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Improved Design of Cost Model for Post-earthquake Reconstruction Engineering Based on Neuralnetwork Algorithm

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Abstract Traditional neuralnetwork algorithms applied to post-earthquake reconstruction (for the convenience of the following text, post-earthquake reconstruction is abbreviated as PER) engineering cost models have problems of low convergence, slow operation speed, and low accuracy of engineering cost prediction results. In order to change this situation, this paper applied the improved neuralnetwork algorithm to the PER project cost model, and applied the neural network refined particle swarm optimization method to optimize the initial neural network weight, so as to avoid the local optimization of neural network in the training process. The prediction results of neural network based on particle swarm optimization were compared with those of traditional neural network. Through experimental analysis, this article concluded that the improved neuralnetwork algorithm had a higher accuracy in predicting the cost of PER projects. Its accuracy in predicting the engineering cost of 120 samples was much higher than that of 60 samples. Moreover, when predicting the engineering cost of 120 samples, the error values of different samples were all within 2%. The improved neural network technology can greatly improve the accuracy and stability of engineering cost prediction. The improved neural network technology has greatly improved its performance compared to regression analysis, fuzzy mathematics, grey prediction, and traditional neural network algorithms. The cost model of PER engineering based on improved neuralnetwork algorithms has a very broad application space for PER in the future.

Index Terms Engineering Cost Model, Neuralnetwork Algorithm, Post-earthquake Reconstruction, Improved Algorithms

I. Introduction

The restoration and resettlement work in areas affected by earthquakes includes many aspects of livelihoods and is a complex system engineering. The reconstruction of earthquake stricken areas has generated a significant demand for cement, steel, metals, and transportation materials used in buildings. If these materials are not carefully monitored and counted, the disaster area would inevitably become a heavy and trapped area that consumes resources and damages the environment. Therefore, disaster management projects must include construction engineering and project costs, which must be analyzed and monitored.

Engineering cost is widely used in the field of engineering construction. It can not only analyze the performance of structural health monitoring of civil engineering, but also design engineering models reasonably. Nicolas Manzini carried out a detailed experimental evaluation of multiple combinations of Global Navigation Satellite System (GNSS) receivers and antennas, and focused on the performance analysis of civil engineering structural health monitoring with an optimal monitoring application cost-effective solution [1]. Mehrdad Masoudnejad adopted a multi-criteria decision-making method to propose cost-effective engineering models based on productivity indicators. The results of its research indicated that equipment and technology have the greatest impact on engineering safety costs [2]. Mohammadsaeid Parsamehr reviewed the challenges that plagued traditional construction management and the construction management decision-making solutions for building information model design [3]. Abdulwahed Fazeli proposed a semi-automated cost estimation method based on building information models, which enables practitioners to estimate project costs based on different design scenarios through accurate and agile systems [4]. Qinghua Jiang analyzed the influencing factors of construction cost and selected six factors as inputs for the estimation model. Then, a backpropagation neural network estimation model was established and trained through 10 samples [5]. The application of engineering cost in the field of construction engineering is not only limited to the construction of public buildings, but also plays an important role in the construction of PER projects. However, it is rarely documented in literature.

Neural network technology is also involved in construction engineering and has good application performance in building structure and material analysis. Xinbo Qi applied machine learning based on neural networks to additive manufacturing [6]. Baoxian Li proposed a new method for automatic classification of pavement cracks using deep convolutional neural networks on image blocks cropped from 3-dimensional pavement images [7]. Panagiotis G. Asteris discussed the performance of ant colony algorithm to optimize the connection weight of feedforward neural network model [8]. Yuerong Tong proposed a polynomial fitting algorithm based on neural networks [9]. The application of neuralnetwork algorithms in the current stage is very limited, and there may be better application space for improving neuralnetwork algorithms. However, there is little research on the application of improved neuralnetwork algorithms in PER engineering cost models.

In order to improve the accuracy of PER engineering prediction, this article analyzed the necessity of PER and engineering cost, classified the factors that affect the cost of earthquake reconstruction engineering, and proposed an improved earthquake reconstruction engineering cost model using an improved neuralnetwork algorithm. By accelerating the convergence speed of the algorithm, the cost data was modeled and the model parameters were determined to obtain efficient and accurate earthquake reconstruction project cost budgets. The application of improved neuralnetwork algorithms through experimental analysis has greatly improved the prediction accuracy of post-earthquake engineering reconstruction, while also possessing excellent computational performance.

II. Necessity of PER and Engineering Cost

II. A.Necessity of PER

Recently, earthquakes and other disasters have occurred frequently, not only destroying lives, but also endangering social security and bringing great harm to community governance [10], [11]. Post disaster reconstruction makes the material, economic, spiritual, and psychological recovery of the disaster area urgent, and the time, quality, cost, and safety of reconstruction projects are the focus of people's attention. The PER of the disaster area has generated a large amount of resources through the rapid initiation of reconstruction, investment of funds, and full participation of all communities. Various projects and funds have been used in the recovery and reconstruction process of the disaster area. The most effective way to effectively utilize limited construction resources and maximize social and economic benefits is to strengthen project cost control and management, improve cost control and management level, reduce project costs, and achieve the goal of reducing resource waste and saving construction funds while ensuring project quality and construction time.

II. B.Evaluation of Factors Affecting the Cost of Reconstruction Projects after Earthquakes

The budgeting process for PER projects is very complex, mainly because it is influenced by many important factors [12]. When preparing cost estimates, it is necessary to summarize information about the economic situation of earthquake stricken areas, national governments, and residents in the affected areas, as well as the technical and structural conditions of buildings before the earthquake, and national policies. In order to clarify the characteristics of various key influencing factors, the important factors that affect the cost of PER projects are divided into three categories: factors unique to earthquakes, factors related to the technical condition of building structures before earthquakes, and factors related to residents' political and economic data.

II. C.Necessity of Engineering Cost

For construction projects, the accuracy and timeliness of project cost estimation are also important factors [13]. Before starting a construction project, a feasibility study should be conducted on the entire project to determine whether it is worth constructing and developing. In order to estimate the cost of a project, it is usually necessary to analyze it based on data from completed projects and constantly changing market information, such as the cost of building materials. With the development of current technology, more advanced planning cost management technologies have emerged, such as using expert systems, project reasoning, informatics, neural networks, and other methods to achieve most solutions. The advantages of neural networks are very obvious: information collection, parallel reasoning, adaptive learning, and fault-tolerant neural networks play a very important role in engineering cost estimation.

In the practice of the construction industry, in order to scientifically control construction costs, it is necessary to understand the importance of cost control [14], [15]. On the one hand, project cost control helps to improve resource efficiency, control construction costs, and support the long-term development of modern construction projects. On the other hand, project cost control helps to reduce the risks of project construction, achieve established construction goals, and strictly control the use of resources in construction projects.

With the rapid development of the market economy, construction enterprises have undergone a series of changes, including acceptance, construction organization, resource allocation, application, and cost management

[16]. The close connection between cost management and planning, construction, materials, mechanical equipment, finance, and other key areas urgently requires personnel, general construction, operations, cost management, and other daily activities, from cost budgeting at the beginning of construction to the scientific use of cost engineering in the pre-construction stage. From construction cost management to final cost control, it is necessary to understand all the processes and factors that directly affect costs, and adopt measures such as separation of responsibilities, consistency of objectives, and permission review to closely integrate project cost management with the current situation, achieve effective integration of cost management and two-way cost control, and ultimately achieve closure of construction.

III. Application of Neural Networks in Construction Engineering Cost

Neural networks are an emerging discipline of distributed intelligence. This algorithm is used to train a suitable neural network. The technology cost estimation system consists of four modules, namely sample input module, sample training module, error analysis module, and cost estimation module. The technology cost estimation module is directly related to the efficiency and scientific rationality of technology cost estimation. In years of research and practice in the field of engineering cost, many engineering cost methods have been formed.

In the post disaster reconstruction stage, the proposed neural network-based prediction method is aimed at analyzing the problems encountered in the current field of engineering cost accounting. The current issue has been transformed into a measure of building performance. Then it is normalized by calculating the parameters of the neural network system. For neural networks with hidden layers, the neural network prediction model is best approximated by an arbitrary nonlinear function. In addition, the actual prediction effect should consider the hidden layer of the neural network more, so it is best to use a hidden layer neural network when selecting the network. Therefore, the analysis and research of neural networks would focus more on analyzing the applications of neural network systems in different fields.

III. A. Normalization of Input Vectors

The input variables used to construct a neural network prediction model mainly come from a set of individual project specific overview indicators, that is, all parameters of the construction project. These variables represent different physical quantities of buildings, with very different numerical ranges and specific parameters. However, in the operation of neural network prediction systems, there are strict requirements for the range of input variables. The range of input variables is usually defined between zero and one, so the way data is input into the model is usually converted to values that are within an acceptable range. If variables such as area and land area are numerical, it is necessary to further convert these values to fall within this acceptable range.

III. B. Learning Neural Networks

When establishing a neural network prediction model, applying theory can provide a more complete approximation of each network function, where the network structure typically consists of a hidden layer, an output, and multiple inputs. However, generally speaking, the antisymmetric function is more practical than the non symmetric function. The most commonly used antisymmetric function is the hyperbolic tangent.

III. C. Optimizing the Network

When establishing a neural network prediction model, the number of samples used for training the network is limited. There is a direct relationship between the number of samples required for training the network and the number of input variables. Therefore, if there is a sufficient number of samples, it can fully meet the requirements of the learning network and better select variables. Variable selection is one of the most important steps in economic modeling and prediction research, but the selection process is full of many difficulties. However, under nonlinear conditions, the current methods are not applicable and further changes in the process are needed. Therefore, the selection of variables for nonlinear models requires a wider range of models. For models with different expressions, it is possible to mistakenly select the same variable. Even if the form of the model is correctly defined, introducing inappropriate variables cannot guarantee the reliability of the model and the accuracy of the resulting prediction results, directly leading to the failure of modeling and prediction.

IV. Cost Model for PER Engineering Based on Improved Neuralnetwork Algorithm

Construction engineering is a wide-ranging activity that encompasses internal and external relationships. The production and business processes are influenced by various factors, and engineering cost models can be applied to engineering estimation in pre-investment planning decisions. The investment decisions and feasibility analysis of design projects directly affect the company's investment decisions, construction scope, design decisions, and investment returns, playing a very important role.

IV. A. Traditional Engineering Cost Model

Regression analysis method is based on a large amount of historical statistical data, using statistical processing and induction techniques to determine the relationship between relevant variables, and is a method of engineering cost estimation for predicting future changes. It is easy to apply and can estimate engineering costs faster. The cost model of regression analysis is very suitable, but it should be analyzed based on similar design examples.

The fuzzy mathematics method is based on a set of existing projects that are similar to the proposed project. It uses fuzzy mathematics theory to quantify the degree of similarity between projects, establishes a suitable mathematical model, and obtains the cost estimate of the proposed project. The basic method of estimation is to use fuzzy mathematics to describe similar projects, select appropriate neural networks, and use fuzzy project features as input values of the network. It can start from the form of information dissemination, guide the network to obtain one-sided project costs, develop a training network, input the feature values of this project into the training network, and obtain the estimated unilateral project costs. This network is trained to input one hundred operation estimation models based on fuzzy neural networks and ideas, and explore materials and functions in front of specific engineering costs using mobile phones. This can be seen as training, and then the neural network is executed to convert spatial engineering functions into material evaluation. This can also be seen as a mapping process, and the mapping has very nonlinear characteristics, making it difficult to express engineering based on this.

The grey prediction method is applied to project cost estimation, identifying a group of projects from existing projects that are most similar to the proposed project, conducting grey correlation analysis between projects, and using cost data from similar existing projects to estimate the cost of the proposed project. Grey systems are mainly studied as undefined systems, which may contain both partially black, partially white, and possibly partially gray data. By using grey system methods and modeling techniques to create these known information, it is possible to mine important information hidden in system observations and use it to obtain accurate descriptions and understandings of the real world. This method requires less and limited experimental observation data and its distribution, and is easy to learn and expand.

IV. B. Improved Engineering Cost Model

Neural networks can identify complex nonlinear systems. Therefore, they need to train a sufficient number of samples, so that the network can recognize the correct correspondence between the a-dimensional input space and the b-dimensional output space during execution (testing). Algorithm process:

The first step is to initialize the values and thresholds. Random values within the range of $(-1,+1)$ are assigned to each connection weight $\{c_{ij}\}$ and $\{d_{jt}\}$, as well as thresholds $\{\alpha_p\}$ and $\{\beta_q\}$.

The second step is to give the output.

$$X^l = (x_1^l, x_2^l, \cdots, x_m^l) \tag{1}$$

In the formula, m is the number of influencing factors considered.

The expected result is:

$$Z^l = (z_1^l, z_2^l, \cdots, z_m^l) \tag{2}$$

Step 3: The output signal of the hidden layer is:

$$g_j^l = f\left[\sum c_{ij} x_i^l - \alpha_p\right], p = 1,2,\cdots,s \tag{3}$$

The output signal of the input layer is:

$$h_j^l = f\left[\sum d_{jt} b_j^l - \beta_q\right], q = 1,2,\cdots,t \tag{4}$$

The fourth step is weight correction. Starting from the output layer, the error signal propagates back along the connection path for weight correction.

The fifth step is to train the network until it reaches the expected error accuracy.

IV. B. 1) Estimating Labor Costs

Labor costs are easily influenced by price indices. To estimate labor costs, a price index can be defined, which basically includes the labor cost index for each professional project and the labor cost index for construction.

Among them, the labor cost index of the construction industry is particularly important. In the following steps, without changing the main values of the labor cost index for each professional construction industry, it is analyzed:

$$I_D^e = \frac{\frac{E_{Di}}{N_i}}{\frac{E_{Do}}{N_o}} \times 100 = \sum I_{ij}^E \cdot Y_j^e \times 100 \tag{5}$$

In the formula: E_{Di} is the project baseline period; E_{Do} is the labor cost during the project baseline period; N_i is the reference period for building materials; N_o is the building area during the project reference period.

IV. B. 2) Price Evaluation of Machinery Usage Fees

The estimation of machinery costs is basically the same as the estimation of labor costs: selecting the main construction machinery, analyzing and estimating the proportion of each construction machinery in the total machinery cost based on project cost data, and using the weighted average method to calculate and obtain the price index of the machinery. The calculation formula is as follows:

$$I_n = \sum \left(\frac{Q_{ij}^n}{Q_{oj}^n} \times 100 \times Y_j^n \right) = \sum \left(I_{ij}^n \cdot Y_j^n \right) \tag{6}$$

In the formula: I_n represents the price index of the total cost of machinery; I_{ij}^n represents the unit price index of the j-th construction machinery; Q_{ij}^n represents the unit price of the j-th construction machinery during the reference period i; Q_{oj}^n represents the unit price of the j-th construction machinery during the reference period o; Y_j^n represents the share of the j-th construction machinery in the total mechanical cost.

IV. B. 3) Material Cost Evaluation

The evaluation formula for material cost is as follows:

$$I_D^r = \sum I_{ijk}^r \cdot Y_{jk}^r \tag{7}$$

In the formula: I_D^r represents the cost index of building engineering material costs; I_{ijk}^r represents the individual cost index of the k-th main material in category j; Y_{jk}^r represents the proportion of the j-th and k-th main materials in the material cost.

V. Application of Engineering Cost Model

In order to test the applicability of the engineering cost prediction model based on the improved neuralnetwork algorithm in earthquake reconstruction projects in this article, the cost model was applied to the budgeting of 60 and 120 samples, and the resulting budget values were compared with the actual project costs to obtain error estimates. For statistical convenience, the error rates obtained in this article were all positive values. The results are shown in Table 1:

Table 1: Comparison results of actual and predicted values

Actual costing value (thousand dollars)		16365.5	10333.6	23651.4	32156.9	8632.3	42631.4	52316.8
60 samples	Budget result (thousand dollars)	15773.2	9735.8	24842.8	34621.7	8264.7	39853.7	53998.4
	Error value (thousand dollars)	-592.3	-597.8	1191.4	2464.8	-367.6	-2777.7	1681.6
	Error rate (%)	3.62	5.79	5.04	7.66	4.26	6.52	3.21
120 samples	Budget result (thousand dollars)	16326.4	10142.3	23690.5	32731.7	8654.7	41932.7	52944.3
	Error value (thousand dollars)	-39.1	-191.3	39.1	574.8	22.4	-698.7	627.5
	Error rate (%)	0.24	1.85	0.17	1.79	0.26	1.64	1.20

When predicting the engineering cost of 60 samples, the error values of different samples were relatively high, with an error rate higher than 3%. However, when predicting the engineering cost of 120 samples, the error values of different samples were all within 2%. The improved neuralnetwork algorithm has a higher accuracy in predicting the cost of PER projects, and it is better at analyzing samples with more data. Its accuracy in predicting the engineering cost of 120 samples is much higher than that of 60 samples.

In order to demonstrate the superiority of the improved neuralnetwork algorithm in the application of post disaster reconstruction engineering costs, this article compared and analyzed the improved neuralnetwork algorithm with traditional neuralnetwork algorithms. The first 20 samples were used as training samples, and the remaining 5 samples were used as test samples. Then, the test sample data was imported into the construction cost estimation model for disaster area reconstruction, and the results were analyzed to verify the effectiveness of the improved neuralnetwork algorithm. The results are shown in Figure 1:

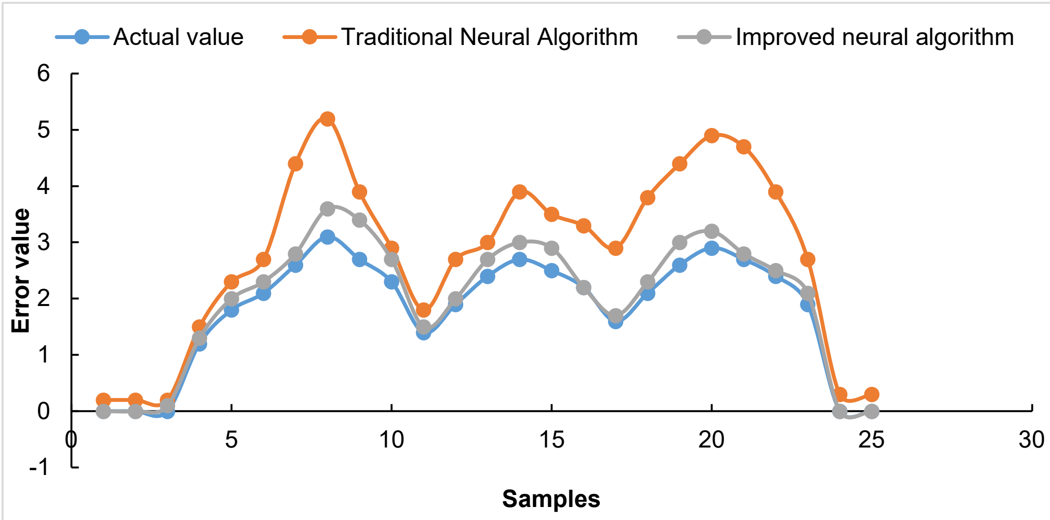

Figure 1: Evaluation results of different neuralnetwork algorithms

When using traditional neuralnetwork algorithms to estimate the cost of PER projects in disaster areas, the estimated results differed significantly from the actual values, with a maximum error of 5.2 and low accuracy. When applying improved neuralnetwork technology, the estimated results were relatively close to the actual values without significant differences, with a maximum error of 3.6, which was 1.6 less than traditional technology and relatively stable. Therefore, adopting improved neural network technology can greatly improve the accuracy and stability of engineering cost prediction.

This article selected the actual engineering cost values of four disaster stricken areas for comparative analysis using regression analysis, fuzzy mathematics, grey prediction, traditional neural network algorithms, and improved neuralnetwork algorithms. The application effects of the five methods for constructing post disaster reconstruction engineering cost prediction models in actual engineering costs were analyzed. The four selected regions were recorded as A, B, C, and D, and the cost of their engineering costs (in thousands of yuan) was recorded in Table 2:

Table 2: Cost of construction

	Total project cost	Labour cost	Machinery usage cost	Material costs	Other costs
A	23654.5	15355.5	3152.5	3935.2	1211.3
B	13655.5	8532.6	1325.4	2654.6	1142.9
C	9365.3	4635.9	1665.2	2236.5	827.7
D	5654.5	3216.2	952.1	1232.2	254

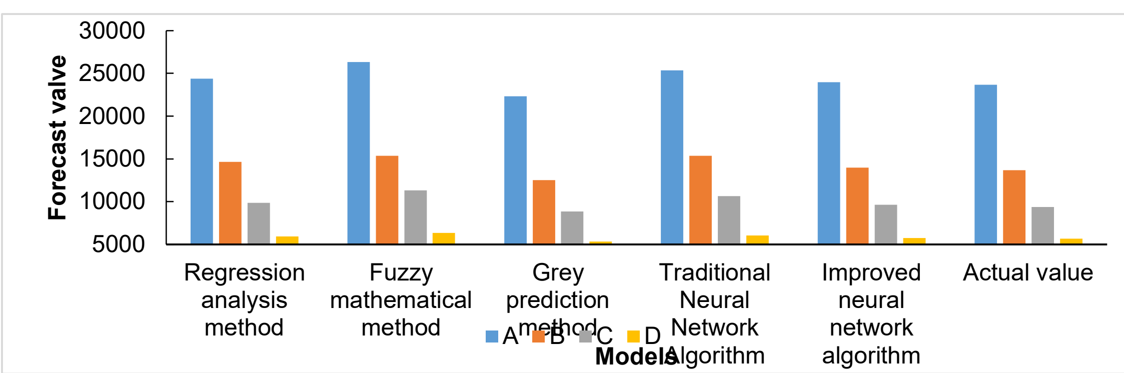

Figure 2: Forecast results of different models

The total cost of engineering in various regions was analyzed using five post disaster reconstruction engineering cost models, and the results were recorded in Figure 2:

When five models were used to predict the total project cost in four affected areas, it was found that the total project cost predicted by the improved neuralnetwork algorithms was closer to the actual value, i.e., its prediction accuracy was the highest. Secondly, the prediction accuracy of the post disaster reconstruction project cost prediction model using regression analysis method was relatively high. Thirdly, the prediction accuracy of the grey prediction method post disaster reconstruction project cost prediction model was relatively high. However, in field tests, it was found that when the grey prediction method was applied to the post disaster reconstruction project cost prediction model, the predicted results were often lower than the actual values. Therefore, in practical applications, further predictions needed to be made based on the characteristics of different algorithms to make the predicted values close to the actual values. Based on this, planning for project costs would play an important role in post disaster reconstruction.

In addition to improving the accuracy of post disaster reconstruction project cost prediction, this article further analyzed the performance of the engineering cost prediction model based on improved neuralnetwork algorithms to determine whether the model can meet the expected prediction results of the public in post-earthquake prediction. To this end, a scoring system was adopted, and model evaluation professionals evaluated the PER project cost model using regression analysis, fuzzy mathematics, grey prediction, traditional neural network algorithms, and improved neuralnetwork algorithms. The maximum score was 100 points. The results obtained were summarized in Table 3:

Table 3: Model performance analysis

PER engineering cost model	Convergence	Interference resistance	Computational speed	Logic connectivity
Regression analysis method	56	63	62	49
Fuzzy mathematical method	62	57	69	70
Grey prediction method	58	62	52	57
Traditional Neural Network Algorithm	69	58	64	61
Improved neural network algorithm	73	72	75	63

For the investigation of the convergence of the PER engineering cost model, it was concluded that the convergence of the engineering cost prediction model of the improved neuralnetwork algorithm was stronger than the convergence of the engineering cost prediction model of the traditional neural network algorithm, and stronger than the convergence of the engineering cost prediction model of the fuzzy mathematical method. The engineering cost prediction model based on improved neuralnetwork algorithm in this article had the advantage of strong convergence.

The anti-interference score of the PER engineering cost model based on regression analysis was 63; the anti-interference score of the PER engineering cost model based on fuzzy mathematics was 57; the anti-interference score of the PER engineering cost model based on grey prediction method was 62; the anti-interference rating of the PER engineering cost model based on traditional neuralnetwork algorithms was 58; the anti-interference rating of the PER engineering cost model based on improved neuralnetwork algorithms was 72. It can be seen that the PER engineering cost model based on improved neuralnetwork algorithms had the strongest anti-interference performance.

The computational speed rating of the PER project cost model based on the improved neuralnetwork algorithm was 13 points higher than that of the PER project cost model based on the regression analysis method, 6 points higher than that of the PER project cost model based on the fuzzy mathematical method, 23 points higher than that of the PER project cost model based on the gray prediction method, and 11 points higher than that of the PER project cost model based on the traditional neuralnetwork algorithm. The improved neuralnetwork algorithm greatly improved the computational speed.

The logical connectivity of PER engineering cost models using regression analysis, fuzzy mathematics, grey prediction, traditional neuralnetwork algorithms, and improved neural network algorithms was 49 points, 70 points, 57 points, 61 points, and 63 points, respectively. Through comprehensive comparison, it was found that the logical connectivity of the PER engineering cost model based on the improved neuralnetwork algorithm was second only to the logical connectivity of the PER engineering cost model based on fuzzy mathematics.

The performance of the PER engineering cost model based on the improved neuralnetwork algorithm in this article is superior to the other four PER engineering cost models in terms of strong convergence, anti-interference, and fast budget speed. However, its logical budget connectivity needs further improvement. Overall, the improved neural network algorithm has many performance advantages and high practicality in the cost model of PER engineering. Its shortcomings can be further studied to achieve accurate prediction of PER engineering costs.

VI. Conclusions

Earthquake events occur from time to time, and they often pose a threat to people's property and lives, causing great panic among the public and causing extreme unrest in the entire society. Based on this, it is necessary to help people in disaster areas recover their homes and carry out post disaster reconstruction. Therefore, it is necessary to evaluate and analyze the engineering cost of post disaster reconstruction, that is, to conduct engineering cost analysis. However, existing engineering cost models often have low prediction accuracy, which brings great stability to engineering cost prediction. Based on this, this article used an improved neuralnetwork algorithm to design a cost model for PER projects, and analyzed its practical application and performance. At the same time, a comparative analysis was conducted with four common PER engineering cost models based on regression analysis, fuzzy mathematics, grey prediction, and traditional neural network algorithms. It was found that the improved neuralnetwork algorithm based PER engineering cost model in this paper not only has high prediction accuracy, but also has high convergence, anti-interference, and budget speed. The PER engineering cost model based on improved neuralnetwork algorithm in this article has a relatively wide application space in post disaster prediction, and can be expanded to apply to the prediction of post-earthquake engineering cost.

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