PSO-Optimized Grey-BPNN Hybrid Model for Predicting Construction Project Costs

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This paper combined the grey prediction model with a back-propagation neural network (BPNN) and optimized BPNN parameters using particle swarm optimization (PSO) to predict the cost of construction projects. Simulation experiments were conducted. In the experiment, the GM (1,1) was combined with a BPNN improved by PSO to predict the cost of construction projects. Forty construction project samples were used, among which 30 were included in the training set, and the remaining 10 were included in the test set. The influence of the number of BPNN hidden layer nodes and the type of activation function on the algorithm performance was tested in the experiment. Moreover, the model was compared with the grey prediction model GM (1,1) and the traditional BPNN model. It was found that the proposed prediction model was more accurate in predicting the construction project cost than the other two models. The mean absolute error (MAE) and root mean square error (RMSE) of the GM (1,1) model were 0.287 and 0.045, respectively. The MAE and RMSE of the traditional BPNN model were 0.113 and 0.020, respectively. The MAE and RMSE of the proposed prediction algorithm were 0.067 and 0.013, respectively.

Povzetek: Predstavljen je hibridni model GM(1,1)-BPNN, optimiziran s PSO, za napoved stroškov gradbenih projektov. Algoritem učinkovito obvlada negotovost podatkov, izboljša točnost in preseže tradicionalne metode napovedovanja.

1 Introduction

The direct cost of a construction project [1,2] can be directly calculated using relatively stable unit prices and demand quantities; however, the indirect costs have more uncertain factors [3,4], resulting in a very complex prediction of the construction project cost. Grey system theory [5] is suitable for construction project cost prediction with difficulty in data collection and a low degree of data integrity. In addition, a grey system can reduce the randomness and volatility of the original data through accumulated generating operations. However, the traditional grey prediction model still has the problem of poor fit in the face of a complex and changeable construction cost environment, so it needs to be improved [6]. The related woks are reviewed in Table 1. These studies have all analyzed how to plan construction projects and predict construction costs. Some of the studies focused on the planning of the construction project phase, some on the labor costs of construction workers, and some on the relevant indicator parameters that can be used for construction project costs. This paper combined the back-propagation neural network (BPNN) algorithm with the grey prediction model to forecast the construction project costs and used the particle swarm optimization (PSO) algorithm to assist the training of the BPNN algorithm to improve the prediction accuracy. The grey prediction model can construct a new sequence of the cost of construction project samples, thereby reducing its volatility and randomness. The BPNN algorithm uses the activation function of the hidden layer to uncover the hidden patterns from the new sample sequence. This paper integrated the grey prediction model with the BPNN algorithm. The PSO algorithm was used to optimize the BPNN parameters for the cost prediction of construction projects, and then simulation experiments were carried out. This paper aims to use the grey prediction model, BPNN algorithm, and PSO algorithm to improve the accuracy of construction project cost prediction and reduce the root mean square error (RMSE) of the prediction results to less than 0.02. The novelty of this paper lies in combining the grey prediction model GM (1,1) with the BPNN algorithm and then using the PSO algorithm to train and adjust the parameters of the BPNN algorithm to improve the prediction performance. The limitations of this paper are that the scale of the sample set used in the simulation experiment was small, the types of other prediction algorithms used for comparison when verifying the prediction performance of the algorithm were few, and the contribution of the improved part was not tested, resulting in a low generalization of the test results. Therefore, the future research direction is to increase the scale of the sample set and the types of other prediction algorithms and use ablation experiments to verify the contribution of the improved part.

Table 1: Related works

Author	Research content	Research results
Ock et al. [7]	Propose a future cash flow modeling algorithm for construction companies in the project planning stage.	The simulation test results verified that the algorithm can effectively manage project liquidity.
Faghih et al. [8]	Propose a framework to develop a vector error correction model.	The experimental results suggested that the model is suitable for predicting short- and long-run movements of the average hourly earnings of construction labor.
Elfahham [9]	Employ the engineering cost index to forecast the cost of construction projects.	The final results verified the effectiveness of the engineering cost index.

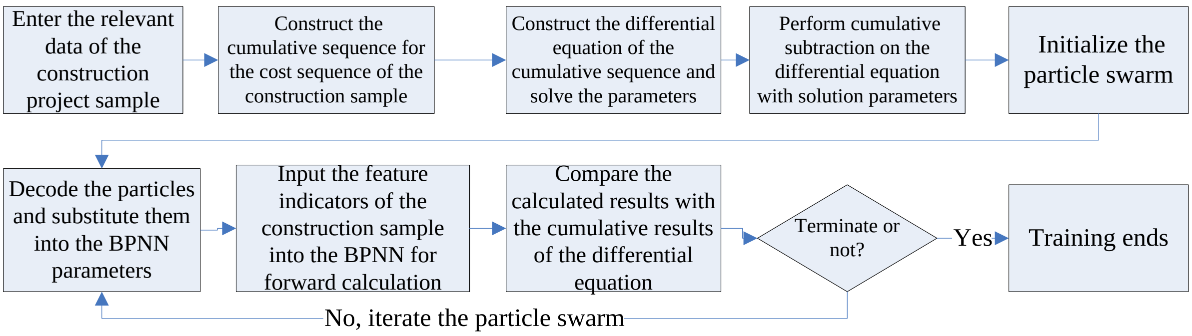
2 Construction cost prediction algorithm

Accurately predicting construction project costs is a key link to enable the smooth progress of the project, control the budget, and optimize the allocation of resources. Due to the influence of many factors, the cost of construction projects has great volatility and randomness, which makes it difficult for the traditional method to satisfy the needs of modern construction project management [10,11].

For the cost of multiple construction project samples, the grey prediction model can construct a new sequence of the cost of these samples and fit the law to predict the new cost. However, the grey prediction model only considers the relationship between the sample costs in the sequence and ignores other factors that affect the construction cost, such as building type, wall type, and types of doors and window [12].

The basic principle of the proposed prediction algorithm is to use the GM (1,1) model to construct a new sequence of the project sample cost to reduce the volatility of the original construction project cost data and use the new sequence to train the BPNN. During the training, the prediction result obtained by the BPNN is compared with the new cost sequence to determine whether the error converges. If it does not converge, the PSO algorithm is used to adjust the parameters of the BPNN. The training flow of the prediction algorithm is displayed in Figure 1.

Figure 1: Training process of the prediction model.



① The data related to the collected construction project samples, including the construction project cost and the characteristic indicators (influencing factors) that affect the cost [13], are input.

② The cost sequence of the samples is processed by accumulation:

$$\begin{cases} x^0 = (x^0(1), x^0(2), x^0(3)\cdots, x^0(n)) \\ x^1 = (x^1(1), x^1(2), x^1(3)\cdots, x^1(n)) \\ x^1(n) = x^0(n) + x^1(n-1) \end{cases}, \quad (1)$$

where x^0 is the cost sequence of n construction project samples, $x^0(n)$ is the cost of the n-th construction project sample, $x^1(n)$ is the cumulative cost of the n-th construction project sample, and x^1 is the cumulative cost sequence of the n-th construction project sample [14].

③ The differential equation of the cumulative sequence of the construction project cost is constructed:

$$\begin{cases} \frac{dx^1}{dt} + ax^1 = u \\ (a,u)^T = (B^T B)^{-1} B^T Y \\ B = \begin{bmatrix} -z^1(2) & 1 \\ -z^1(3) & 1 \\ \vdots & \vdots \\ -z^1(n) & 1 \end{bmatrix} \\ Y = \left[x^0(2), x^0(3), \cdots x^0(n)\right]^T \\ z^1(n) = 0.5(x^1(k) + x^1(k-1)) \end{cases}, \quad (2)$$

where a and u are the parameters to be solved in the differential equation, t is the time parameter used to represent the order in the cost accumulation sequence, and $z^1(n)$ is the n-th adjacent average in the adjacent average sequence [15].

④ The obtained parameters a and u are substituted into the differential equation, and then the predicted construction project cost under the grey prediction model can be obtained through the cumulative subtraction formula:

$$x^0(k+1) = (1-e^a)(x^0(1) - \frac{u}{a})e^{-ak}, \quad (3)$$

where $x^0(k+1)$ is the grey prediction cost of the $k+1$-th construction sample according to the order in the initial cost sequence.

⑤ The particle swarm is initialized, and a certain number of particles is randomly generated in the search space.

⑥ The particles of the particle swarm are decoded by converting the particle coordinates into the weight parameters of the BPNN and substituting them into the BPNN formula.

⑦ The characteristic index of the construction sample is input into the BPNN for forward calculation:

$$y = f(wx+b), \quad (4)$$

where x is the input characteristic index, w is the weight parameter, b is bias, and y is the output result.

⑧ The output of BPNN forward calculation is compared with the corresponding construction project grey prediction cost.

⑨ Whether the training is terminated is judged. If the training times reach the preset threshold or the difference between the BPNN forward calculation result and the grey prediction cost converges to stability, the training will be stopped; otherwise, the particle swarm is iterated [16]. The formula is:

$$\begin{cases} v_{i,t+1} = \varpi v_{i,t} + c_1 r_1 (p_i - x_i) + c_2 r_2 (p_g - x_i) \\ x_{i,t+1} = x_{i,t} + v_{i,t+1} \end{cases}, \quad (5)$$

where $v_{i,t+1}$ and $x_{i,t+1}$ are the velocity and position of particle i after one adjustment, $v_{i,t}$ and $x_{i,t}$ are the current velocity and position of particle i, ϖ is the inertia weight of a particle, c_1 and c_2 are learning factors, r_1 and r_2 are numbers randomly generated within the range of 0 to 1, p_i is the historically optimal position of particle i, and p_g is the current optimal position [17]. Return to step ⑥ after particle swarm iteration.

3 Simulation experiment

3.1 Experimental data

This paper took 40 office building project samples of a similar scale as the subject of the simulation experiment. The relevant index variables (i.e., characteristic indicators and cost per square meter) of the project samples and the quantization methods are shown in Table 2, and the index variables of some samples are shown in limited space.

Table 2: Sample related indicators and part of the sample

Symbol	Variable name	Quantization method	Sample 1	Sample 2	Sample 3
T1	Basic configuration	Stripe foundation is denoted as 1; precast pile foundation is denoted as 2; box foundation is denoted as 3.	1	2	3
T2	Door and window engineering	Wood doors and windows are denoted as 1; aluminum doors and windows are denoted as 2; plastic-steel doors and windows are denoted as 3.	2	1	3
T3	Floor inside the building	Cement mortar floor is denoted as 1; tile floor is denoted as 2; fine stone concrete ground is denoted as 3.	2	3	2
T4	Interior wall decoration	Cement mortar is denoted as 1; rough surface is denoted as 2; mixed mortar is denoted as 3; coating is denoted as 4.	3	4	3
T5	Exterior wall decoration	Exterior wall coating is denoted as 1; stone wall is denoted as 2; ceramic tiles are denoted as 3.	1	3	2

T6	Wall structure	Frame-shear structure is denoted as 1; frame structure is denoted as 2; brick-concrete structure is denoted as 3; shear-wall structure is denoted as 4.	3	3	3
T7	Number of floors	The actual number of floors (unit: floor).	6	5	4
O	Cost per square meter	Actual value (unit: yuan/m)	596.3	754.3	652.5

3.2 Experimental setup

When conducting the simulation experiment, the first 30 samples out of 40 served as the training set, and the remaining 10 were used as the test set. The relevant parameters of the construction prediction algorithm model included ten particles, ϖ = 0.8, and c_1,c_2 = 1.5. The number of input layer nodes in the BPNN part was set to 7 according to the number of characteristic indicators, the activation function of hidden layer nodes was sigmoid, and the output layer output a cost prediction result.

In addition, the influence of the number of nodes in the hidden layer and the type of activation function on the algorithm prediction performance was tested. The number of nodes in the hidden layer was set as 4, 5, 6, 7, 8, 9, 10, 11, and 12, and the type of activation function was set as tahn, relu, and sigmoid.

To further validate the accuracy of the prediction model, it was compared with the grey model GM (1,1) and the traditional BPNN model. When GM (1,1) performed the prediction performance test, the cost of thirty construction samples in the training set was used as the initial sequence to construct the model. Then, the obtained model predicted the cost of ten samples in the test set. The traditional BPNN model parameters were kept the same as those in the BPNN component of the algorithm. The traditional BPNN model used the original cost of training samples as the reference standard during training and used the deviation between the forward calculation result and the reference standard to adjust the parameters reversely.

3.3 Evaluation criteria

$$\begin{cases} MAE = \dfrac{\sum_{i=1}^{N}\left|y_i - y_i^{cal}\right|}{N} \\ RMSE = \sqrt{\dfrac{\sum_{i=1}^{N}(y_i - y_i^{cal})^2}{N}} \\ R^2 = 1 - \dfrac{\sum_{i=1}^{N}(y_i^{fit} - y_i^{cal})^2}{\sum_{i=1}^{N}(y_i^{cal} - y_{mean})^2} \end{cases}, \quad (6)$$

where MAE is the mean absolute error, $RMSE$ is the root mean square error, R^2 is goodness of fit, y_i is the expected result of the i -th sample, y_i^{cal} is the calculated result of the i -th sample, y_i^{fit} is the expected result of the i -th sample after recalibration, y_{mean} is the mean of the computed outputs from the test sample set.

3.4 Experimental results

In the BPNN part of the prediction model algorithm, the number of hidden layer nodes and the type of activation function could affect the algorithm's accuracy, as shown in Table 3. Under the same number of hidden layer nodes, the RMSE of the algorithm using the sigmoid activation function was smaller.

Table 3: Influence of the number of hidden layer nodes and the type of activation function on the RMSE of the algorithm

Number of hidden layer nodes	Activation function Relu	Activation function Tahn	Activation function Sigmoid
4	0.341	0.321	0.302
5	0.287	0.263	0.241
6	0.259	0.232	0.213
7	0.223	0.202	0.185
8	0.205	0.187	0.123
9	0.213	0.197	0.178
10	0.234	0.215	0.197
11	0.256	0.231	0.214
12	0.275	0.251	0233

The grey prediction model, traditional BPNN, and proposed prediction models were compared. The parameters of the BPNN part in the proposed model adopted the optimal values obtained in the previous test. The scatter distribution of the predicted and actual costs of the three algorithms for the test set samples is presented in Figure 2. The diagonal line in the figure is the standard line. When the predicted cost of the sample is the same as the actual cost, the dot will be on the standard line. However, the prediction model may not be as accurate in the actual situation. Therefore, for the prediction model, the closer the scatter is to the standard line, the better the prediction performance of the prediction model. It can be seen from the figure that the scatter of the proposed algorithm was closest to the standard line, followed by the traditional BPNN model, and the scatter of GM (1,1) was farthest from the standard line.

Figure 2: Scatter distribution of predicted and actual values under different cost prediction models for construction projects

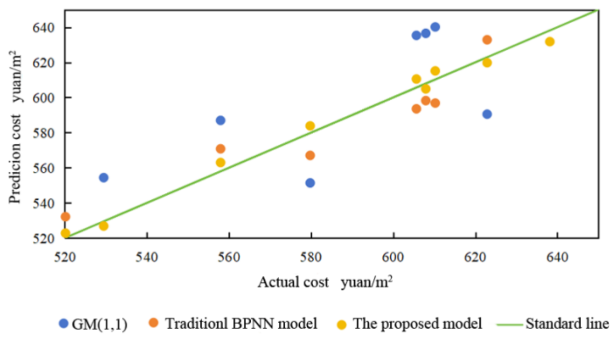


Table 4 shows that the mean absolute error and RMSE of GM (1,1) were the largest, followed by the traditional BPNN model, and the proposed prediction model was the smallest. Moreover, the proposed model had the largest fitting degree, followed by the traditional BPNN model, and GM (1,1) had the smallest degree.

Table 4: Performance of different cost prediction models for construction projects (* indicates a significant difference with GM (1,1), $p < 0.05$; + indicates a significant difference with the traditional BPNN model, $p < 0.05$)

Model	GM (1,1)	Traditional BPNN	The proposed model
MAE	0.287	0.113*	0.067*+
RMSE	0.045	0.020*	0.013*+
R^2	0.637	0.724*	0.759*+

4 Discussion

In the modern construction industry, the accuracy and predictive ability of project cost are directly related to the project feasibility, return on investment, and overall economic efficiency. With the continuous advancement of China's urbanization process and the continuous expansion of the scale of infrastructure construction, the investment amount involved in construction projects is increasing. Characteristics such as long project cycles, numerous uncertain factors, and large cost fluctuations are becoming more prominent. Therefore, how to scientifically and accurately predict the cost of construction projects has become the core issue of common concern to government authorities, construction units, design institutions, and construction companies. Traditional methods for predicting project cost mainly rely on statistical means such as empirical judgment, quota estimation, regression analysis, or time series models. Although these methods can reflect the cost change trend to a certain extent, they often have problems such as low prediction accuracy, poor adaptability, and weak modeling ability for nonlinear relationships when facing the actual engineering environment with limited data samples, incomplete information, and complex and variable influencing factors. Especially in the current context where emerging technologies such as green buildings, prefabricated buildings, and intelligent construction are constantly emerging, traditional prediction models are increasingly unable to meet the increasingly complex engineering management needs. Against this backdrop, grey prediction models in grey system theory have received extensive attention because it is suitable for dynamic prediction problems under the conditions of small samples and poor information. The GM (1,1) model, as one of the most fundamental and widely applied models in grey prediction, has the advantages of simple modeling, high computational efficiency, and no need for a large amount of historical data support. It has achieved good application results in many fields. However, the standard GM (1,1) model also has certain limitations. For example, it has high requirements for the smoothness of the original data sequence and is sensitive to mutation points, and the prediction results are easily affected by the initial values. These limitations may lead to relatively large deviations in the actual prediction of project costs. For this reason, this paper used the BPNN to further explore the patterns therein to improve the prediction accuracy. Then, a simulation experiment was carried out. During the experiment, 40 building project samples were taken as the subject, among which 30 were used as training samples and the other 10 were used as test samples. Then, a comparison was made with the standard GM (1,1) and the traditional BPNN models.

As to the BPNN used in the optimized GM (1,1) model, regardless of the activation function used, as the number of hidden layer nodes increased, the RMSE of the BPNN first decreased and then increased. Under the same number of hidden layer nodes, the BPNN adopting the sigmoid activation function had a smaller mean squared error. The reasons are analyzed. An increase in the number of hidden layer nodes enabled the algorithm to obtain more detailed sample features, thus making the summarized rules closer to the non-linear rules hidden in the samples. Therefore, as the number of hidden layer nodes increased, the RMSE of the BPNN algorithm gradually decreased. However, when the number exceeded a certain value, the fitting of the non-linear rules by too many nodes instead interfered with each other. In the BPNN, this is manifested as a gradual increase in the RMSE. In terms of the prediction performance of the cost of construction projects, the prediction error of the standard GM (1,1) was the largest, followed by the traditional BPNN model, and the error of the optimized model was the smallest. The reasons are analyzed. Although the standard GM (1,1) can handle the dynamic prediction problem of small samples under the condition of poor information, it has a relatively high requirement for the smoothness of the sample data sequence, and the prediction result is easily affected by the initial value. The traditional BPNN model used the activation function in the hidden layer to fit the non-linear rules in the samples. Therefore, its prediction performance was better than that of the standard GM (1,1). The optimized model used the standard GM (1,1) to construct a new cost sequence to reduce the volatility of the original data. Then, the new sequence was used to train the BPNN. The hidden layer of the BPNN was utilized to fit the non-linear pattern, further improving the prediction performance of the algorithm.

5 Conclusions

This paper combined the grey prediction model with a BPNN and optimized BPNN parameters by using PSO to predict the cost of construction projects. Then, simulation experiments were carried out. In the experiment, the influence of the number of BPNN hidden layer nodes and the type of activation function on the algorithm performance was first tested. Then, the proposed model was compared with the grey prediction model GM (1,1) and the traditional BPNN model. When the number of hidden layer nodes was 8 and the type of activation function was sigmoid, the proposed algorithm achieved the lowest RMSE. In the scatter diagram, the scatter distribution of the proposed algorithm was closest to the standard line. The mean absolute error and RMSE of GM (1,1) were the largest, followed by those of the traditional BPNN model, while the errors of the prediction algorithm were the smallest.

6 References

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