Research of Teacher’s Performance Evaluation Model Based on AHP and Improved PSO-BP Neural Network

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Abstract. The teacher’s performance evaluation is an important guarantee for the development of higher education. In view of the limitations of traditional analytic hierarchy process in the teachers' performance comprehensive evaluation and the shortcomings of BP neural network in the teachers' performance comprehensive evaluation, such as non-convergence and large prediction error, the paper proposed an evaluation index system based on analytic hierarchy process as input of BP neural network, and used dynamic inertial weight and multiple empirical particles to improve PSO algorithm and optimize the weights and thresholds of BP network, established teacher's performance evaluation model. The simulation results show that the model effectively reduces the number of network iterations, improves the prediction accuracy, and has a good application prospect in the teacher's performance evaluation.

Introduction

Comprehensive evaluation of teachers' performance is system engineering with heavy workload and cumbersome statistics. It is also an important guarantee for the development of higher education. Through scientific evaluation, schools can not only objectively judge the ability of teachers to teach and educate people, but also guide teachers to make continuous progress according to performance indicators. Teachers can also clearly understand their own shortcomings and improve them. At present, the researches of scholars mostly focus on building evaluation index system and calculating index weight, such as: literature [1] constructs comprehensive evaluation index system from four aspects of teaching, teachers' morality, scientific research and skills, calculates index weight with traditional analytic hierarchy process; literature [2] constructs comprehensive evaluation index system from four aspects of comprehensive quality, teaching work, social work and personnel training, and directly stipulate the proportion of the underlying index.

However, there are many factors involved in the comprehensive evaluation of teachers' performance, including qualitative index and quantitative index. These factors restrict and influence each other. No single evaluation method can guarantee the comprehensiveness and scientificity of evaluation [3]. Therefore, this paper combines Analytic Hierarchy Process (AHP) and Back Propagation Neural Network (BP Neural Network) to select performance evaluation index as input of the neural network from five aspects: comprehensive quality, daily teaching, teaching research, scientific research and serving the society; and uses improved PSO algorithm to optimize BP network, so as to effectively raise high accuracy of comprehensive evaluation of teachers' performance.

Comprehensive Evaluation Index System of Teacher Performance Based on AHP

AHP is a systematic analysis method combining qualitative and quantitative analysis proposed by American operations research institute Saaty [4-5] in the 1970s, which is relatively effective in the comprehensive evaluation of multi-factors, multi-criteria and multi-scheme [6]. In the paper, AHP is used to determine the index weight. The specific steps are as follows:

Step 1: Constructing Hierarchical Structure Model. This paper regards university teachers' performance evaluation as the general target level A, and sets up the first-level indicators from five
aspects: comprehensive quality $B_1$, daily teaching $B_2$, teaching research $B_3$, scientific research $B_4$ and social service $B_5$. Then, according to the first-level index, 16 second-level indexes are improved and a hierarchical structure model is constructed.

Step 2: Determining the Weight of Indicators. The paper uses the 1-9 scale method [7] to construct the judgment matrix, calculates the index weight by the square root method, and test the consistency of the judgment matrix at last. The random consistency ratio CR is less than 0.1, the judgment matrix has satisfactory consistency, and otherwise the judgment matrix needs to be adjusted.

Take the total target layer A as an example, the judgment matrix and weight is shown in Table 1.

| A | B1 | B2 | B3 | B4 | B5 | Weight |
|---|----|----|----|----|----|--------|
| B1 | 1  | 1/5| 1/3| 1/3| 1  | 0.074  |
| B2 | 5  | 1  | 3  | 3  | 5  | 0.428  |
| B3 | 3  | 1/3| 1  | 1  | 3  | 0.212  |
| B4 | 3  | 1/3| 1  | 1  | 3  | 0.212  |
| B5 | 1  | 1/5| 1/3| 1/3| 1  | 0.074  |

In Table 1, the value of $\lambda_{\text{max}}$ is 5.074, CI is 0.019, and CR is 0.017. CR is less than 0.1, so the judgment matrix A has satisfactory consistency.

According to the above calculation method, the paper constructs the comprehensive evaluation index system of University teachers' performance and shows in Table 2.

| Level 1 index | Level 2 index | Weight | Note |
|---------------|---------------|--------|------|
| Comprehensive quality $B_1$ | Political attitude $C_{11}$ | 0.106 | $\lambda_{\text{max}}=3.065$  
CI=0.032  
CR=0.056<0.1 |
|  | Teachers' ethics $C_{12}$ | 0.593 |
|  | Diligent and honest $C_{13}$ | 0.301 |
| Daily teaching $B_2$ | Faculty load $C_{21}$ | 0.164 | $\lambda_{\text{max}}=3.014$  
CI=0.007  
CR=0.012<0.1 |
|  | Supervisor evaluation $C_{22}$ | 0.521 |
|  | Student evaluation $C_{23}$ | 0.315 |
| Teaching research $B_3$ | Quality engineering $C_{31}$ | 0.644 | $\lambda_{\text{max}}=3.004$  
CI=0.002  
CR=0.004<0.1 |
|  | Professional reform $C_{32}$ | 0.125 |
|  | Curriculum reform $C_{33}$ | 0.231 |
| Scientific research $B_4$ | Book $C_{41}$ | 0.127 | $\lambda_{\text{max}}=4.093$  
CI=0.031  
CR=0.035<0.1 |
|  | Paper $C_{42}$ | 0.310 |
|  | Project $C_{43}$ | 0.514 |
|  | Achievements $C_{44}$ | 0.049 |
| Social service $B_5$ | Contest guiding $C_{51}$ | 0.629 | $\lambda_{\text{max}}=3.019$  
CI=0.010  
CR=0.011<0.1 |
|  | Outside training $C_{52}$ | 0.232 |
|  | Enrollment service $C_{53}$ | 0.139 |

In Table 2, the values of CR in judgment matrix $B_1$-$B_5$ are all less than 0.1, so they all have satisfactory consistency.

**BP Neural Network Based on Improved PSO**

In this paper, the improved global optimization PSO algorithm is used to optimize the connection weights and thresholds between adjacent layers of BP neural network, so as to improve the convergence speed and prediction accuracy of the network, and construct the improved PSO-BP neural network to improve the prediction accuracy of evaluation model.
**PSO algorithm optimization strategy.** Inertial weight is a very important parameter in standard PSO algorithm \[^8\]. The larger the inertia weight is, the stronger the exploration ability is; the smaller the inertia weight is, the stronger development ability is \[^9\]. The paper adopts the method of dynamic adjusting inertia weight \[^10\], and makes inertia weight satisfy the equations (1):

\[
w(k) = \begin{cases} 
1 \times \frac{t}{\text{MaxNum}} + 0.25 & 0 \leq \frac{t}{\text{MaxNum}} \leq 0.5 \\
-1 \times \frac{t}{\text{MaxNum}} + 1.25 & 0.5 < \frac{t}{\text{MaxNum}} \leq 1
\end{cases}
\]

(1)

where \(t\) is the current iteration number, MaxMum is the maximum iteration number, and the inertia weight value increases linearly from 0.25 to 0.75, then decreases linearly to 0.25.

The paper observes the flight behavior of particles, summarizes the flight path of particles, and adjust the weakening selection behavior by introducing empirical particles, so as to optimize the individual extreme value \(Pb_i\) and the group extreme value \(Pgb\), thus improves the convergence speed and accuracy of PSO algorithm.

The updated Formula of Individual Extreme (2) is defined as

\[
Pb_i'(t) = \begin{cases} 
Pb_i(t) & i < 2 \\
r_1 \times Pb_i(t) + r_2 \times Pb_m(t) + r_3 \times Pb_n(t) & i \geq 2
\end{cases}
\]

(2)

where \(Pb_i'\) is the updated individual extreme value. \(Pb_i\) is the current individual extreme value. \(Pb_m\) and \(Pb_n\) are the experienced individual extreme values; they are randomly selected from previous ones in the same generation. \(r_1, r_2\) and \(r_3\) are random values between -0.5 and 1.5, and their sum is 1.

The updated Formula of global Extreme (3) is defined as

\[
Pgb'(t) = r_1 \times Pb_1(t) + r_2 \times Pb_2(t) + r_3 \times Pb_3(t)
\]

(3)

where \(Pgb'\) is the updated global extreme value. \(Pb_1, Pb_2\) and \(Pb_3\) are three best individual extremes from the same generation. \(r_1, r_2\) and \(r_3\) are random values between -0.5 and 1.5, and their sum is 1.

**BP and PSO Algorithms Fusion.** Firstly, establish the relationship between PSO solution space and BP network structure. The solution space dimension of PSO is the dimension of particle position vector and velocity vector, which can be expressed by the combination of node numbers in each layer of BP network. Its value is the sum of the number of weights and thresholds in BP neural network. Secondly, establish the relationship between PSO fitness and the total error of BP network. The total error formula of BP is the fitness function of particles, and the fitness value of particles is the total error, which is accumulated by all training data during the forward propagation. Finally, establish the relation between PSO evolution formula and BP network weight and threshold. After each iteration, use the updated particle swarm optimal position to assign values for weights and thresholds of BP, to make the network has better convergence speed and prediction accuracy.

**Simulation Experiment and Analysis**

The paper pre-processes the sample data at first, then makes simulation experiment between the standard BP algorithm, linear PSO-BP algorithm and improved PSO-BP algorithm, and finally compares and analyzes results from four aspects: convergence speed, prediction accuracy, relative error and mean square error.

**Data Preprocessing.** The data of paper is based on the 2017 annual performance appraisal results of the college of computer science, Wuhan Qingchuan University. Combining with the index weight in Table 1-2, the range of each index and evaluation target is set as \([0, 10]\), and develop the model of comprehensive evaluation of University teachers' performance. The paper selects fifteen teachers in our college for performance evaluation, as shown in table 3.
Table 3. Sample data.

| No | C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 | C19 | C20 | C21 | C22 | C23 | C24 | C25 | C26 | C27 | C28 | C29 | C30 | C31 | C32 | C33 | Result |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1  | 10  | 10  | 10  | 7   | 8   | 9   | 5   | 5   | 4   | 10  | 10  | 10  | 5   | 5   | 10  | 5   | 8   | 10  | 8.080 |
| 2  | 10  | 10  | 10  | 8   | 8   | 9   | 5   | 5   | 2   | 5   | 10  | 10  | 5   | 5   | 10  | 5   | 8   | 7.564 |
| 3  | 10  | 10  | 10  | 9   | 8   | 9   | 10  | 5   | 2   | 5   | 10  | 10  | 5   | 5   | 10  | 5   | 8   | 8.035 |
| 4  | 10  | 10  | 10  | 8   | 8   | 9   | 5   | 5   | 4   | 5   | 10  | 10  | 5   | 5   | 5   | 5   | 8   | 7.721 |
| 5  | 10  | 10  | 10  | 8   | 8   | 9   | 5   | 5   | 4   | 10  | 10  | 5   | 5   | 10  | 5   | 8   | 7.533 |
| 6  | 10  | 10  | 10  | 8   | 8   | 9   | 5   | 5   | 8   | 5   | 10  | 10  | 5   | 5   | 2   | 5   | 8   | 2.05 |
| 7  | 10  | 10  | 10  | 9   | 9   | 10  | 5   | 5   | 2   | 5   | 10  | 10  | 10  | 10  | 4   | 8.085 |
| 8  | 10  | 10  | 10  | 9   | 7   | 8   | 9   | 5   | 10  | 5   | 5   | 5   | 5   | 3   | 5   | 8   | 6.868 |
| 9  | 10  | 10  | 10  | 8   | 7   | 9   | 5   | 5   | 4   | 5   | 10  | 10  | 5   | 5   | 2   | 5   | 10  | 6.784 |
| 10 | 10  | 10  | 10  | 8   | 8   | 9   | 5   | 5   | 2   | 5   | 5   | 5   | 2   | 5   | 8   | 6.715 |
| 11 | 10  | 10  | 10  | 8   | 7   | 8   | 9   | 5   | 5   | 2   | 5   | 5   | 5   | 10  | 10  | 10  | 6.954 |
| 12 | 10  | 10  | 10  | 10  | 9   | 8   | 9   | 5   | 10  | 5   | 10  | 5   | 10  | 5   | 10  | 9   | 8.151 |
| 13 | 10  | 10  | 10  | 9   | 8   | 9   | 10  | 5   | 2   | 5   | 10  | 10  | 5   | 8   | 10  | 8   | 8.700 |
| 14 | 10  | 10  | 10  | 8   | 8   | 9   | 10  | 5   | 2   | 10  | 5   | 5   | 5   | 2   | 5   | 8   | 7.475 |
| 15 | 9   | 10  | 10  | 7   | 8   | 9   | 5   | 10  | 5   | 5   | 10  | 5   | 10  | 5   | 10  | 9   | 10  | 7.071 |

In Table 3, the first 13 sets of data are training samples, and the last two sets are test samples. The paper uses normalization processing method with linear function Conversion, and makes each sample data can participate in network training in the same important position. Through experimental comparison, the network structure of improved PSO-BP model is 16-10-1; the particle swarm size of the prediction model is 20; the particle dimension is 181. The initial position component is a random number between -1 and 1. The current velocity component is a random number between -0.5 and 0.5. The maximum iterations number is 2000 of the algorithm and the minimum error is 0.001.

**Experimental results and analysis.** The algorithm convergence analysis and the network output curve analysis are shown as Figure 1 and Figure 2.

In Figure 1, the convergence speed of standard BP is slow and it is still not convergent at the maximum iterations; linear PSO-BP algorithm has fell into local fitness value of 0.207 at the early stage and it still could not jumped out at the maximum iterations; the fitness value of improved PSO-BP algorithm keeps a good decreasing trend, and the algorithm can achieve the minimum error at 203 iterations.

In Figure 2, the real values of the three algorithms are basically in line with the expected values. However, the standard BP algorithm and linear PSO-BP algorithm have obvious deviations in many sample points, while the improved PSO-BP algorithm only has large errors in samples 14 and 15.

The relative error value comparison of three algorithms is shown in Table 4.
Table 4. Relative error value comparison of three algorithms.

| No | Exp | Standard BP | Linear PSO-BP | Improved PSO-BP |
|----|-----|-------------|---------------|----------------|
|    |     | Reality | Err (%) | Reality | Err (%) | Reality | Err (%) |
| 1  | 8.08 | 8.117 | 3.669 | 7.906 | 17.419 | 8.089 | 0.945 |
| 2  | 7.564 | 7.588 | 2.422 | 7.408 | 15.646 | 7.544 | 1.983 |
| 3  | 8.035 | 8.053 | 1.832 | 8.455 | 41.972 | 8.041 | 0.585 |
| 4  | 7.721 | 7.666 | 5.517 | 7.566 | 15.454 | 7.734 | 1.264 |
| 5  | 7.533 | 7.498 | 3.505 | 7.961 | 42.849 | 7.539 | 0.603 |
| 6  | 7.205 | 7.045 | 15.979 | 8.046 | 84.063 | 7.192 | 1.283 |
| 7  | 8.085 | 8.102 | 1.732 | 8.296 | 21.144 | 8.110 | 2.542 |
| 8  | 6.868 | 7.011 | 14.316 | 7.312 | 44.385 | 6.876 | 0.809 |
| 9  | 6.784 | 7.004 | 21.987 | 7.142 | 35.766 | 6.800 | 1.561 |
| 10 | 6.715 | 6.905 | 19.018 | 6.911 | 19.578 | 6.719 | 0.431 |
| 11 | 6.954 | 6.917 | 3.677 | 7.135 | 18.133 | 6.924 | 2.957 |
| 12 | 8.151 | 8.150 | 0.071 | 8.085 | 6.559 | 8.126 | 2.511 |
| 13 | 8.7 | 8.604 | 9.585 | 8.507 | 19.264 | 8.633 | 6.706 |
| 14 | 7.475 | 7.276 | 19.932 | 7.994 | 51.933 | 7.237 | 23.810 |
| 15 | 7.071 | 7.344 | 27.321 | 8.280 | 120.932 | 6.954 | 11.713 |
| Avg_Err (%) | 0.074 | 0.814 | 0.004 |

In Table 4, Exp expresses the expected output. Reality shows the real output. Err denotes the relative error and adopts the percentage mode. Avg_Err denotes the average relative error. Compared with other algorithms, the Average Error value of the improved PSO-BP algorithm is only 0.004%, and it is obviously better than others.

The MSE is an important index of the BP network mode [11]. The MSE of three algorithms is shown in Table 5:

Table 5. MSE comparison of three algorithms.

|        | Standard BP | Linear PSO-BP | Improved PSO-BP |
|--------|-------------|---------------|----------------|
| MSE    | 0.0051      | 0.0387        | 0.0003         |

In Table 5, the MSE of the improved PSO-BP algorithm is only 0.0003 and it is obviously better than others.

Summary

BP neural network is suitable for the comprehensive evaluation and modeling of University teachers’ performance with non-linear characteristics, but it has some problems. This paper uses the dynamic inertia weight which increases at first and then decreases, and combines the PSO algorithm of multi-empirical particles to optimize the weights and thresholds of BP network. The improved model can quickly give evaluation results and ensure strong fault-tolerant ability. However, the learning samples of the model depend on the evaluation results of AHP, so the evaluation method proposed in this paper cannot completely replace the traditional AHP, but provides a more accurate and efficient new way of thinking for the comprehensive evaluation of University teachers’ performance.

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