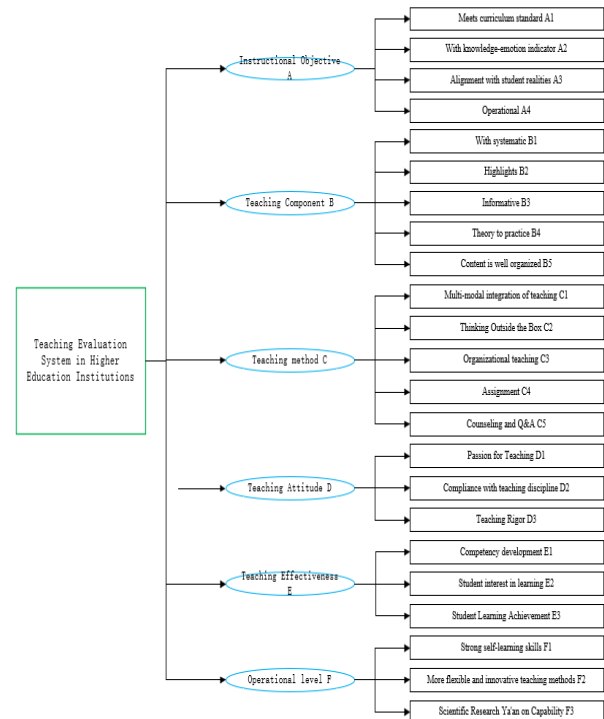


Figure 1 Analysis of teaching evaluation indexes in higher education institutions

3 Principal Component Analysis Methods

Principal Component Analysis (PCA) is one of the most widely used algorithms for data dimensionality reduction. The main idea of PCA is to map high-dimensional data features to low dimensions. The low-dimensional k -dimensions are the brand-new orthogonal features, also known as principal components. They are the k -dimensional features reconstructed based on the original high-dimensional n -dimensions. Assuming the dataset is X , the main steps to select the feature values with contribution rate greater than 99% as the new features of the dataset are as follows:

Step 1: Standardized processing of indicator characteristics. To eliminate the differences in the magnitude between different influence factors, the original data matrix of wheat evapotranspiration influence factors was standardized, and the standardized matrix Z was obtained using the Z-Score method, where n the number of samples and d the dimensions of the sample indicator characteristics.

Step 2: Determine the matrix of correlation coefficients between indicators Σ and calculate the equation of correlation coefficients between each hand:

$$\sigma_{ij} = \frac{\sum_{k=1}^n (z_{ki} - \bar{Z}_i)(z_{kj} - \bar{Z}_j)}{\sqrt{\sum_{k=1}^n (z_{ki} - \bar{Z}_i)^2 (z_{kj} - \bar{Z}_j)^2}} \quad (1)$$

Where z_{ki} denotes the standardized value of the i th indicator for the k th sample; \bar{Z}_i is the mean value of the i th hand; σ_{ij} is the covariance of the vectors Z_i .

Step 3: Determine the correlation coefficient matrix's characteristic roots and eigenvectors Σ . The symmetric positive definite matrix $\Sigma = [\sigma_{ij}]_{d \times d}$ is necessarily orthogonally similar to the diagonal matrix Λ , i.e:

$$U^T \Sigma U = \Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_d \end{bmatrix} \quad (2)$$

where, assuming $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d$. It U is an orthogonal matrix consisting of eigenvectors corresponding to the eigenroots.

Step 4: Determine the contribution of the matrix Σ . Calculate the assistance of the principal component ω_i :

$$\omega_i = 1 / \sum_{j=1}^d \lambda_j \quad (3)$$

Step 5: Determine the number of principal components k . Sort the pieces one at a time according to the magnitude of the contribution rate, determine the information retention threshold after decoupling α , and if the cumulative contribution rate of the first k components ρ is more significant than α , then the number of principal components is k .

$$\rho = \sum_{i=1}^k \omega_i \quad (4)$$

Step 6: Output the k indicator features associated with the principal components.

4 Gray Wolf Optimization Algorithm for Optimizing Random Forest Methods

Due to the Random Forest (RF) for the parameter selection being more subjective, resulting in RF learning ability robustness being called worse, the evaluation of classification results could be better [20]. To overcome the problem of poor RF training results, this paper proposes a random forest method based on the gray wolf optimization algorithm to optimize the hyperparameters.

4.1 Random Forest Approach

Random Forest (RF) is composed of many decision trees, and there is no association between different decision trees. A decision tree is a straightforward algorithm that is highly explanatory and in line with human intuitive thinking. It is a supervised learning algorithm based on if-then-else rules. When evaluating the classification task, a new input sample enters, letting each decision tree in the forest judge and classify respectively; each decision tree will get a classification result of its own; which classification result of the decision tree has the most classifications, then the random forest will take this result as the final result. The RF journey diagram is shown in Figure 2, and the specific steps are as follows:

Step 1: A sample size of n is drawn n times with putbacks, one at a time, resulting in n samples. These selected n samples are used to train a decision tree as samples at the root node of the decision tree.

Step 2: When each sample has d attributes when each node of the decision tree needs to split, m attributes are randomly selected from these d attributes to satisfy the condition $m \ll d$. Then, some strategy (e.g., information gain) is used to choose one point from these m attributes as the split attribute for that node.

Step 3: Each node in the decision tree formation process should be split according to step 2 (it is easy to understand that if the next time the node elects an attribute that was just used in the splitting of its parent node, then the node has reached a leaf node and does not need to continue splitting). Until it can no longer divide, note that there is no pruning throughout the decision tree formation process.

Step 4: Build many decision trees according to step 1~3 so that they constitute a random forest.

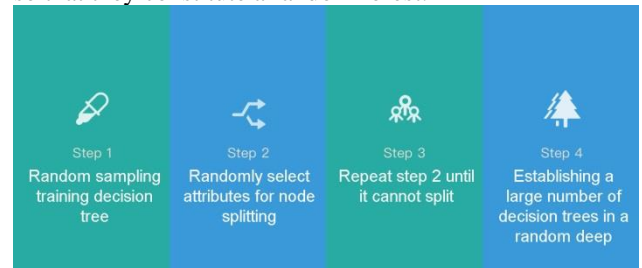


Figure 2 Schematic diagram of random forest

4.2 Gray Wolf Optimization Algorithm

In recent years, various meta-heuristic optimization algorithms have been proposed and improved by many scholars to be applied to their research. However, the No Free Lunch (NFL) theory [21] states that no single algorithm can be considered general for solving all the optimization pros. Thuo thus, the approach encourages researchers to seek to develop more effective optimization algorithms to solve the problems they are studying. While researching swarm intelligence optimization algorithms, many algorithms with excellent performance have

emerged. This paper uses Grey Wolf Optimization (GWO) as the theoretical basis for the corresponding research.

The social hierarchy within the gray wolf population inspires the GWO algorithm. The head wolf α has the privilege of making decisions for the pack, including hunting, defense, and rest. The second-ranked wolf, named β , is the successor to the head wolf α . The third-ranked wolf is named δ and obeys the orders of the superior head wolf α and wolf β [22]. The remaining wolves are of the lowest rank and must abide by the demands of the head wolf α , wolf β , and wolf δ . In GWO, the optimal solution in the population is denoted as x_α , the suboptimal solution and the third optimal solution are characterized as x_β and x_δ , respectively, and the remaining individuals are represented as x . The predatory behavior of grey wolves inspires the optimization mechanism of GWO, and it can be divided into the following three steps:

- (1) To stalk, pursue, and approach prey;
- (2) Surrounding prey and harassing it to stop it;
- (3) Attacking prey.

In GWO, wolf-hunting behavior is expressed as

$$D_p = |c \cdot x_p - x| \quad (5)$$

$$x = x_p - A \cdot D_p \quad (6)$$

Respectively. A and c are parameter vectors, and the following equation computes the values of each dimension of the vectors:

$$A_j = 2a \cdot r_1 - a, \quad r_1 \sim U(0,1) \quad (7)$$

$$c_j = 2r_2, \quad r_2 \sim U(0,1) \quad (8)$$

Random variables obey a uniform distribution from 0-1. The parameter decreases from 2-0 as the algorithm iterates.

$$a = 2 - 2 \cdot FES / FES_{\max} \quad (9)$$

In the GWO, x_α , x_β , x_δ these are the three optimal solutions for the current population and are considered the

three potential locations for the prey x_p . The x three

head wolves guide the x_α individual gray wolf, x_β and

x_δ for updating as shown in the following equation:

$$\begin{cases} D_\alpha = |c_\alpha \cdot x_\alpha - x| \\ D_\beta = |c_\beta \cdot x_\beta - x| \\ D_\delta = |c_\delta \cdot x_\delta - x| \end{cases} \quad (10)$$

$$\begin{cases} x' = x_\alpha - A_\alpha \cdot D_\alpha \\ x'' = x_\beta - A_\beta \cdot D_\beta \\ x''' = x_\delta - A_\delta \cdot D_\delta \end{cases} \quad (11)$$

$$x = (x' + x'' + x''') / 3 \quad (12)$$

In GWO, the parameter a can affect the search range of the solution population. A takes the value in the interval [0,2]. In the early stage of the algorithm iteration, the value of a is greater than 1, which makes the individuals of the population far away from the optimal solution and explore the solution space more; in the late stage of the algorithm iteration, when a is less than 1, the individuals of the population gradually approach the optimal solution and develop locally around the optimal solution. The randomness of the scale vector c affects the search

distance D_p and helps to prevent the population from falling into a local optimum. After obtaining a new

person, the algorithm updates x_α , x_β , x_δ according to the individual fitness values. When the termination condition is satisfied, it is the optimal solution.

4.3 Optimization of Random Forest Method Ideas Based on Gray Wolf Optimization Algorithm

The random deep forest (PCA-GWO-RF) evaluation model based on the principal component analysis method and GWO algorithm is divided into a data preprocessing module, optimization parameter module, and random forest algorithm module, as shown in Figure 3. Firstly, PCA is used to screen the teaching evaluation indexes. The RF module uses GWO optimization parameters to decode for RF hyperparameters to construct a random forest tree; then the RF is trained using the incoming training data from the data module; the optimal use of the test set is evaluated to obtain the error between the real value and the actual output value.

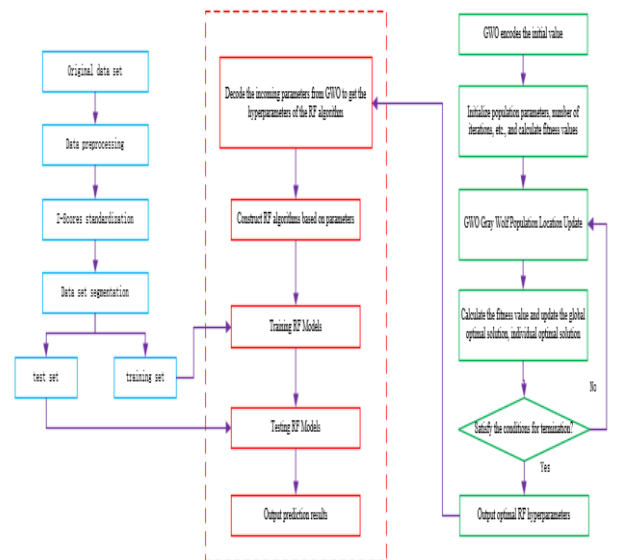


Figure 3 PCA-GWO-RF modeling diagram

To improve the accuracy of the DELM neural network, the RF hyperparameters are optimized using the GWO algorithm, i.e., the number of decision trees and the minimum number of leaves of the RF algorithm are optimized. This paper uses the actual number encoding method to encode the number of decision trees and the minimum number of leaves. This paper adopts accuracy as the fitness function to reflect the training RF advantages and disadvantages accurately.

According to the coding method and fitness function, the steps of the random forest assessment method based on principal component analysis and gray wolf optimization algorithm are as follows:

Step 1: The raw data were preprocessed using the Z-Score method, and PCA was used to screen the factors affecting the evapotranspiration. The selected data were divided into a test set and a training set;

Step 2: The improved GWO algorithm encodes the initial parameters of the RF and also initializes the algorithm parameters such as population parameters, iteration number, etc.; initializes the population and calculates the fitness function value;

Step 3: Generate new gray wolf pack locations using the GWO location update strategy;

Step 4: Calculate the fitness function value and update the global optimal solution and individual optimal solution;

Step 5: Judge whether the termination condition is satisfied. If it is comfortable, exit the iteration, output the optimal RF hyperparameters, and execute step 6; otherwise, continue to complete step 3;

Step 6: Decode the parameters of the GWO-based optimization network to obtain the hyperparameters of the random forest, i.e., the number of decision trees and the minimum number of leaves;

Step 7: Construct the GWO-RF evaluation model, train the model using the training set to get the evaluation model, and input the test set into the model to get the evaluation results.

5 Experiment and Result Analysis

To validate the performance of the proposed teaching evaluation method for teachers in higher education institutions, the assessment results of the proposed algorithm are analyzed and discussed in this section by selecting the teaching evaluation data of the case higher education institutions.

5.1 Simulation Environment Setting

This paper, MATLAB 2021a is used to write the program, and the test environment is Windows 10 system; the processor is AMD Ryzen 9 5900HX with Radeon Graphics, and the RAM is 16.0 GB. The experimental dataset is selected from the teaching evaluation data of the case higher vocational colleges and universities in the first half of the year 2022 as the training set of the evaluation model, the teaching evaluation data of subject higher

vocational colleges in the second half of 2022 as the test set of the evaluation model. The specific parameter settings of the electricity price prediction algorithm proposed in this paper and the comparison prediction method are shown in Table 1.

Table 1 Parameter settings of English teaching quality evaluation methods

Arithmetic	Parameterization
BP	Number of input nodes 50, number of intermediate nodes 70, number of output nodes 1
SOA-BP	SOA parameters: max. Number of iterations 50, number of populations as in GWO-RF; other parameters as in BP
SVM	C=100,σ=0.1
RF	The number of trees is 100
GWO-RF	GWO parameters: maximum number of iterations 50, population size obtained by learning

5.2 Selection of teaching evaluation indexes for higher vocational colleges and universities by principal component analysis

According to the principal component analysis method of teaching evaluation indexes of higher vocational colleges proposed in this paper, the data of teaching evaluation indexes of higher vocational colleges are analyzed. The indexes with higher contributions to the teaching evaluation of higher vocational colleges are selected through dimensionality reduction, and the results of the principal component analysis are shown in Figure 4. As can be seen from Figure 4, the cumulative contribution rate of the first 13 leading component indicators to the teaching evaluation indicators of higher vocational colleges has reached 95%. The results show that the first 13 indicators can represent the leading indicators covering the teaching objectives, teaching contents, teaching methods, teaching methods, learning attitudes, teaching effects, business level, etc., further indicating that this paper's teaching evaluation index system is reasonable.

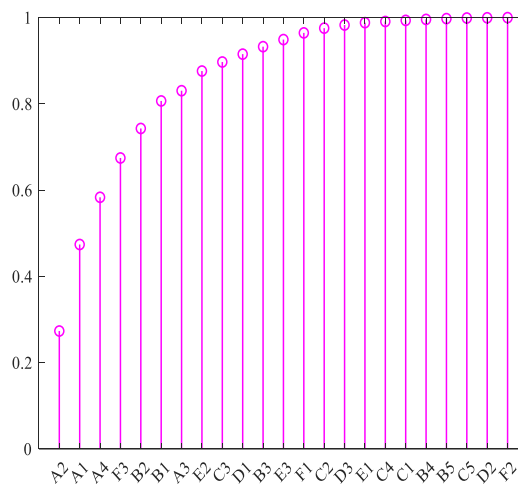


Figure 4 Results of Principal Component Analysis of Evaluation Indicators of Higher Education Institutions

5.3 Analysis of assessment results

To find the optimal effect of the PCA-GWO-RF-based teaching evaluation model for higher vocational colleges, the PCA-GWO-RF parameters are set and analyzed. To show the superiority of the proposed method, the evaluation method proposed in this paper is compared with other evaluation models.

To investigate the impact of the population size of the GWO algorithm and the number of RF decision trees on the performance of the teaching evaluation model of PCA-GWO-RF higher vocational colleges and universities, the evaluation data after dimensionality reduction is used to test the teaching quality evaluation model and to count the accuracy under different combination parameters. Figure 5 shows the influence of varying population sizes and the number of decision trees on the performance of the teaching evaluation model based on PCA-GWO-RF higher vocational institutions. It can be seen from Figure 5 that the accuracy increases with the increase in wolf population size, and the accuracy increases with the increase in the number of decision trees. In summary, the number of GWO population size is taken as 30.

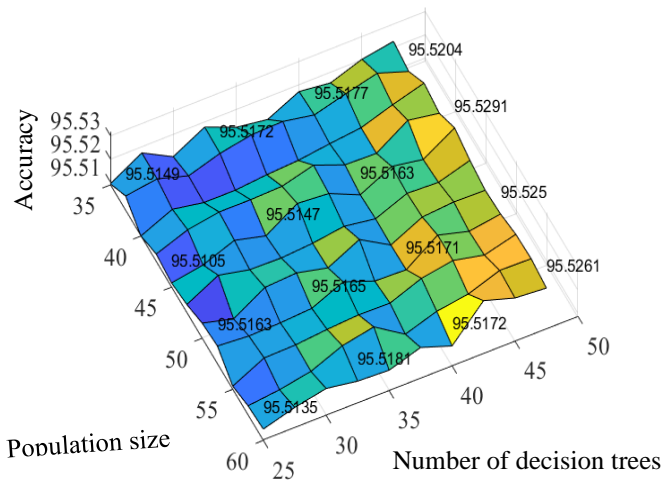
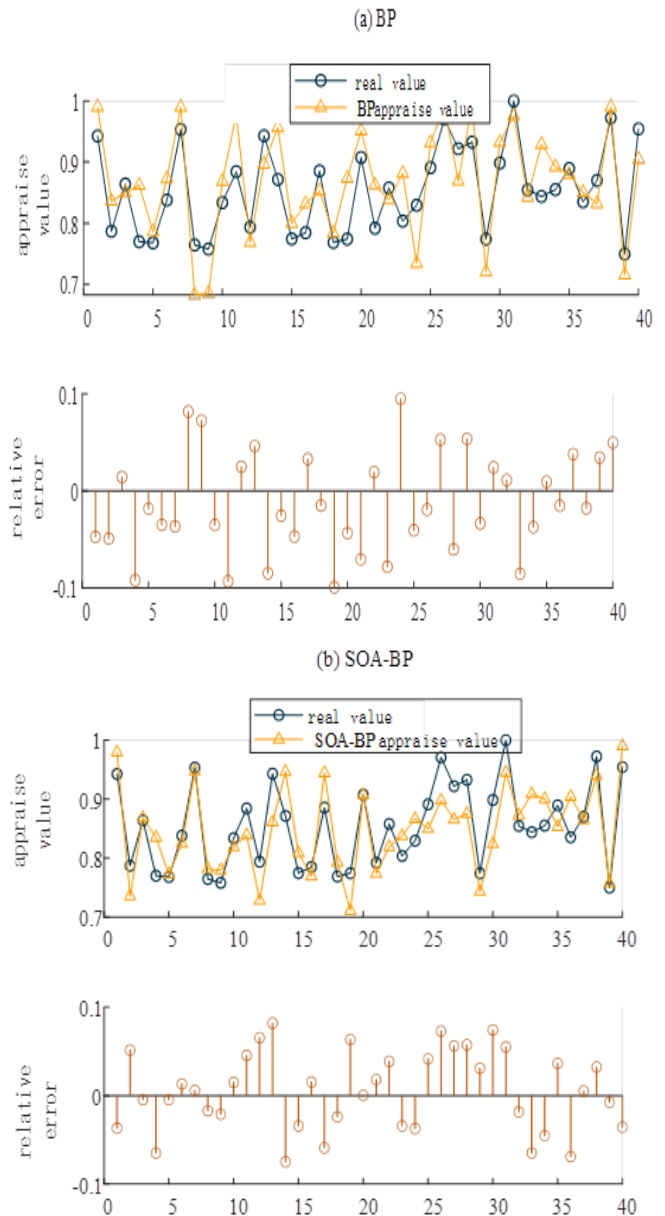


Figure 5 Effect of different population sizes and number of decision trees on the performance of PCA-GWO-RF evaluation

Based on the above parameter analysis, the population size of the PCA-GWO-RF-based teaching evaluation model for higher education institutions is 30, which subsection compares the performance of the GWO-RF, BP, SOA-BP, SVM, and RF methods using the test set.

Figure 6 gives the evaluation results of the data of the sample set of teaching evaluation tests for teachers in higher vocational colleges and universities based on different algorithms. As can be seen from Figure 6, the evaluation accuracy of GWO-optimized RF is better than other algorithms. The statistical results show that the evaluation error of the teacher teaching evaluation model

for higher vocational colleges and universities with GWO optimization RF on the test set data is not greater than 0.02, which is smaller than the evaluation error of other evaluation model methods, indicating that the model has a high evaluation accuracy.



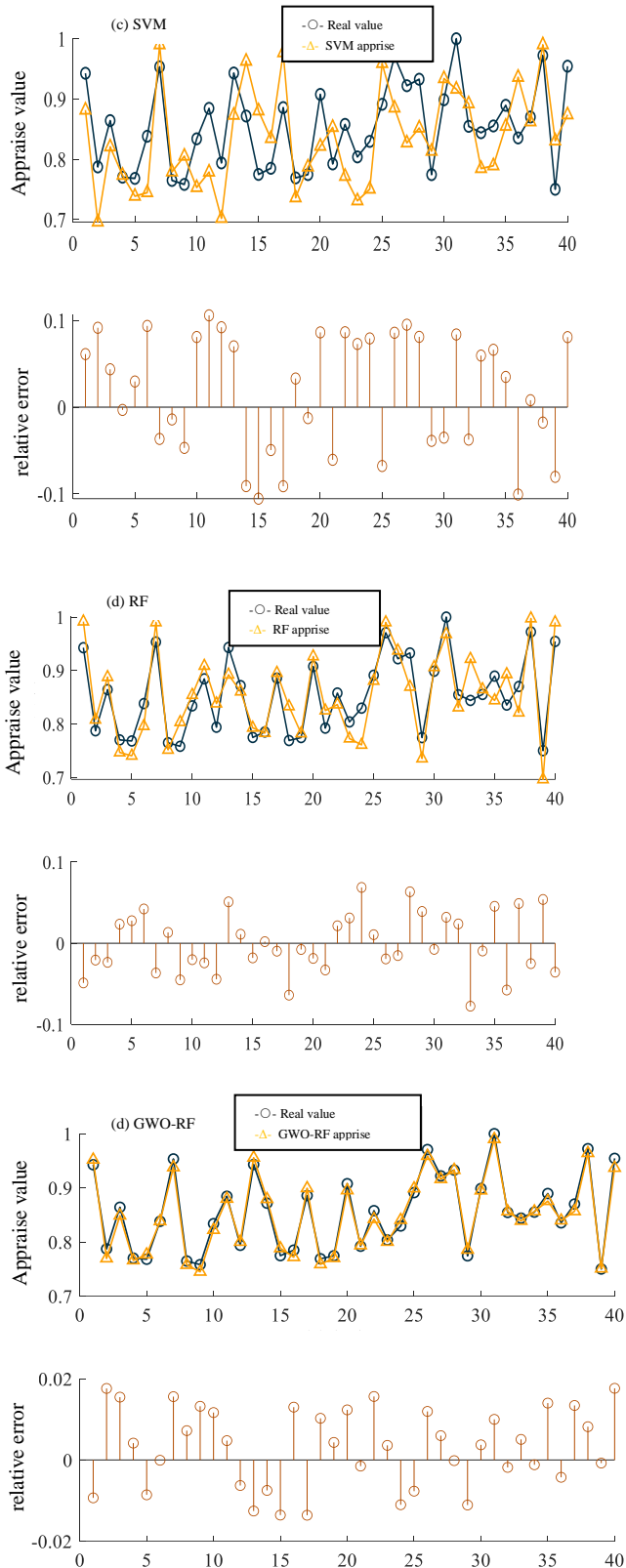


Figure 6 Evaluation results of test samples of different modeling methods

6 Conclusion

Aiming at the current teaching evaluation method of teachers in higher vocational colleges and universities, which has the problems of low accuracy and instability, this paper proposes a teaching evaluation method of teachers in higher vocational colleges and universities based on the GWO optimization algorithm to optimize the random forest. The process uses principal component analysis to reduce the dimensionality of the teacher teaching evaluation index system of higher vocational colleges and universities; the GWO algorithm is used to optimize the random forest and construct the teacher teaching evaluation method of higher vocational colleges and universities. Through simulation, the following conclusions are drawn: the PCA method is used to extract important teaching evaluation indexes of teachers in higher vocational colleges, which can cover the main indexes of teaching objectives, teaching contents, teaching methods, teaching methods, learning attitudes, teaching effects, business level, etc.; the accuracy of the RF evaluation model optimized based on GWO is better than that of the other models; the evaluation model proposed in this paper does not perform well in some of the samples, the Further improvement of PCA-GWO-RF prediction stability is the following research focus.

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