

The Distribution of Teaching Staff in Colleges and Universities based on Neuropsychology

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Objectives: At present, quality education has gradually been recognized by the whole society, and a consensus has been reached on its importance, which has put forward stricter requirements for the distribution of faculty in universities. **Methods:** In this paper, based on neuropsychology, the distribution of teaching staff in colleges and universities was studied, and the model of talent evaluation and distribution was constructed. **Results:** Firstly, the generalized regression neural network was optimized by genetic algorithm. Then, the genetic algorithm's generalized regression neural network calculation process was designed. **Conclusion:** Finally, with the example of teacher resources in a university, the algorithm in this paper was tested. The results show that the results of the generalized regression neural network optimized by genetic algorithm can match the actual situation very well, and the method is feasible with certain advantages.

Keywords: neuropsychology; genetic algorithms; neural networks

Tob Regul Sci.™ 2021;7(5-2):4682-4692

DOI: doi.org/10.18001/TRS.7.5.2.33

Today, quality education has gradually been recognized by the whole society, and has formed a consensus on its importance. Colleges and universities belong to the important base of talent training, and they always revolve around the quality education to promote the implementation of the distribution of teachers in colleges and universities. It is a required stage for the development of higher education to cultivate outstanding talents of business level and quality¹. The evaluation of the comprehensive quality of innovative talents is the party's educational policy and the goal of college education. Colleges and universities should adopt a scientific and reasonable method to comprehensively evaluate the characterization information of innovative talents reflected in various aspects in a certain period². As a kind of student evaluation system, it has been recognized by many colleges and universities in its comprehensive quality education and the comprehensive quality of

innovative talents³. At present, many colleges and universities have taken it as a breakthrough point to promote quality education and improve the comprehensive quality of innovative talents⁴. From the perspective of the actual development of higher education to promote the quality, it has entered a new level of development. There are still some deficiencies in the evaluation of innovative talents, especially the allocation of resources. This problem has become a restrictive factor, which has restricted the development of quality education in colleges and universities⁵. Therefore, a reasonable and perfect operation ability distribution system of university faculty can effectively guide the comprehensive training of innovative talents, and also improve the effectiveness of quality work in colleges and universities⁶. But nowadays, the evaluation of the comprehensive quality of innovative talents is basically qualitative analysis. Therefore, quantitative analysis is rare and is not detailed⁷. Based on this, based on the analytic

hierarchy process, the fuzzy evaluation model of innovative talents was studied in this paper.

The term neuropsychology was proposed by E.G.Boring (a famous professor of psychology at the Harvard University) in 1929 based on the work of K.S.Lashley⁸. Lashley is a famous behaviorist psychologist in the United States, and he devoted his whole life to the study of the relationship between the function and behavior of animal brain⁹. For the first time, he established a quantitative relationship between the two and created an experimental science to explain complex behavior in terms of brain function¹⁰. Since then, some basic questions about the relationship between the psychological (behavior) and the brain have become the main content of Neuropsychology¹¹. The term "neuropsychology" was raised at that time, but it was systematically discussed as a discipline in the book *Principles of Neuropsychology* published by Leah, a Soviet scholar, in 1973¹². In the early twentieth Century, the development of neuroscience made progress in the two aspects of cortical cell structure and cortical nerve fiber structure¹³. K. Broadman distinguished the brain from the cerebral cortex in 47 regions, while the German psychiatrist P.E. Fletcher Cecilia owned the most prominent work¹⁴. However, psychologists or neuropsychologists are most concerned with the structure of the tissue and the relationship between fiber road and function¹⁵. On the basis of sufficient data accumulation in neuropsychology, E.G. first proposed the name of neuropsychology in 1929¹⁶. Among them, the most famous is the Canadian neurosurgeon W. Penfield¹⁷. In the 40s of last century, he took advantage of the chance of craniotomy in the Department of neurosurgery. Later, he worked with others to study the afferent, efferent fiber pathways and the cortical structures associated with human speech activities, and he developed the modern research on the correlation between behavior and brain function in a wide range¹⁸.

There are many ways to evaluate the compound talents. The traditional methods include permutation, scoring, classification, factor analysis and so on¹⁹. Practice has proved that these methods have certain rationality, but they are still not perfect enough, and they have not penetrated into the calculation of compound

employee job fit. At present, in order to improve the core competitiveness of enterprises, many high-tech enterprises have introduced the theory of artificial intelligence into the management of enterprises²⁰. Genetic algorithm is a kind of artificial intelligence technology which is widely used. Generalized regression neural network has strong nonlinear mapping ability and flexible network structure, and is highly fault-tolerant and robust, so it is suitable for nonlinear problems. In the approximation ability and learning speed, it has a strong advantage over other neural networks. The network finally converges to the optimal regression surface with more sample size accumulating, and the prediction effect is also good when the sample data is less. In addition, the network can also predict unstable data.

METHODS

Optimal Analysis of Neural Network

The order used in this arrangement is in accordance with the alternate arrangement of the center and the width. The specific way to encode every chromosome string is: in order to arrange every adjustment weight in a certain order, it is necessary to first arrange the different centers and the corresponding width in sequence. At the same time, the number of network nodes, P, is preset. In the process of computation, P is adjusted according to the approximation degree of the calculated value, so that the final training result of the neural network can achieve the expected accuracy requirement or the accuracy of training result is no longer improved. In this way, the length of each chromosome string is: MP+P+NP. Among them, M is the number of input nodes; P is the number of hidden nodes; N is the number of output nodes.

The first is the generation of the initial population. When the population is large, the diversity of the individual can be increased, and the optimal solution is easy to find, but the time of convergence of the algorithm will also be prolonged. When the number of the population is very small, the convergence speed of the algorithm can be accelerated, but it also increases the possibility of falling into the local minimum. Then, the fitness function is constructed. As the main index to describe individual performance in

genetic algorithm, the bigger the fitness value is, the better the individual performance is. The smaller the fitness value is, the worse the individual performance is. In genetic algorithms, the fitness must be a number greater than or equal to 0. Based on 2 basic principles, the objective function is transformed into fitness function: fitness degree must be greater than or equal to 0. The direction of change of objective function should be consistent with the changing direction of fitness function in the process of optimization. The precision function of the network needs to reach the minimum required training radial basis neural network. The error between the expected output of the network and the actual output determines the accuracy of the accuracy, so the fitness function is as follows:

$$fitness = \frac{1}{\sum_{i=1}^N \sum_{j=1}^K [Y_j(i) - \bar{Y}_j(i)]^2} \quad (1)$$

Among them, $Y_j(i)$ and $\bar{Y}_j(i)$ represent the time input and expected output of the training data i at the j output connection; K and N represent the number of output nodes and the number of input data. The selection operation is the betting wheel selection (proportional selection) method used in this article. This selection operation is the most common choice in genetic calculation. In this selection method, the wheel is the sum of the fitness of all individuals. According to the size of each individual's fitness, each individual corresponds to some parts of the wheel in the wheel. The selected individual is the individual corresponding to the place where the pointer rotates on the wheel. The specific methods of applying computer operation are: calculating the fitness after the cumulative fitness of individuals and groups all ancestors; establishing the corresponding relationship between individual and $[0, \sum F]$, and the basis is the size of the individual's fitness value; generating a random number in the range of $[0, \sum F]$; selecting an individual corresponding to the region in which the random number is located. It can be seen from this process that the greater the individual fitness is, the greater the probability of being chosen is. Then it comes with the cross operation. Based on the real number coding in this paper, the 3-point arithmetic crossover scheme is chosen as the cross operation mode of this paper. The specific step is that 3 random

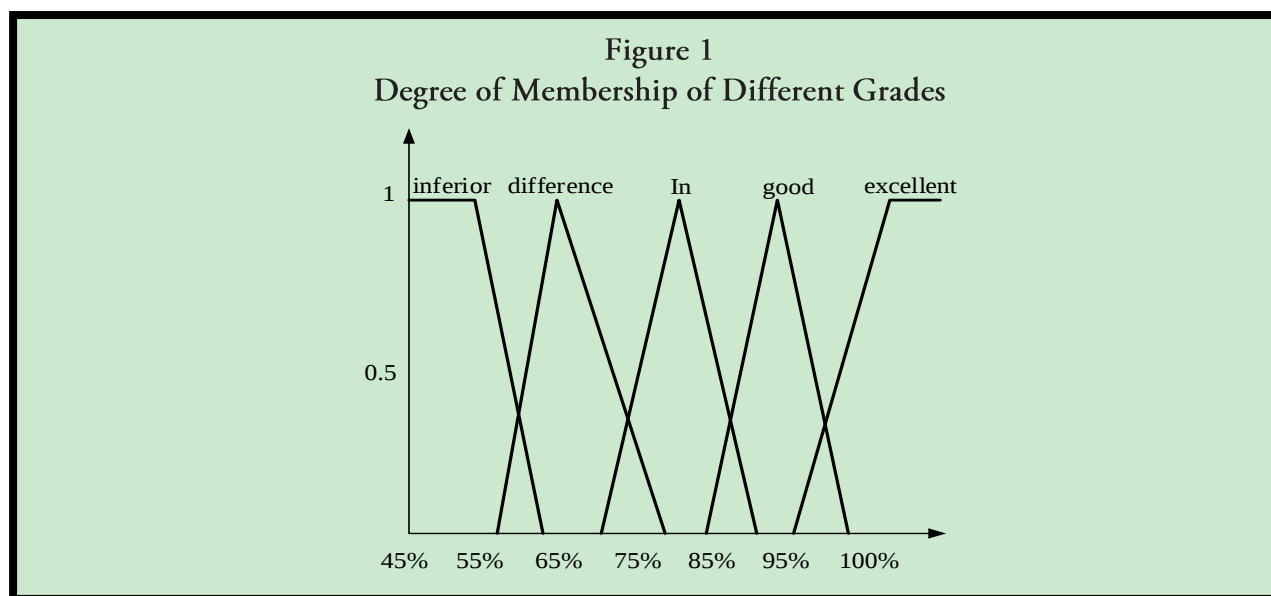
numbers are first generated and then converted to the real number position that needs to be crossed. Finally, the arithmetic crossover method is used to calculate the 3 pairs of real numbers to produce the next generation of groups. Arithmetic crossover can be used to perform the operation of X_k and Y_k in the parent chromosom

e:

$$\begin{cases} X_k^{l+1} = \beta X_k^l + (1-\beta)Y_k^l \\ X_k^{l+1} = \beta Y_k^l + (1-\beta)X_k^l \end{cases} \quad (2)$$

In the formula, β represents a constant in the range of values (0, 1). Then, in binary encoding, the selected variant is calculated. If it is "1", it becomes "0", and if it is "0", it becomes "1". However, the real number coding is far different from the binary code. The 2-point variation method is used in this article. First of all, the location of the variation point is randomly generated, and the method is the same as the selection method of the intersection point. Then, within the range of parameter values, 2 random numbers are generated. They are used to replace all real numbers of the variation points. The replacement of the new individual is selected as the next generation of chromosomes.

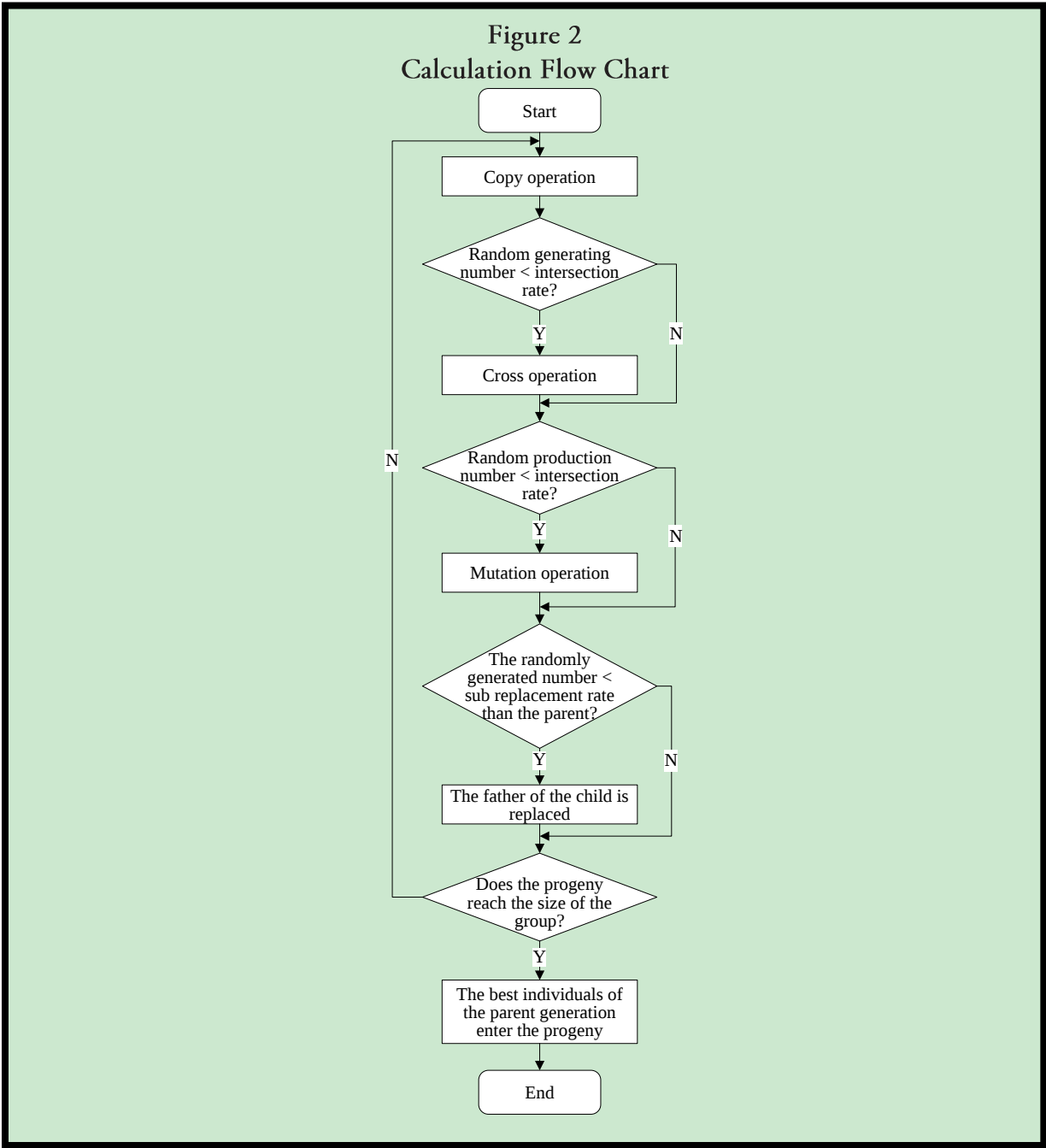
The commonly used triangular membership function is used to determine the degree of membership of each grade. In order to eliminate the unreasonable phenomenon caused by the adjacent level jump, the data in the middle point is processed by fuzzy processing. The midpoint of each level is regarded as a demarcation point. When the index enters the middle point of the interval, the membership degree of the index is 1. When entering the middle point of the adjacent interval, the degree of membership of this grade is 0. According to the characteristics of the index, a membership function of each grade can be obtained by the membership function of 1 and 0 in the interval (or the corresponding comment V in the area). Its function curve is shown in figure 1.



Process Design of Generalized Regression Neural Network

According to the optimization method of generalized regression neural network in front of the genetic algorithm, the calculation model of the design process is as follows: in order to meet the training requirements, the original data needs to be pre-processed; in order to generate the initial population and evolutionary algebra, based on the population size and coding, it is necessary to use the random function generator to initialize population; for the 3 important parameters of generalized regression neural network, it is necessary to decode operations on chromosomes. In order to calculate the output of the input training sample, it is necessary to use the structural formula of the generalized regression neural network. In order to transform between objective function values (network actual output and expected output errors) and fitness values, fitness function must be used to transform related values. At the same time, the function can be used to evaluate the fitness of the individual in the group. In the formula: $Y_j(i)$ is the output of the generalized regression neural network; $\bar{Y}_j(i)$ is the expected output. The optimal preservation strategy is used to find out whether the individuals with the highest and lowest fitness

value in the group and the value of judgment fitness meet the convergence precision. If it is able to meet the requirements, this step can end; if it is unable to meet the requirements, the next step can be started. Whether evolutionary algebra reaches the maximum evolutionary algebra needs to be judged. If it is able to meet the requirements, this step can end; if it is unable to meet the requirements, the next step can be started. Through genetic manipulation, a new generation of populations is generated. The generalized regression neural network used to observe the error between calculation results and practical parameters must be tested by samples, and it is a generalized regression neural network obtained after the above training process.



Selection of Sample Data

Neural network for human job matching calculation requires a certain number of known samples as training set to train neural network, and then it can carry out the comprehensive evaluation of large data. The sample set of the training network should be an authoritative evaluation result of high credibility, and they can be evaluated manually by experts. The index data

person in charge of the Department's score on each index in the index system, as follows.

Table1
Market and Customer Service Department Combined Talent Ability Expert Score

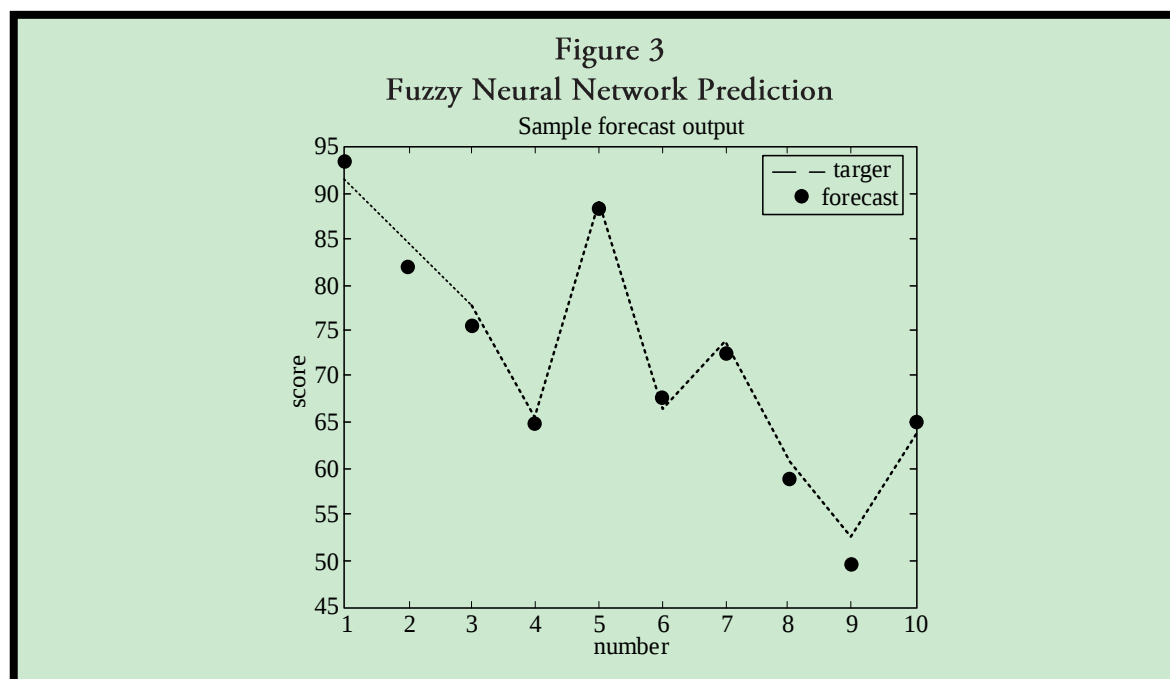
	Exter nal experts	General manager	Executive general manager	Lee	Other
Number	1	1	1	1	5
Weight value	2	4	4	2	1
Score	2	4	4	2	5
The total score	17	17	17	17	17
Divided proportion	11.6 %	23.6%	23.4%	11.7%	29.74%

RESULTS

Comprehensive Quality Prediction of Talents

With the related data of students' occupation in a school as the sample data, network training was carried out to make the error fall within the required range and determine the weight of the internal structural parameters of the network. There were 11 indicators used for occupational assessment, so the number of neurons in the input layer was 11. The number of the output neurons of the model was determined by the profession. In order to make a better analysis of it, the four categories of occupations were trained and analyzed. The network had been trained for

the management post, the technical post, the administrative post and the further study. When the management post was trained, only the sample data output from the management post was 1, while the output value of the sample data in other posts was 0. When the technical post was trained, only the sample data output from the technical post was 1, while the output value of the sample data in other posts was 0. When the administrative post was trained, only the output of the sample data of the administrative post was 1, while the output value of the sample data in other posts was 0. Then, the model that had been completed was finally tested. The results are shown in figure 3.



From the results of the evaluation, the expected output obtained by the expert evaluation was basically consistent with the actual output calculated by the fuzzy neural network model. Only individual samples failed to meet the expected requirements because of the impact of human factors in the acquisition process.

Matlab was established. In order to verify the effectiveness of the capable post matching model, 55 validation samples were used to verify the model. The influencing factors of the checked sample were used as input. The results of 15 validation samples are listed below, and the results are as follows:

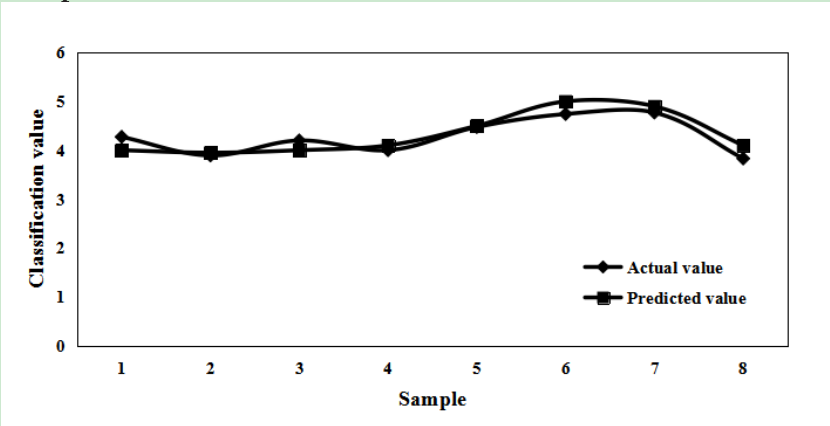
Calculation of the Matching Degree of Man And Post and the Distribution of Talents

Neural network for human job matching calculation requires a certain number of known samples as training set to train neural network, and then it can carry out comprehensive evaluation of large data volume. The sample set of the training network should be an authoritative evaluation result of high credibility, and they can be evaluated manually by experts. In this article, a company's market and customer service department was chosen as a research sample. In the sample of the company's market and customer support department, 100 sets of sample data were taken out as training samples. The other 55 sets of data were selected as test samples. According to the design steps of the fourth chapter, the simulation model based on

Table2
Comparison Between the Predicted Value and The Actual Value

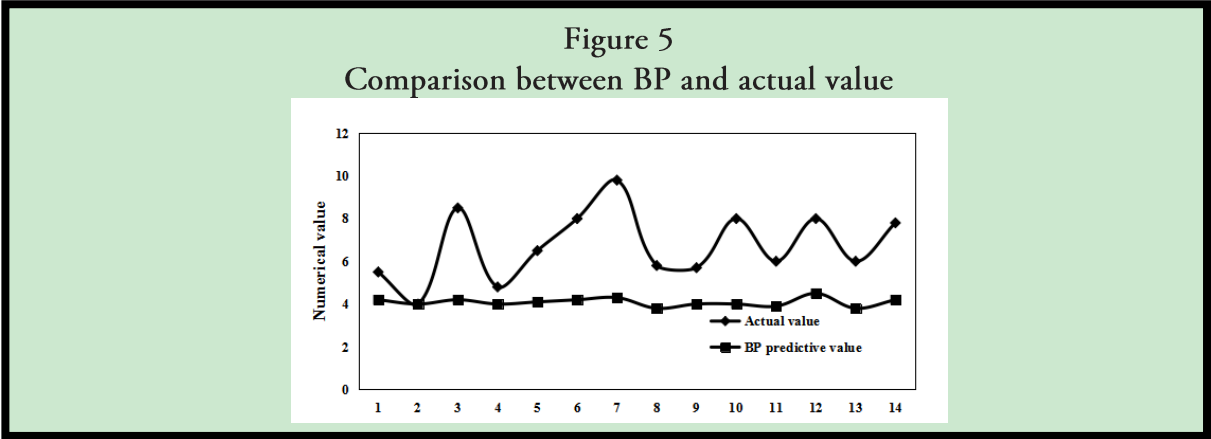
Serial number	Actual value	Predicted value	Error
1	4.2736	4.2232	0.0504
2	3.8924	3.9741	-0.0817
3	4.3225	4.2630	0.0595
4	4	4.0363	-0.0363
5	4.4748	4.5596	-0.0848
6	4.7416	4. 8290	-0.0874
7	4.7716	4.8208	-0.0492
8	3.83	3.9516	-0.1216

Figure 4
Comparison Between the Predicted Value and the Actual Value



Then, based on the BP neural network, the post matching of the compound talents was evaluated. The main idea was: based on the optimized generalized regression neural network for data processing, BP neural network was used to train and learn the obtained data, and compare the results with the training results based on genetic algorithm, and then feasibility and advantages of using generalized regression neural network to train employees to be matched could be obtained. Comprehensive evaluation of BP artificial neural network method based on the aforementioned results are as follows: 100 samples described above used the BP network model for training, but other 55 sample data

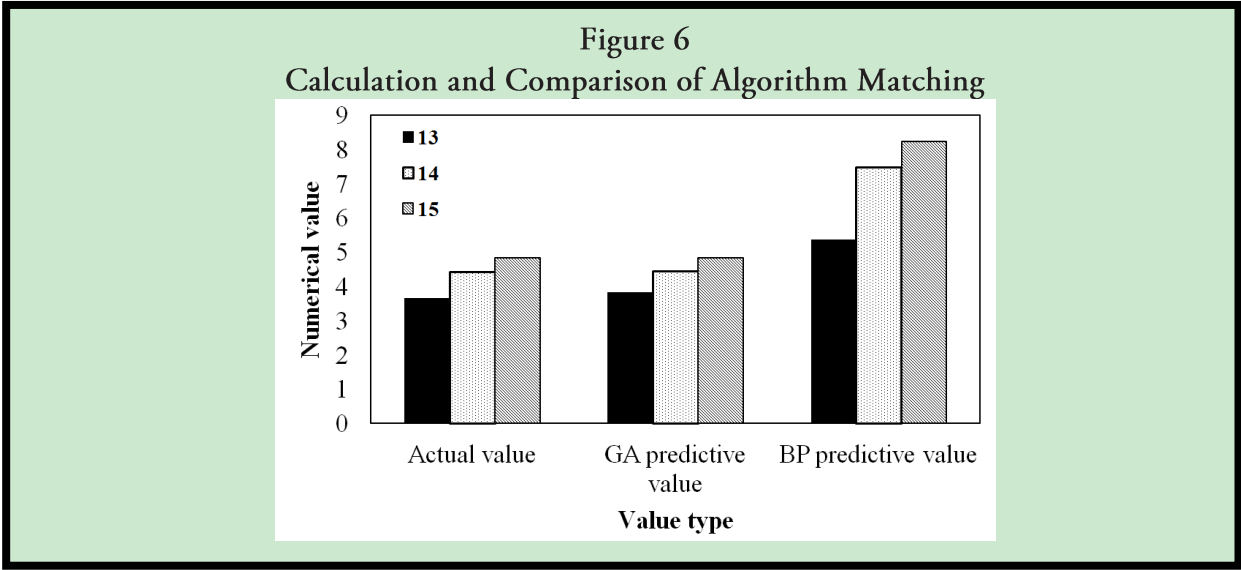
were brought into the previously trained model, thus obtaining 55 BP neural networks based on the evaluation results. With 15 neural networks as an example, the results are as shown in the following figure.



Through the verification results, it can be seen that the actual output of the 9 test data was not consistent with the target output, but the difference between the 6 test data and the actual output was relatively small, so the accuracy of using the BP model was not high.

Secondly, with the comparison and analysis of genetic algorithm based on genetic algorithm and

BP neural network, the algorithm and the generalized regression neural network based on genetic algorithm used in this paper were used to analyze the calculation results of the post matching of compound talents in aviation high-tech enterprises. The following results were obtained:



From the simulation results, it can be seen that the training accuracy of genetic algorithm based generalized regression neural network proposed in this paper was much higher than that of BP algorithm, and the difference between it and actual value was also small. The introduction of genetic algorithm makes the method of generalized regression neural network can find

the global optimal solution. Human resource management is the key to the management of Aeronautical high-tech enterprises. The generalized regression neural network based on genetic algorithm mentioned in this paper can be used to calculate the job matching problem in the human resource management of enterprises. By building the BP neural network model and the

generalized regression neural network model proposed in this paper, it can be seen that the method mentioned in this paper can find the global optimal solution compared with the traditional BP algorithm and so on, and it can get more accurate prediction values through less training steps. It is proved that the method proposed in this paper is feasible in the study of the calculation of the ability to match the post.

DISCUSSION

At present, with the rapid economic development in China, the demand for talents is large and demanding in all industries. They require considerable practical abilities, and the distribution of applied talents is crucial to the development of enterprises and industries. Today, the quality education has gradually been recognized by the whole society, and the society has formed a consensus on its importance. Colleges and universities are the important base for the training of talents. Based on this, in this paper, based on the concept of neuropsychology, the reform of the distribution pattern of teachers in colleges and universities was studied. The thought of computational calculation method was used to construct the model of talent evaluation and distribution. Through genetic algorithm, the generalized regression neural network was optimized and the operation process was designed. Then, with the college staff as an example, the algorithm was tested. The test results show that the generalized regression neural network optimized by genetic algorithm can evaluate the quality of talents well, and it has a high accuracy. The result of the research for the job matching calculation is in good agreement with the actual situation, which shows that the method is feasible with certain advantages in solving such problems.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

Acknowledgements

The study was supported by the Outstanding Youth Project of Hunan Provincial Department of Education (19B445), The Innovation Development of Hunan Industrial Workers of Made in China 2025 of Hunan Province: based on the Perspective of Enterprise growth.

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