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Improving Residential Construction Cost Prediction with PSO-BP Neural Network Optimization

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Abstract:

The prediction of costs for residential construction projects has been a prominent research focus for scholars both domestically and internationally. To identify a more efficient and precise prediction method, this study introduces the particle swarm optimization (PSO) algorithm to enhance the Backpropagation (BP) neural network, resulting in the establishment of the PSO-BP neural network model. Seven influencing factors were identified as feature indicators through literature review and expert interviews. The study utilized 35 sample data points from publicly completed residential projects in Anhui Province over the past five years. The implementation was carried out using MATLAB software coding. The findings reveal that the PSO-BP neural network prediction has an average absolute relative error of 0.30019%, which is significantly lower than the 0.41029% error of the standard BP neural network. This indicates that the PSO-BP neural network offers superior accuracy and precision in predicting construction costs.

Keywords:

Construction engineering, cost prediction, PSO-BP neural network, MATLAB.

1. Introduction

In 2021, the scale of construction industry has reached up to 29 trillion yuan, becoming one of the pillar industries of national economic development, and scholars at home and abroad attach great importance to the research related to construction engineering. It can provide an important basis for project feasibility study and design selection, and can largely influence the construction unit's investment decision on the project, and the success of the forecast can bring great convenience to many parties.

The project cost prediction is usually done by collecting the data of cost characteristics of similar projects built in advance and then analysing and predicting the cost of the project to be built through certain mathematical models [1]. Among the many methods, BP neural network has received more and more attention from experts and scholars. However, because the accuracy of BP neural network prediction is greatly influenced by the subjectively set weights and input layer data, and has disadvantages such as slow convergence speed, relevant algorithms need to be introduced to optimize it.

In view of this, this paper takes the residential construction project in Anhui Province as the research object to study the prediction of its cost, uses the particle swarm algorithm optimization BP neural network (PSO-BP) method, selects the appropriate engineering characteristics index, uses MATLAB software to simulate, establishes the prediction model, and compares the prediction results under the PSO-BP method with the traditional BP neural network results. The accuracy and the prospect of using the particle swarm algorithm optimized BP neural network (PSO-BP) are explored.

2. Current status of research

With the continuous development of big data, BP neural network has been widely used as a part of machine learning. Sun Anli et al. used the influencing factors of engineering cost as the input of BP neural network and conducted an experimental simulation using actual engineering data to obtain the estimated cost of power transmission line project through a 3-layer network structure, and the results showed that the model can accurately estimate the project cost and is suitable for evaluating the advantages and disadvantages of pre-project comparison options [2]. By studying and analysing the characteristics of assembly building cost estimation, Liang Haibiao concluded that the traditional estimation method cannot reflect the estimated amount of assembly building project cost quickly and effectively and accurately, proposed the applicability and reasonableness of BP neural network principle, and established the assembly building project cost estimation model by using MATLAB software tool, and verified the applicability and reliability of BP neural network model in assembly The applicability and reliability of the BP neural network model in the estimation of construction projects were verified by comparing the predicted and actual values. Based on the project division of UHV transmission line projects, Xu Li et al. analysed and identified the main factors affecting the cost of UHV transmission line projects, and used factor analysis to measure 18 of the main influencing factors, and took the 5 factors obtained as input and the project unit cost as output to construct a cost prediction model based on BP neural network, using 9 domestic built and under construction The results prove that the prediction model is feasible and highly accurate in predicting the cost of UHV transmission line projects, and provides a new way of thinking and implementation for the optimization of management in the whole life cycle of UHV projects [3].

Meanwhile, some scholars have also started to introduce various optimization algorithms into the field of project cost prediction. Jinhao Xie et al. conducted a comparison experiment using BP model and GA-BP model with 30 sets of sample data collected, and obtained the conclusion that both the single BP neural network prediction model and the GA-optimized prediction model have excellent prediction effect on project cost [4]. Wenlong Teng et al. established a MEA-BP neural network energy consumption prediction model for prediction and found that the energy consumption prediction results of the MEA-BP model had high accuracy and practical application value, and the energy consumption facilities and energy use methods were controlled and improved accordingly through the energy consumption monitoring platform, which enhanced the energy saving efficiency of water, electricity, heating and gas and realized the optimal energy consumption control and effective energy use [5]. Jiaqi Fu preliminarily selected 13 project cost indexes based on the references, and eliminated the correlation between the indexes by combining the principal component analysis method. The principal component score value was input into the I-GGO-BP model as the independent variable for training and simulation, and the prediction results were compared and analysed with the traditional BP neural network and the traditional gray Wolf algorithm model. The results show that the I-GGO-BP neural network model is more stable and accurate [6].

BP neural network, as a machine learning algorithm that simulates the working principle of human brain neural network, can build the prediction model of the problem through multiple training and learning, but since it is essentially an algorithm for local exploration of optimal solutions, it is easy to take the local extreme value as the global optimal solution. In this paper, to address the shortcomings of BP neural networks that easily fall into the local optimization trap, we propose the use of particle swarm algorithm optimization BP neural network (PSO-BP) method to build the cost prediction model and optimize the traditional BP neural network, while improving the convergence speed.

3. Related knowledge

3.1. BP neural network model

BP neural network has excellent nonlinear mapping ability, generalization ability and error tolerance ability, and is capable of self-learning through error correction. Its structure and training method are relatively simple, and can be divided into three neural networks according to the number of layers of the network: input layer, implicit layer and output layer, and if the implicit layer of them is multi-layer, the overall is also multi-layer neural network, and the structure is shown in Fig. 1.

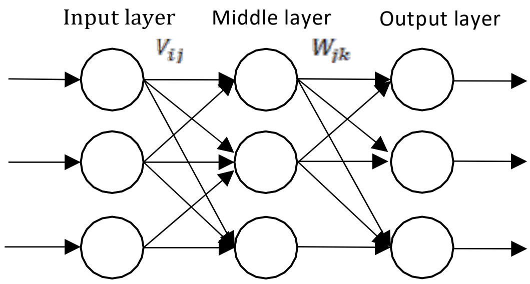

Fig. 1 BP neural network structure diagram

The propagation of BP neural network exists in both forward and reverse directions. In the forward propagation process, each neuron simply transmits data to each other, and the weights and thresholds of each connection layer do not change. The input layer, which is connected to the outside world, is the first to input data information, which is passed to the neurons in the implicit layer. Through the activation function and other means, the implicit layer processes the data and finally outputs the information through the output layer. When the difference between the output value of the output layer and the actual value is too large resulting in failure to meet the requirements, back propagation will occur, at which time it will go through adjusting the weights and thresholds of each connection layer and return the data to the input layer to repeat the forward propagation step until the requirements are met, and then the data will be output. However, determining the structure of bp neural network still lacks a theoretical basis, while in the process of practical application, it also has the disadvantages of slow convergence, easy to fall into the local minimal value point network instability.

3.2. BP neural network model

The particle swarm optimization algorithm (PSO) is a population intelligence algorithm proposed by J. Kennedy and R. C. Eberhart. In the PSO algorithm, the particles, as potential solutions to each optimization problem, have a value that determines the value taken from the objective function, which is called Fitness Value (FV). These particles search after the current optimal particle in the solution space and update their position by two optimal solutions, an individual optimal solution remembered from their own experience and a global optimal solution obtained from the experience of other particles. In this way, it performs constant movement, constantly changes its position, updates its own fitness value, and thus finds the optimal solution.

The advantage of the PSO algorithm is that it requires fewer parameters to be designed and has a larger exploration space than other algorithms. In the optimization of BP neural network, it is easy to achieve the desired effect when used, and it is good to make up for the problems and slow convergence of BP neural network in updating the weights and threshold values.

The process of particle swarm algorithm for improving BP neural network is shown in Fig. 2. The key point is to find the most suitable weights and threshold values for each particle, which requires the particle swarm algorithm to continuously encode and optimize the values taken during the transfer of each network structure.

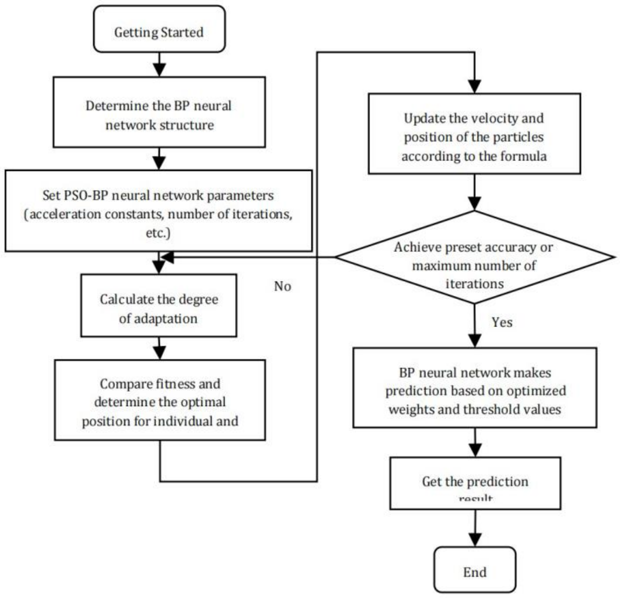

Fig. 2 Flowchart of particle swarm implementation of optimized BP neural network

3.3. Engineering cost

Engineering cost refers to the cost to be spent in the process of building construction. The meaning of engineering cost varies with the perspective of the subject, and it can be defined from the perspective of the construction unit and the market transaction. In this paper, the total price of the actual transaction in the market is predicted from the perspective of the market transaction, i.e., the selected single-party cost.

Project cost prediction is the prediction of the cost of the whole project. In the early stage of construction project, the staff will analyse and count the cost data of similar construction projects in the past, and then summarize the law on the basis of the statistical analysis of the previous project data, analyse it deeply, and then project the cost data of a similar project at present or in the future, which is the process of project cost prediction.

4. Selection of indicators

4.1. Determination of characteristic indicators

The determination of characteristic indicators is the premise of prediction model establishment. Due to the complexity and specificity of construction projects, there are many indicators that have an impact on their cost, but each indicator has a large or small impact, so it is necessary to consider all factors and select the most important ones from them, which can ensure the accuracy of the model and also improve the efficiency.

Table 1 Literature statistics of engineering cost index factors

Authors	Engineering cost impact factors
Fu Jiaqi (2022)	Above-ground construction area, underground construction area, foundation type, building structure type, average floor height above ground, seismic rating, etc.

Shang-Ang Liu (2022)	Project management level, number of floors in the building, floor height, seismic strength, total floor area, structure form, foundation type, etc.
Jinhao Xie and Wenchang Liu (2022)	Seismic strength, floor height, foundation type, total floor area, structure type, project management level, and total number of building stories
Xu Wenhui (2021)	Foundation type, structure type, floor area, number of floors,installation works, etc.
Dong Na (2021)	Total construction area, structure form, number of floors above ground, number of households, staircase ratio, project location, etc.
Chen Xiaoli (2020)	Standard floor height, foundation type, floor area, structure form,seismic grade, engineering cost index, etc.
Yang Jingyue (2015)	Above-ground construction area, underground construction area, foundation type, structure type, seismic class, project management level, above-ground floor height, building height, etc.

The index factors selected for construction project cost prediction in the existing literature are statistically sorted out, as shown in Table 1. due to the small amount of relevant information of the construction projects in the initial stage, often only the basic parameters such as structure and foundation of the project can be determined. This paper combines the frequency of index factors and the practical application in construction projects, and finally determines seven main influencing indexes of cost in the decision-making stage of construction projects, among which, the first three are quantitative factors and the remaining are qualitative factors, as shown in Table 2.

Table 2 Project cost prediction indexes

Indicator number	Indicator type		Indicator name	Unit
①	Input set indicators	Quantitative Indicators	Total floor area	M^2
②			Total number of floors	Floor
③			Standard floor height	M
④		Qualitative Indicators	Structure form	None
⑤			Basic type	None
⑥			Seismic rating	None
⑦			Project managementlevel	None
⑧	Output set indicators		Single-party cost	$Yuan/m^2$

The data selected in this paper come from the Quanta index network, and since the project unit cost is influenced by more factors due to different regions, only residential projects in Anhui Province that are public and completed from 2018 to 2022 are selected, and 35 samples containing complete data are obtained by aggregation and collation under the premise of ensuring the validity of the data. The independent variable of the model is the processed 7 characteristic indicators, and the dependent variable of the model is the unilateral cost, the first 28 samples are used as the training set, and the last 7 samples are used as the test set.

4.2. Quantification of qualitative indicators

In the selected sample data, qualitative indicators, such as structural form and seismic rating, etc., cannot be input directly into the calculation as quantitative indicators such as total floor area and standard floor height, etc., in accordance with the actual data of the samples. In orderto input these qualitative indicators into the model for calculation, it is necessary to quantify them, for example, the structural form is quantified as 1 for shear wall structure, 2 for frame structure, and so on. The specific quantitative treatment is shown in Table 3.And the results after quantification are shown in Table 4.

Table 3 Quantification method of qualitative index

Structure form		Basic type		Seismic rating		Project management level	
Shear Wall Structure	1	Pile foundation	1	Level 1	1	Excellent	1
Framing Structure	2	Full Foundation	2	Level 2	2	Good	2
Frame Shear Wall Structure	3	Independent foundation	3	Level 3	3	Medium	3
		Raft slab foundation	4	Level 4	4	Poor	4

Table 4 Quantitative data of qualitative indicators

Sample	Total floor area(m^2)	Total number of floors (floor)	Standard floor height (m)	Structure form	Basic type	Seismic rating	Project management level	Single-party cost (yuan/ m^2)
1	4896.24	18	2.9	1	2	3	1	2085.54
2	9519.36	18	2.95	1	1	3	1	2389.23
3	11719.89	21	2.9	1	1	4	2	1618.16
4	1003.79	7	2.9	2	3	3	1	2266.34
5	10254.19	24	3.15	3	1	3	1	2703.51
6	18885.44	22	3.7	3	1	3	2	1755.1
7	2417.92	9	2.9	3	1	3	1	2417.92
8	24070.47	34	2.9	3	1	3	1	1554.33
…								
32	6837.55	4	3.1	2	3	4	1	2711.74
33	7756.13	6	3.9	2	1	2	1	2436.34
34	14838	34	2.9	3	1	3	2	1470.6
35	10341.47	15	2.92	3	2	4	2	1359.47

5. Prediction model based on PSO-BP neural network

5.1. Design of model structure

The input quantities of the model are the seven characteristic indicators selected in section 4.1 according to the actual application characteristics of construction projects, which are represented by X_1 to X_7; the output quantity of the model is the prediction result, and the single-party cost is selected as the output quantity, which is represented by Y. The mean square error of the neural network is used as the adaptation degree of the particle swarm algorithm, and the adaptation degree is calculated by calling sub-functions to realize the process of implementing the specific neural network model [7], as shown in Fig. 3.

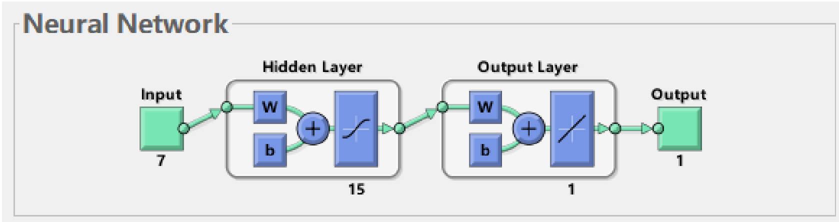

Fig. 3 Structure of the prediction model

The training number of the model is 1000, the training target is 0.0001, and the learning rate is 0.01. The relevant parameters of the PSO algorithm are shown in Table 5, where the number of populations N of the particle swarm algorithm is 20, the acceleration constants c_1 = 0.5, c_2 = 1.1, the range of particle velocities is [-1,1], the range of particle positions is [-5,5], and the maximum number of iterations is 200.

Table 5 Relevant parameters of PSO algorithm

N	Constant acceleration	Particle flight speed range	Particle position range	Maximum number of iterations
20	c_1=0.5 c_2=1.1	[-1,1]	[-5,5]	200

5.2. Training and Prediction of the Model

5.2.1. Training of the model

According to the network parameters and network structure determined in Section 5.1, the PSO-BP model is built by MATLAB software coding implementation, and the sample data are imported, in which the first 17 groups are the training samples of the neural network and the last 8 groups are the test samples of the neural network, and the PSO-BP neural network is trained to obtain the fitness curve, as shown in Fig. 4.

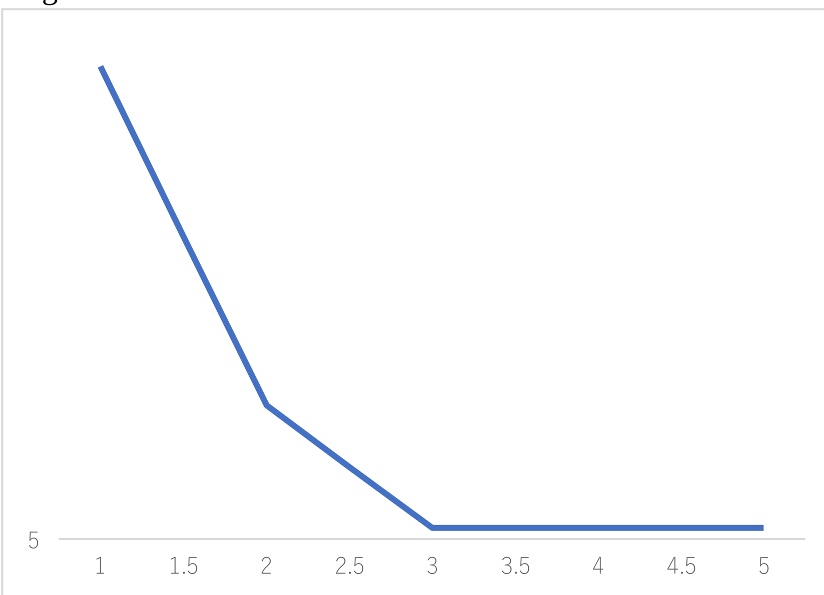

Fig. 4 PSO-BP neural network adaptation curve as shown

5.2.2. Prediction of the model

The trained samples were subjected to the prediction of single BP neural network and PSO-BP neural network respectively to obtain the predicted values of single-party cost before and after optimization, and the comparison results are shown in Table 6.

Table 6 Comparison of BP and PSO-BP network prediction results

Test sample	Single-party cost sample value (yuan/m^2)	Single-party cost prediction value(yuan/ m^2)	
		BP neural network	PSO-BP neural network
29	1660.74	1659.769	1660.003
30	1326.11	1326.27	1326.476
31	2387.95	2387.938	2390.106
32	2711.74	2712.728	2716.472
33	2436.34	2440.343	2442.895
34	1470.6	1471.355	1470.144
35	1359.47	1360.585	1359.625

In order to measure the prediction accuracy of the PSO-BP neural network model and the BP neural network model, the relative error and the average absolute value of the relative error of the two models were obtained by calculating the difference between the predicted value and the sample value, as shown in Table 7.

Table 7 Comparison of prediction errors between PSO-BP neural network and BP neural network

Test sample	Relative error (%)		Average absolute value relative error (%)	
	PSO-BP neural network	BP neural network	PSO-BP neural network	BP neural network
29	-0.14079	0.584478		
30	-0.1549	-0.12095		
31	-0.90804	0.005119		
32	-1.38012	-0.36442	0.30019	0.41029
33	-1.04602	-1.6429		
34	0.823032	-0.51328		
35	0.705487	-0.82008		

According to the experimental results in Table 6 and Table 7, it can be seen that both the BP neural network and the PSO-BP neural network model have played a good role in cost prediction. The BP neural network has a large prediction error for test samples 33 and 35, while the PSO-BP neural network has a large prediction error for test samples 32 and 33. In most other cases, the predicted value of samples is very close to the real value. From the perspective of average absolute relative error, the two models have similar effects, but the relative error of PSO-BP neural network is slightly smaller, indicating that its accuracy is higher.

6. Conclusion

In this paper, the cost prediction model based on PSO-BP neural network is proposed through the research and analysis of the existing construction project cost prediction. For residential buildings in Anhui Province, seven characteristic indicators were selected to improve the learning efficiency of the model while also ensuring certain characteristics. The feasibility of the developed model was verified by simulating through MATLAB software using 35 complete sets of sample data. The prediction data before and after optimization by the particle swarm algorithm are compared, and the results show that both models can predict the single-party cost more accurately. It contributes to the field of engineering cost prediction and has certain reference value.

However, only 35 sample data were selected, the sample size is not large enough, and further research is needed to collect a larger amount of data, as well as to improve the accuracy of the models to avoid chance. At the same time, the relative error difference between the two models is not large enough to clarify whether the PSO-BP neural network prediction model is more effective, and the parameters of the model need to be set further to improve the stability and credibility of the PSO-BP neural network model. Therefore, for decision makers, the model needs to be used and selected carefully when the model is not mature enough.

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