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Research on Employee Performance Management Method Based on Big Data Improvement GWO-DELM Algorithms

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Abstract

INTRODUCTION: Accurate and objective human resources performance management evaluation methods are conducive to a comprehensive understanding of the real and objective situation of teachers, and are conducive to identifying the management, teaching and academic level of teachers, which enables teacher managers to have a clear understanding of the gaps and problems among teachers.
OBJECTIVES: Aiming at the current human resources performance management evaluation method, there are evaluation indexes exist objectivity is not strong, poor precision, single method and other problems.
METHODS: This research puts forward an intelligent optimisation algorithm based on the improvement of the depth of the limit of the learning machine network of human resources performance management evaluation method. (1) Through the analysis of the problems existing in the current human resources performance management, select the human resources performance management evaluation indexes, and construct the human resources performance management evaluation system; (2) Through the multi-strategy grey wolf optimization algorithm method to improve the deep learning network, and construct the evaluation model of the human resources performance management in colleges; (3) The analysis of simulation experiments verifies the high precision and real-time nature of the proposed method.
RESULTS: The results show that the proposed method improves the precision of the evaluation model, improves the prediction time.
CONCLUSION: This research solves the problems of low precision and non-objective system indicators of human resource performance management evaluation.

Keywords: human resource performance management evaluation, deep extreme learning machine, grey wolf optimisation algorithm, Levy flight strategy.

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1. Introduction

The development and reform of educational Institutions could not be separated from the quality of teaching, academic level and whether the students trained can adapt to the society, ultimately depends on the level of teachers, therefore, the cultivation of high-quality teacher team is a key factor in the competitiveness of educational Institutions [1]. At present, China's education management is in the field of high-speed development stage, but also to deepen the reform and overcome the difficulties of the stage, but also the transformation and upgrading of the stage, the increasing number of students, making the demand for high-quality human resources is increasing day by day, so that the demand for teacher team management is increasing day by day, but still unable to meet the requirements of China's education management of the development of a new era and the students' ability to adapt to the community to improve their learning ability to improve the demand [2]. Human resource performance management evaluation as a key part of human resource management, the results of which can determine the teacher's title evaluation, job allocation, salary arrangements, welfare measures, rewards and punishments, but also an objective basis for teachers' career planning [3]. Accurate and objective human resources performance management evaluation method is conducive to a comprehensive understanding of the real and objective situation of teachers, and is conducive to identifying the management, teaching and academic level of teachers, so that teachers' managers have a clear understanding of the gaps and problems between the teachers, and solve the exposed problems in a timely manner, and continuously improve the education system [4]. Therefore, how to specify, standardise and objectify the development of human resources performance management system and construction of performance management evaluation method is the current needs of the reform and development of the field of education management in the new era, which is of great practical significance [5].

The evaluation method of human resource performance management , as the key technology of human resource performance management , is not only related to the selection of performance management evaluation indexes, but also related to the algorithm of performance management evaluation model [6]. In order to improve the effect of human resource performance management in institutions, the specific quantitative, rational and standardised nature of evaluation indexes and evaluation methods are becoming more and more important, and are being researched and paid attention to by experts and the field of education [7]. College human resources performance management evaluation according to the performance management needs, through the analysis of the work of college staff, the construction of the performance evaluation plan, the use of appraisal and interviews and other ways to achieve the performance evaluation results, and feedback to improve the quality of teaching and teaching management [8]. Currently, performance management evaluation methods include fuzzy comprehensive evaluation method [9], machine learning method [10], deep learning method [11]. Madhavkumar theoretically proposes that the performance management evaluation system should satisfy fairness and reliability, and indicates that effective evaluation methods should maintain a balance between assessment and development[12]; Ugoani uses hierarchical analysis to construct a diversified performance management method by selecting performance-related influencing factors[13]; Kutieshat and Farmanesh analyse the reasonableness and validity of the human resource performance management methods by means of questionnaires. thereby improving the objectivity and fairness of the evaluation system[14]; Binjai and Indrawan deal with the performance evaluation weights of public security intelligence personnel through fuzzy theory, and proposes diversified incentives and methods so as to improve the efficiency of human resource management[15]; Beuzelin et al. construct a university performance management method by adopting an intelligent algorithm to optimize and improve the support vector machine, so as to improve the evaluation accuracy[16]; Whelan et al. construct a performance evaluation system, establishing an evaluation model based on the intelligent optimisation algorithm to improve the deep learning method, which provides new ideas for the human resources evaluation model[17]. In view of the above literature analysis, the existing human resources performance management evaluation methods have the following shortcomings: 1) the performance management cognition is not comprehensive enough, which makes the performance evaluation indexes have limitations; 2) the subject of performance management evaluation is too single and not diversified enough; 3) the evaluation is only from the qualitative point of view, and there is a lack of objective and quantitative research; 4) the evaluation of performance management is only confined to the teachers' team, and it is not suitable for the promotion of performance evaluation at the level of all staff members of educational Institutions. the level of all staff in higher education [18].

Deep Extreme Learning Machine (DELM) is a deep learning model based on Extreme Learning Machine (ELM). Compared to traditional deep learning models, DELM does not require backpropagation algorithms and therefore has faster training speed and better generalisation performance [19]. Grey Wolf Optimizer (GWO), a swarm intelligence optimisation algorithm proposed in 2014 by Mirjalili et al, scholars from Griffith University, Australia. Inspired by grey wolf group predatory behaviour, the GWO algorithm simulates the leadership hierarchy and hunting mechanism of grey wolves in nature. The classification of grey wolves into four types was used to simulate hierarchical strata. In addition, the three main phases of searching for prey, encircling prey and attacking prey are also simulated. It has been successfully used in the fields of workshop scheduling, parameter optimisation and image classification [20].

Aiming at the problems existing in the current evaluation method of human resource performance management , this paper proposes the evaluation method of human resource performance management based on the multi-strategy intelligent optimisation algorithm to improve the deep learning network. The main contributions of this paper are :

(1) analysing the problems of human resource performance management , selecting relevant indicators,

and constructing the evaluation index system of performance management ;
(2) improving the grey wolf optimization algorithm by using multiple strategies, combining with the deep limit learning machine, and proposing the evaluation model of performance management ;
(3) verifying the method of this paper through simulation, which has a higher evaluation accuracy and real-time performance.

2. Human resource performance management evaluation system

By analysing the existing performance management problems , we extract the evaluation indexes of human resource performance management , and construct the evaluation system of human resource performance management .

2.1. Problems with current performance management

According to the university human resource performance questionnaire and platform resources statistical analysis, the following major problems exist in the current performance management in universities [21], in Figure 1.

Insufficient knowledge of concepts

Performance management is not only a way to improve teaching quality and management efficiency, but also an educational management concept. At present, the current performance management system and methods of educational Institutions have not penetrated into all aspects of the staff, and its cognitive concept has not been understood and implemented by each staff member. Higher education staff only believe that performance management is performance appraisal, did not recognise the performance management of the school planning prospects and development and reform; over-emphasis on the "after the fact evaluation" of performance management evaluation, pay attention to the form of performance management appraisal, the lack of timeliness [22-23]; for the application of performance appraisal results after performance appraisal, lack of feedback to improve the performance management approach and staff development. The application of performance evaluation results after performance appraisal lacks feedback to improve performance management methods and staff development paths.

Poor development planning

Performance management and the development of educational Institutions is closely related, but there are still educational Institutions development planning only stays in the leadership of educational Institutions, but do not be specifically implemented. The current strategic planning objectives of universities are not clear, making the development goals of the staff ambiguous; performance evaluation for educational Institutions to achieve results, failed to synchronise the application of future development planning, making the cumulative problem more and more.

Inadequate regulatory feedback

Supervision and feedback is an essential part of the objective implementation of performance evaluation and the application of results, and the current performance management of educational Institutions lacks effective communication feedback and supervision and openness, which is mainly manifested in the following two aspects. First, the departmental managers only talk about the advantages and not the disadvantages, the performance appraisal is a formality, the supervision of the fairness and openness is not enough, lack of justice; second, the lack of staff from the performance appraisal to find problems, but also the lack of problems in the improvement of the work, so that the performance appraisal reduces the effect, and do not effectively improve the quality of teaching and management efficiency.

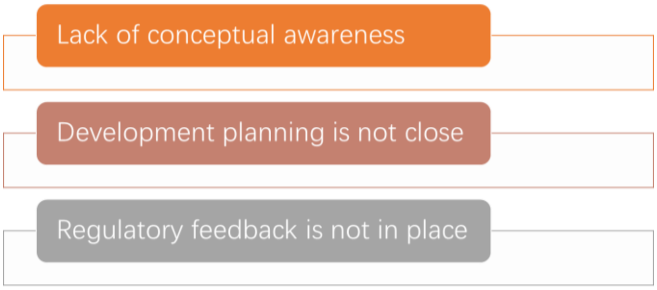


Figure 1. Problems with current performance management model

2.2. Construction of evaluation index system

The evaluation system of English teaching takes the key elements of teaching, scientific research and others [24] as the first-level indicators, and the teaching workload, teaching content, academic lectures, teaching effects, awards for teaching achievements, supervision of master's degree/doctoral degree, teaching methods and innovations, publications, subject projects, publication of theses, awards for scientific research, participation in the work of the party and government, interpersonal relationship situation, professional ethics level, academic level, title, knowledgeable situation and other 17 influencing factors as secondary indicators [25], fully embodies the whole process of evaluation of human resources performance management in universities, and constructs a scientific, objective and comprehensive evaluation system of human resources performance management , the specific schematic diagram is shown in Figure 2.

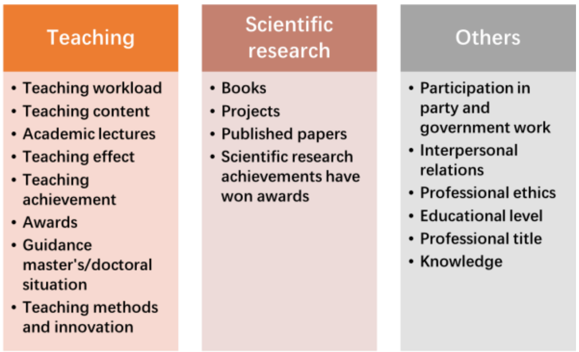


Figure 2. Evaluation index system for human resources performance management in higher education institutions

3. Deep Limit Learning Machine

Extreme Learning Machine (ELM) is a single hidden layer feed-forward neural network [26], whose biggest advantage is its fast learning speed, and its specific structure is shown in Figure 3. For a l hidden layer node the ELM can be expressed as equation (1).

$$f_{ELM}\left(x_i\right)=\sum_{j=1}^{l}\beta_j g\left(a_j x_i+b_j\right), i=1,2,\cdots,N \quad (1)$$

Where $\beta_j=\left[\beta_{j1},\beta_{j2},\cdots,\beta_{jn}\right]$ denotes the output weight of the j th hidden layer unit, $a_j=\left[a_{j1},a_{j2},\cdots,a_{jm}\right]$ denotes the input weight of the j th hidden layer unit, b_j denotes the bias of the j th hidden layer unit, and $g(\cdot)$ denotes the activation function of the hidden layer unit.
The ELM output error is equation (2).

$$\begin{aligned} E &= \sum_{i=1}^{N}\left\| f_{ELM}\left(x_i\right)-y_i\right\| \\ &= \left\|\boldsymbol{H}\left(\boldsymbol{a},\boldsymbol{b}\right)\cdot\beta-\boldsymbol{y}\right\| \end{aligned} \quad (2)$$

Where, $\boldsymbol{H}$ denotes the output of the hidden layer unit, β denotes the output weight and $\boldsymbol{y}$ denotes the desired output. In ELM algorithm, by determining $\boldsymbol{a}$ and $\boldsymbol{b}$, $\boldsymbol{H}$ is uniquely determined. The output weights are solved by equation (3):

$$\boldsymbol{\beta}^{*}=\boldsymbol{H}^{-1}\cdot\boldsymbol{y} \quad (3)$$

where $\boldsymbol{H}^{-1}$ denotes the Moore-Penrose generalized inverse matrix of the matrix $\boldsymbol{H}$.
The output weights of the deep limit learning machine consisting of multiple limit learning machine self-encoders are presented by equation (4):

$$\boldsymbol{\beta}^{*}=\boldsymbol{H}^{-1}\left(\frac{1}{C}+\boldsymbol{H}\boldsymbol{H}^{T}\right)^{-1}\cdot\boldsymbol{y} \quad (4)$$

where C represents the regular term coefficients. In order to reduce the complexity of training, two hidden layers are chosen in this paper, and the number of hidden layer units in each layer is learnt from the parametric experiments later.

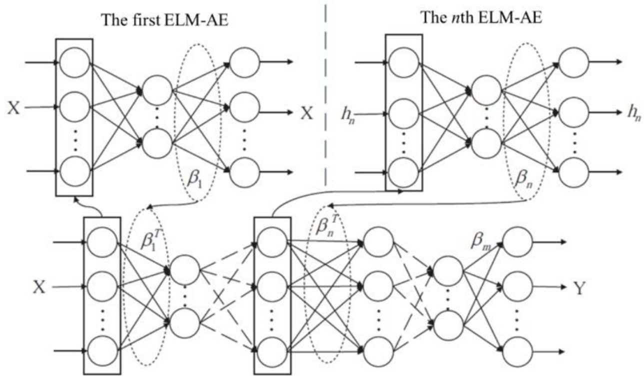


Figure 3. Structure of DELM network

4. Improving the grey wolf optimisation algorithm

4.1. Grey wolf optimisation algorithm

The GWO algorithm is inspired by the social hierarchy within the grey wolf population. The head wolf α has the privilege of making decisions for the pack, including hunting, defence, 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 its superiors, head wolf α and wolf β. The remaining wolves are the lowest ranked and must obey the commands of the head wolf α, wolf β and wolf δ, as shown in Figure 4. In GWO, the optimal solution in the population is denoted as xα, the suboptimal solution and the third optimal solution are denoted as x_β and x_δ, respectively, and the remaining individuals are denoted as x. The optimization mechanism of GWO is inspired by the predatory behaviour of grey wolves, which can be divided into the following three steps:
(1) Stalking, chasing and approaching prey;
(2) Surrounding the prey and harassing it to stop it;
(3) Attacking prey.

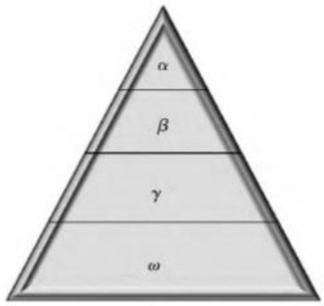


Figure 4. The grey wolf hierarchy
In GWO, wolf hunting behaviour is expressed as equation (5) and (6):

$$\boldsymbol{D}_{\mathrm{p}} = \left| \boldsymbol{c} \cdot \boldsymbol{x}_{\mathrm{p}} - \boldsymbol{x} \right| \quad (5)$$

$$\boldsymbol{x} = \boldsymbol{x}_{\mathrm{p}} - \boldsymbol{A} \cdot \boldsymbol{D}_{\mathrm{p}} \quad (6)$$

where $\boldsymbol{x}_{\mathrm{p}}$ and $\boldsymbol{x}$ denote the locations of the prey and the grey wolf, respectively. a and c are parameter vectors, and the value of each dimension of the vectors is calculated by the following equation(7) and (8):

$$\boldsymbol{A}_j = 2a \cdot r_1 - a, \quad r_1 \sim U(0,1) \quad (7)$$

$$\boldsymbol{c}_j = 2r_2, \quad r_2 \sim U(0,1) \quad (8)$$

where r_1 and r_2 are random variables obeying a uniform distribution from 0-1. The parameter a decreases from 2 to 0 as the algorithm iterates equation (9).

$$a = 2 - 2 \cdot FEs / FEs_{\max} \quad (9)$$

In GWO, $\boldsymbol{x}_\alpha$, $\boldsymbol{x}_\beta$ and $\boldsymbol{x}_\delta$ are the three optimal solutions for the current population and are considered to be the three potential locations for the prey $\boldsymbol{x}_p$. The grey wolf individual $\boldsymbol{x}$ is guided to update by the three head wolves $\boldsymbol{x}_\alpha$, $\boldsymbol{x}_\beta$ and $\boldsymbol{x}_\delta$ as shown in the following equation (10)-(12).

$$\begin{cases} \boldsymbol{D}_\alpha = \left| \boldsymbol{c}_\alpha \cdot \boldsymbol{x}_\alpha - \boldsymbol{x} \right| \\ \boldsymbol{D}_\beta = \left| \boldsymbol{c}_\beta \cdot \boldsymbol{x}_\beta - \boldsymbol{x} \right| \\ \boldsymbol{D}_\delta = \left| \boldsymbol{c}_\delta \cdot \boldsymbol{x}_\delta - \boldsymbol{x} \right| \end{cases} \quad (10)$$

$$\begin{cases} \boldsymbol{x}' = \boldsymbol{x}_\alpha - \boldsymbol{A}_\alpha \cdot \boldsymbol{D}_\alpha \\ \boldsymbol{x}'' = \boldsymbol{x}_\beta - \boldsymbol{A}_\beta \cdot \boldsymbol{D}_\beta \\ \boldsymbol{x}''' = \boldsymbol{x}_\delta - \boldsymbol{A}_\delta \cdot \boldsymbol{D}_\delta \end{cases} \quad (11)$$

$$\boldsymbol{x} = \left(\boldsymbol{x}' + \boldsymbol{x}'' + \boldsymbol{x}''' \right) / 3 \quad (12)$$

In GWO, the parameter a can affect the search range of the solution population. a takes the value of the interval [0,2]. In the early stage of the algorithm iteration, a takes a value greater than 1, which makes the population individuals move 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 population individuals gradually approach the optimal solution and locally exploit around the optimal solution. The randomness of the scale vector c has an effect on the search distance $\boldsymbol{D}_{\mathrm{p}}$ and helps to avoid the population from falling into a local optimum. After obtaining a new population, the algorithm updates $\boldsymbol{x}_\alpha$, $\boldsymbol{x}_\beta$ and $\boldsymbol{x}_\delta$ according to the individual fitness values. When the termination condition is satisfied, $\boldsymbol{x}_\alpha$ is the optimal solution.

4.2. Improvement strategies

In optimisation algorithms, balancing algorithmic global search and local exploration is the key to designing the algorithm. In engineering problems, the number of algorithm parameters directly affects the adaptability of the algorithm. To address these two aspects, a new improved algorithm for GWO-Random Orthorcenter GWO (ROGWO) is proposed in this section. The algorithm is mainly improved in two aspects. Firstly, a new search strategy is proposed to combine the two phases of synthetic design and mirror localisation into one, which enhances the exploratory and adaptive nature of the ISA algorithm. On the other hand, the probability of the algorithm jumping out of the local optimum is enhanced by introducing Levy flights in the local search phase instead of the random wandering strategy of the standard ISA algorithm.

Stochastic centre of gravity strategy

In standard GWO algorithms, the parameter settings are sensitive to the optimisation performance, so the presence of parameters reduces the applicability of the algorithm. To address these issues, this section proposes a new search strategy-Random Orthocenter Strategy (ROS). Its strategy is to take a random point to form a triangle outside the line connecting the element and the global optimal point within the upper and lower bounds, calculate the position of the centre of gravity of the triangle, and place a mirror at the centre of gravity point of the triangle, with the dummy shadow on the extension line of the element and the centre of gravity, according to the position of the centre of gravity of the triangle, so as to implement the algorithm to perform a global or local search.

The centre of gravity is the intersection of the three medians of a triangle, whose coordinates are the arithmetic mean of the coordinates of the three vertices, and the centre of gravity is always located in the interior of the triangle, setting A to be an element, B to be the global optimal point, and R to be a random point.

The coordinates of the centre of gravity of the triangle are calculated as follows equations:

$$LB^j < x_{i,r} < UB^j \quad (13)$$

$$x_{m,i}^j = \frac{x_i^{j-1} + x_{gb}^j + x_{i,r}}{3} \quad (14)$$

Where $x_{i,r}$ is a random point within the upper and lower boundaries and $x_{m,i}^j$ is the centre of gravity of the triangle, which is also the mirror coordinate.

Using the random centre of gravity strategy, a global or local search is performed within the upper and lower boundaries. Since the random points can be selected to form different types of triangles, and the mirror is placed at the centre of gravity of the triangle, the generated virtual shadow is indeterminately away from the optimal point, so this method can really achieve the global search, give full play to the diversity of the population, prevent the algorithm from falling into the local optimum, and improve the algorithm's convergence speed, adaptability and robustness.

Levy Flight Strategy

The standard GWO search strategy is inflexible and lacks the mechanism of jumping out of the local optimum. Levy flight in a stochastic search process on the solution space, which represents a class of non-Gaussian stochastic processes that move in steps obeying the heavy-tailed probability. In Levy flight, by switching between multi-step short-range and long-range search, it can both expand the search range and enhance the local search effect in a specific region, and the foraging trajectories of many organisms in nature are characterised by Levy flight.

Figure 5 shows the results of executing 1200 steps of Levy flight and Brownian motion, respectively, and it can be seen that Levy flight balances the global search and local exploration ability. Levy flight performs a small search in the vicinity of the optimal solution, which improves the local search ability, and it also performs a large global search, which increases the population diversity and ensures that the algorithm jumps out of the local optimum to perform a global search ability.

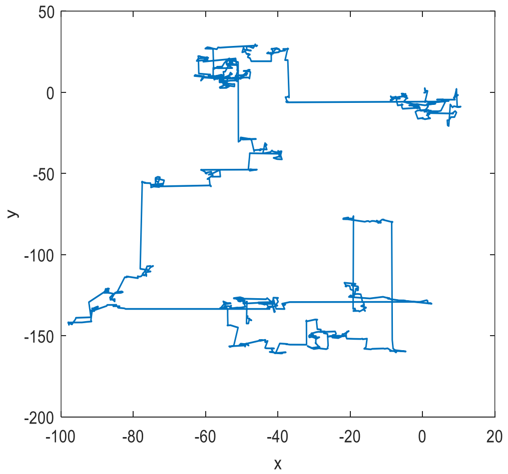


Figure 5. Levy flight strategy

The optimal solution x_{gb} is solved based on the improved local optimization phase of Levy flight as shown below, equation (15):

$$x_{gb} = \left(\mathbf{x}' + \mathbf{x}'' + \mathbf{x}'''\right)/3 + \alpha \oplus Levy(\beta) \tag{15}$$

Where $\alpha > 0$ is the step adjustment factor and $\oplus$ represents the multiplication. α and $Levy(\beta)$ are calculated as follows, equation(16) and (17):

$$Levy(\beta) = \frac{\mu}{|v|^{1/\beta}} \tag{16}$$

$$\alpha = \alpha_0 (x_{gb}^{j-1} - x_{gb}^{j-2}) \tag{17}$$

μ and v obey the following normal distribution, respectively, equation(18) and (19):

$$\mu \sim N(0, \sigma_\mu^2) \ , \ v \sim N(0, \sigma_v^2) \tag{18}$$

$$\sigma_\mu = \left(\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right)^{1/\beta} \ , \sigma_v = 1 \tag{19}$$

Where, Γ is the gamma function, x_{subgb}^{j-1} is the suboptimal solution of the $i-1^{\text{th}}$ iteration, α_0 is set to 0.01, and β is set to 1.5. In the grey wolf search phase, the Levy search strategy is added. Using the Levy flight strategy can carry out effective extensive search, enhance the algorithm's global search ability, and can effectively solve the shortcomings of the basic GWO algorithm falling into the local optimum.

4.3. Steps to improve the GWO algorithm

According to the principle and improvement strategy of GWO algorithm, the specific steps of GWO algorithm are given in this section:

Step 1: Initialize the number of GWO populations with the number of iterations;

Step 2: Initialize the GWO population. Initialize the GWO population using the random uniform distribution strategy, calculate the fitness value, or obtain the current optimal value and optimal solution;

Step 3: Compute the parameter vectors A and c.

Step 4: Selection of strategy. Depending on the size of the random value between r and 0.5, the population individuals are made to choose different position update strategies. If , the grey wolf individual chooses the standard GWO algorithm along with the improved local optimality seeking strategy based on Levy flight; otherwise, the grey wolf individual chooses the random centre of gravity strategy;

Step 5: Calculate the fitness value and select and retain the better solution using an elite selection strategy;

Step 6: Determine whether the number of iterations reaches the maximum number of iterations. If it reaches, output the optimal solution and optimal value; otherwise, return to step 3.

5. Improving the grey wolf optimisation algorithm

5.1. Coding method

In this paper, the real number coding method is used to encode the hidden layer parameters, and the specific coding method is shown in Figure 6. From Figure 6, it can be seen that the coding region is mainly divided into the hidden layer weight values and the hidden layer bias, l the coding dimensions of the two hidden layer units m dimensional inputs are $m \times l + l$, and the coding dimensions of the two hidden layers are $\left(m_1 \times l_1 + l_1\right) + \left(m_2 \times l_2 + l_2\right)$.

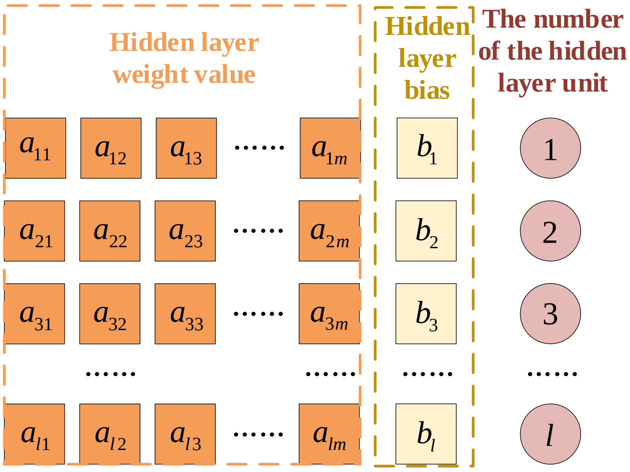


Figure 6. encoded DELM parameters

5.2. Adaptation function and ROGWO-DELM methodology

In order to accurately reflect the training DELM network strengths and weaknesses, this paper uses RMSE as the fitness function.

In Figure 7, According to the coding method and fitness function, the steps of the deep limit learning machine prediction method based on the improved grey wolf optimization algorithm are as follows:

Step 1: The raw data is preprocessed and normalized into test set, validation set & training set;

Step 2: The ROGWO algorithm encodes the initial parameters of the DELM, and also initializes the algorithm parameters such as the population parameters, the number of iterations, etc.; and calculates the fitness function value;

Step 3: Update the location information of the grey wolf population using the random centre of gravity strategy, Levy flight strategy combined with the GWO location update strategy;

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

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

Step 6: Decode the parameters of the ROGWO optimization based network to obtain the hidden layer unit weights and biases of the deep limit learning machine network;

Step 7: Construct the ROGWO-DELM network, train the network using the training set to get the prediction model, input the test set into the prediction model to get the prediction results.

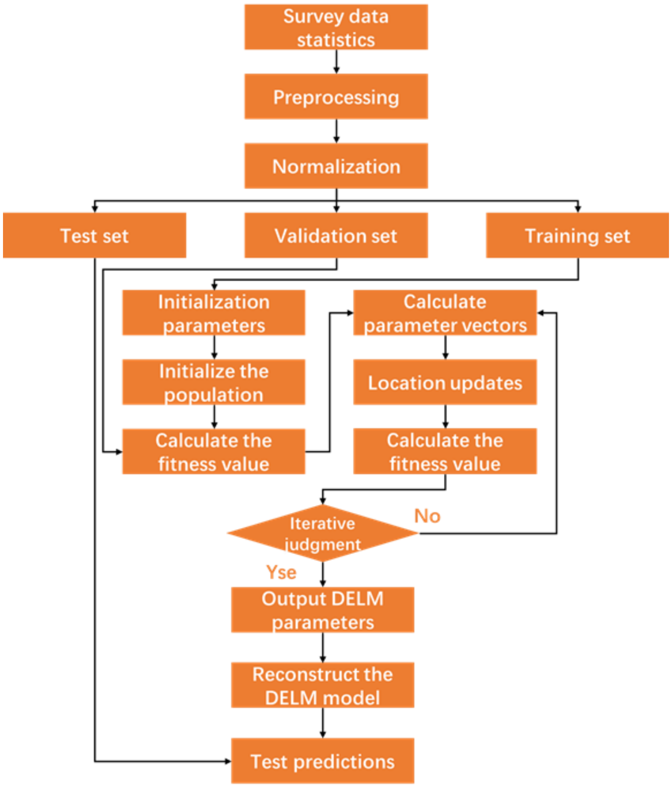


Figure 7. Flowchart of performance management evaluation method for universities based on ROGWO-DELM algorithm

6. Experiments and analysis of results

In order to verify the accuracy and timeliness of the human resource performance management evaluation model proposed in this paper, five evaluation algorithms are selected for comparison, and the specific parameters of each algorithm are set as in Table 1.The data are mainly from the human resource performance management appraisal results, which are divided into a training set, a validation set, and a test set, in which the training set is mainly used to train the model, the validation set is mainly used to compute the fitness value in the optimization process, and the test set is mainly used to test the evaluation model. The experimental simulation environment is Windows 10, CPU is 2.80GHz, 8GB RAM, programming language Matlab2017a.

Table 1. Parameter Settings for EHR Performance Management Evaluation Methodology

arithmetic	parameterization
ELM	Hidden layer node is 50, activation function is radial basis function
GWO-ELM	Hidden layer nodes are 50, activation function is radial basis function, number of populations in GWO algorithm is same as ROGWO-DELM setting, number of iterations is 500
ROGWO-ELM	Hidden layer nodes are 50, activation function is radial basis function, number

	of populations in ROGWO algorithm is the same as ROGWO-DELM setup, number of iterations is 500
DELM	Two hidden layers with 30, 30 nodes in each layer
GWO-DELM	Two hidden layers, the number of nodes in the hidden layer is set as in ROGWO-DELM, the number of populations in the GWO algorithm is set as in ROGWO-DELM, and the number of iterations is 500
ROGWO-DELM	Two hidden layers with 500 iterations of the GWO algorithm, the number of nodes and populations in the hidden layer is analysed by 5.1

6.1. Parameter setting analysis

In order to analyse the impact of the population size of the intelligent optimization algorithm and the number of hidden layer nodes of the extreme learning machine on the performance of performance management evaluation, this paper compares and analyses the performance of performance management evaluation under the conditions of different population sizes and different numbers of hidden layer nodes, respectively. Figure 8 gives a graph of the impact of different population sizes and different numbers of hidden layer nodes on evaluation accuracy, and Figure 9 gives a graph of the impact of different population sizes and different numbers of hidden layer nodes on evaluation time.

From Figure 8, it can be seen that as the population size of the ROGWO algorithm increases, the evaluation value has a tendency to decrease; as the number of hidden layer nodes increases, the evaluation value also decreases. From Figure 9, it can be seen that as the population size of the ROGWO algorithm increases, the prediction time also increases; as the number of nodes increases, the prediction time is increasing. In summary, the intelligent optimization algorithm selected in this paper has a population size of 30 and the number of hidden layer nodes is 60.

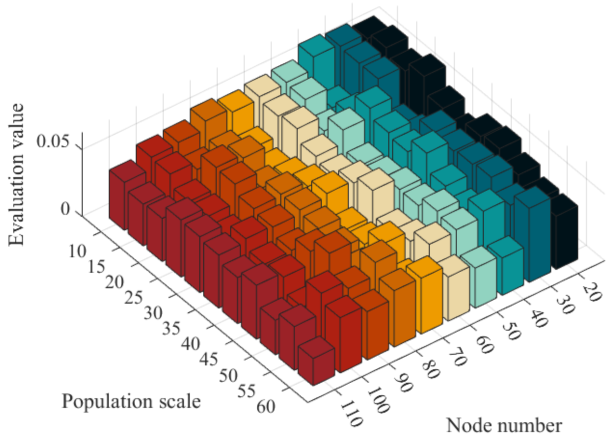


Figure 8. Effect of different population sizes and number of nodes on evaluation accuracy

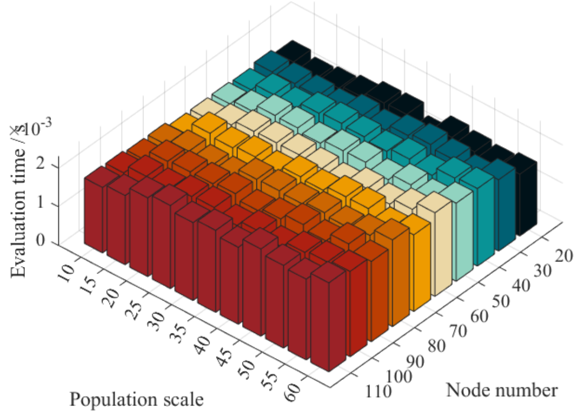
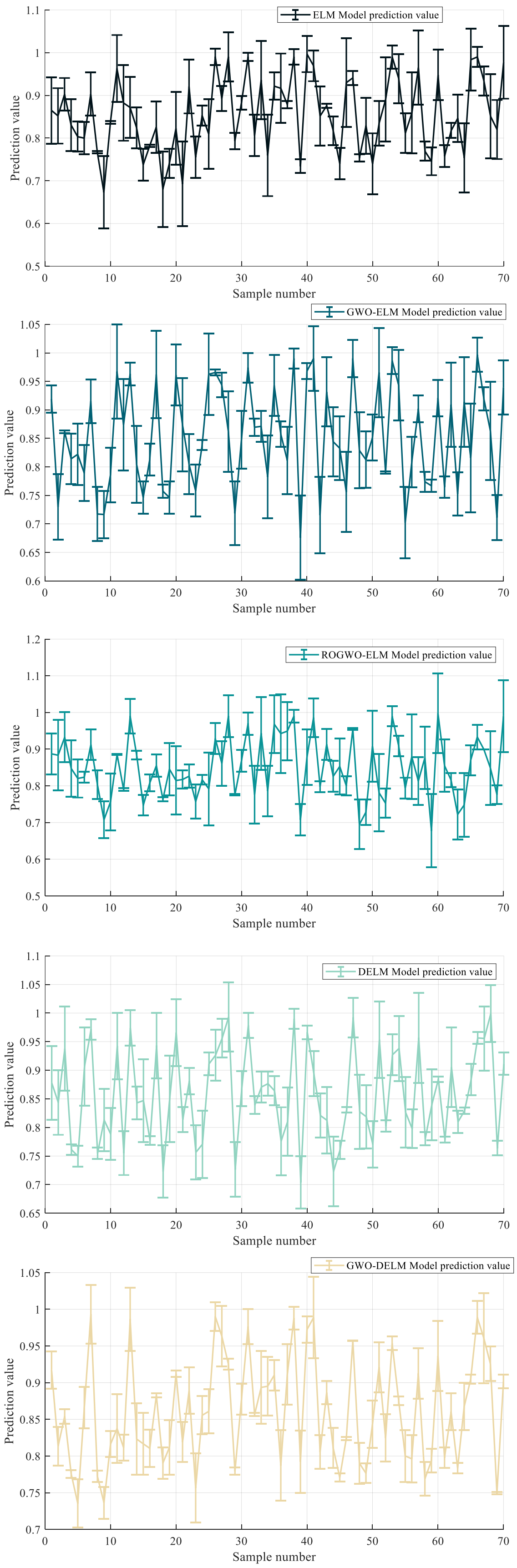


Figure 9. Effect of different population sizes and number of nodes on evaluation time

6.2. Analysis of experimental evaluation values

In order to verify the effectiveness and superiority of the evaluation method of human resource performance management in universities based on the ROGWO-DELM algorithm, ROGWO-DELM is compared with five other models such as ELM, GWO-ELM, ROGWO-ELM, DELM, and GWO-DELM, and the results of the evaluation of each model are shown in Figure 9 and Figure 10.

Figure 9 gives the evaluation results of human resource performance management in universities based on each algorithm. From Figure 9, it can be seen that the evaluation results based on ROGWO-DELM are closer to the real value and the error range is smaller than other algorithms, which indicates that the accuracy of the evaluation method of human resource performance management based on the ROGWO-DELM algorithm is better than that of the ELM, GWO-ELM, ROGWO-ELM, DELM, and GWO-DELM algorithms; comparing the evaluation results of the DELM with the GWO-DELM algorithms shows that the GWO algorithm optimizes the DELM network parameters and improves the evaluation accuracy of the DELM algorithm; comparing the ROGWO-DELM and GWO-DELM algorithms shows that the improvement strategy of the GWO algorithm improves the evaluation accuracy of the DELM algorithm; and comparing the ROGWO-DELM and ROGWO-ELM shows that the DELM network evaluation accuracy is better than ELM. Meanwhile, the evaluation error of university human resource performance management based on ROGWO-DELM is the smallest in general.



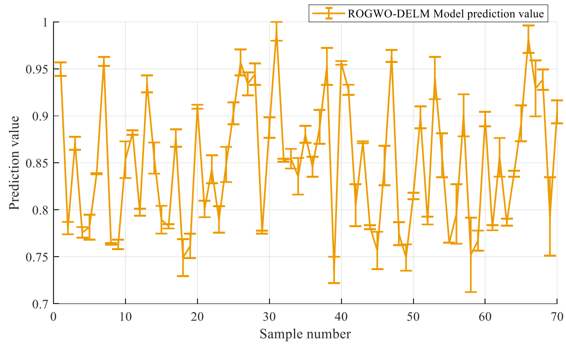


Figure 10. Each algorithm evaluation results

6.3. Analysis of forecast indicators

In order to further verify the superiority of the university human resource performance management evaluation method based on the ROGWO-DELM algorithm, the evaluation results of each algorithm are statistically given in this section, as shown in Fig. 11, Fig. 12 and Fig. 13. As can be seen from Figure 11, the MAE value of university human resource performance management evaluation based on ROGWO-DELM algorithm is smaller than other algorithms, and the evaluation results are better than other algorithms. It can be seen from Figure 12 that the RMSE value of human resource performance management evaluation based on ROGWO-DELM algorithm is smaller than other algorithms and the evaluation effect is better than other algorithms. From Figure 13, it can be seen that the evaluation time of human resource performance management in universities based on the ROGWO-DELM algorithm is smaller than that of the ELM, GWO-ELM, ROGWO-ELM, DELM algorithms, and is comparable to that of the GWO-DELM algorithm, which indicates that the optimization strategy proposed in this paper does not cost too much computational overhead. In conclusion, the evaluation method of human resource performance management in universities based on ROGWO-DELM algorithm works better than other algorithms and meets the real-time requirements.

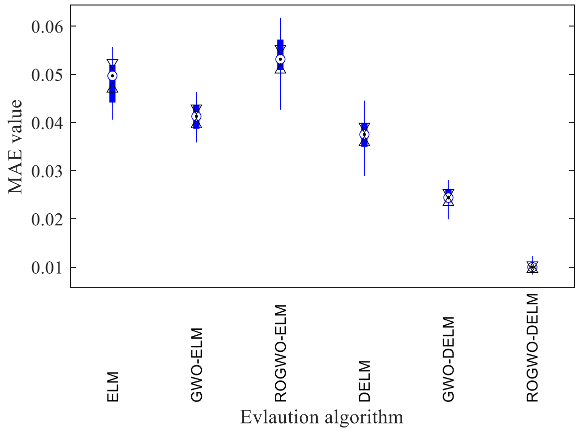


Figure 11. MAE for evaluation of HR performance management in universities based on each algorithm

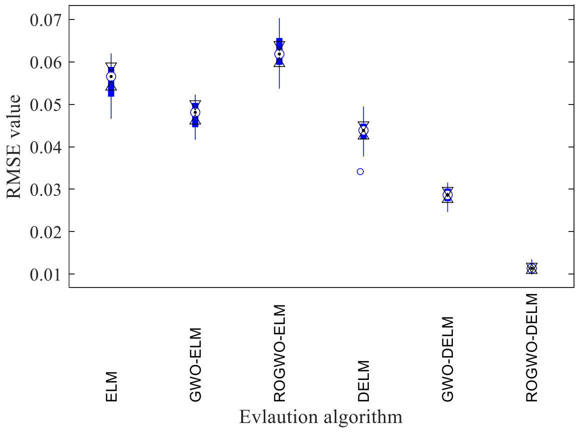


Figure 12. RMSE of HR performance management evaluation in universities based on each algorithm

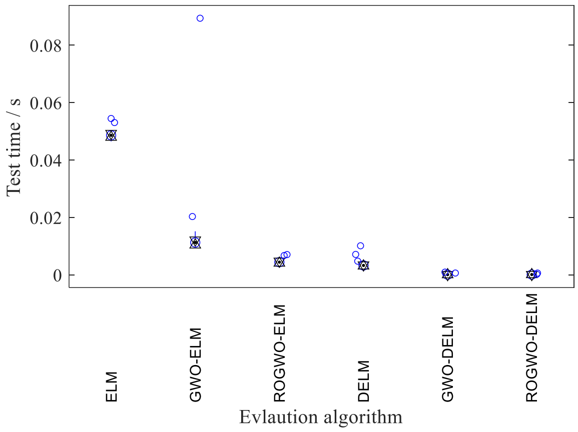


Figure 13. Evaluation time of HR performance management in universities based on each algorithm

7. Conclusion

In order to improve the accuracy and real-time performance of university human resources performance management evaluation model, this paper adopts multi-strategy intelligent optimization algorithm and deep limit learning mechanism to construct university human resources performance management evaluation method. The method constructs the university human resource performance management evaluation index system by analyzing the problems existing in the current performance management approach of universities, selecting the university human resource performance management evaluation indexes based on the whole process of performance appraisal. Using the stochastic center of gravity strategy and Levy flight strategy to improve the grey wolf optimization algorithm, combined with the deep limit learning machine, the human resource performance management evaluation model of educational Institutions based on the ROGWO algorithm to optimize the DELM is proposed. Simulation experiments are carried out using human resource performance data, and the results show that the method proposed in this paper is better than other methods in terms of evaluation accuracy while satisfying better real-time performance.

The Extreme Learning Machine algorithm used in this paper has some limitations in prediction accuracy due to the high randomness of the shallow network parameters. In future work, the introduction of all parameters for optimization will be considered to improve the generalization and accuracy of the algorithm.

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