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Retraction

Retracted: Strategy of Maintainable Renewal of Assembled Residential Buildings Based on PSO-ELM

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] Y. Zhang, Y. Wu, J. Sui, and M. Lee, "Strategy of Maintainable Renewal of Assembled Residential Buildings Based on PSO-ELM," *Mathematical Problems in Engineering*, vol. 2022, Article ID 5813577, 7 pages, 2022.

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Research Article

Strategy of Maintainable Renewal of Assembled Residential Buildings Based on PSO-ELM

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Based on the PSO-ELM model, we analyze the key elements of safety input to respond to accidents and construct and evaluate its resource input optimization scheme. Based on the PSO-ELM cost prediction model, we analyze the key safety inputs for accident response and construct and evaluate the optimal allocation of resources. The results show that improving the technical level of component lifting is the key point of safety management in the construction of assembled buildings; increasing the strength of safety inspection before delivery of components, enhancing the technical performance of component safety status identification, and reasonably planning the frequency of using special transportation vehicles for components are effective ways to achieve the balance of safety, schedule, and cost of the project.

1. Introduction

With the leap-forward development of the economy, the construction industry, represented by residential construction, has become one of the pillars of the national economy [1]. With the continuous improvement of people's quality of life, the problems exposed by the traditional construction industry have become more and more prominent. In the past, residential construction mainly used on-site pouring operation mode, and on the one hand, the ecological environment was seriously polluted, the use of resources was inefficient, and the noise generated during the construction process affected the life of the surrounding residents [2, 3]. On the other hand, construction safety accidents occurred from time to time, and the quality of construction was difficult to be guaranteed. In order to cope with such problems, the government proposes to accelerate the process of residential industrialization, improve the quality of housing, and promote the transformation and upgrading of the construction industry [4].

With the expansion of the construction scale of assembled buildings, the construction activities of assembled buildings are distributed in parallel to their component production, logistics and transportation, on-site assembly, and other operation spaces, which are very prone to construction safety accidents at this stage with insufficient reserves of safety technology and management measures [5]. Facing the increasingly severe construction safety management situation, how to find effective technologies and strategies to deal with safety accidents in the construction of assembled buildings with limited investment in safety resources is a key issue that needs to be solved [6].

As an important carrier of residential industrialization, the development of assembled housing is an important way to achieve green and efficient construction. In September 2016, Premier Li Keqiang emphasized at the State Council executive meeting hosted by the State Council that "assembled construction can accelerate the process of building a new type of urbanization, and assembled construction should be vigorously developed." Assembled construction has huge advantages over the traditional cast-in-place model, and according to the statistics of an assembled house, the construction schedule can be advanced by about 20%, water resources can be saved by about 41%, labor can be reduced by about 9.5%, and construction waste can be reduced by about 56% [7–9].

Compared with traditional housing, assembled housing has obvious advantages in terms of comprehensive quality and social benefits, and because of its industrialized production method, it is highly reproducible, greatly shortens the construction cycle of residential projects, and is energy efficient and environmentally friendly [10]. However, the high cost of assembled housing is an inescapable problem, and how to control the cost and be able to effectively reduce it is the key to promote assembled housing. This paper studies the cost of assembled houses, analyzes the factors affecting the cost of assembled houses, and establishes a cost prediction model by combining the characteristics of assembled houses, based on which it is important to forecast the cost [11].

The cost prediction model established in this paper can quickly estimate the cost of assembled housing projects; however, in the process of predicting the cost of pending assembled housing projects, sufficient sample data are needed to ensure the smooth prediction [12, 13]. Therefore, the construction of the cost prediction model is conducive to the improvement of the enterprise's own engineering information database and the promotion of the enterprise's development in the direction of informationization and digitalization to ensure the enterprise's advantage in the future intelligent era.

2. Related Studies

In recent years, domestic and foreign scholars have made representative research results in the configuration of safety inputs in traditional building construction [14], but it is difficult to apply them directly due to the differences in assembly building projects. Most of the current assembly building construction safety management results stay in the qualitative research stage, and some scholars try to introduce quantitative analysis means such as gray clustering [15], attribute mathematics [16], and finite element [17] to study assembly building construction safety accidents so as to propose management countermeasures [18, 19], and the method can be used to analyze and identify key safety input elements, but its drawback is that it cannot determine the optimal ratios of elemental inputs, while the multiobjective programming (MOP) method can be used to analyze and identify key safety input elements [20–22].

The authors of [23] systematically reviewed the evolution of assembled housing in the UK and analyzed it through a literature review, while suggesting that further research is needed to enrich the field. The authors of [5] used artificial neural network algorithms to establish a dynamic decision system to analyze the factors affecting the development of industrialized housing and found that high cost is the most important influencing factor limiting its development. The authors of [6] compared the costs of four different structural systems of industrialized housing in the UK and concluded that efficiency learning, technological innovation, the establishment of an efficient on-site construction organization mode, and strengthening the production management of prefabricated components can effectively reduce the costs [7]. The authors of [8] established a database of 179 prefabricated assembled houses, and through a detailed case study of five residential communities, the results showed that standardized design can improve the design efficiency and the production scale of prefabricated components. Meanwhile, the authors of [9] found that projects using assembly construction methods are concentrated in the public sector, while the private sector still tends to build using traditional construction methods requiring extensive scaffolding, formwork, wet work on-site, and cast-in-place concrete, despite the advantages of assembly construction over the traditional construction. The authors of [10] introduced an Internet of Things (IoT)-based multidimensional BIM platform (MITBIMP) for real-time visibility and traceability of prefabricated components and validated it with an actual construction project in Hong Kong as a pilot project, showing its good practicality to facilitate decision making and real-time cost control by project builders. The authors of [11] designed and developed a virtual simulation system to support the simulation of the whole process from architectural design to prefabricated component production and construction and installation in order to optimize the construction process of assembled buildings for cost-saving purposes. The authors of [12] proposed an ice formwork system based on high-performance concrete (HPCfr) with a frost-proof design in order to solve the problem of high costs required for the production of precast components, thus reducing the number of labor as well as material wastage during the production of precast components. The authors of [18] took a residential project as an example, and by comparing the construction cost difference between prefabricated assembly type and traditional cast-in-place type, it was found that the prefabricated components and their installation cost were the main factors of the high construction cost of assembly type.

In summary, although scholars have achieved promising results in the study of the cost of assembled housing, there are still gaps compared with developed countries, and further research is needed. Scholars' research on the cost of assembled houses mainly focuses on the analysis of influencing factors, economic analysis, and the method of comparing the cost of assembled buildings with that of cast-in-place structures, which is a single method. The use of intelligent algorithms for cost prediction of assembled houses is relatively rare, so it is necessary to study this aspect to help understand the impact of assembled houses' own characteristics on their costs and to take targeted measures for cost control.

3. Overview of Assembled Housing

The assembled house is mainly built in an industrial way, where the required prefabricated components are processed in a component factory, transported to the construction site, and assembled into a complete residential building through professional joining operations [9]. During the construction of the assembled concrete house, some parts of the building and the prefabricated component connections still need to be poured because they are not installed in the strict sense of "building blocks." The structural system of assembled houses can be divided into concrete, wood, and steel systems depending on the material of the components [3]. When residences are built with the wood structure system, a large amount of forest resources are required, which affects the ecological environment; although residences with the steel structure system can meet the requirements of residential industrialization to the maximum extent, the excessive use of steel causes very high engineering costs, which hinders their large-scale development. Compared with the above two structures, the concrete structure system is more in line with China's national conditions and the concept of ecological protection, so the assembled concrete houses are more frequently used in the field of assembled houses in China. This paper takes assembled concrete houses as the research object, and for the sake of simplicity, the assembled houses appearing in this paper refer to assembled concrete houses exclusively.

4. PSO-ELM Based Cost Prediction Model for Assembled Houses

4.1. Network Structure Design of PSO-ELM. The extreme learning machine is improved from the feedforward neural network, and the design of the network structure is a very important task when using the extreme learning machine for assembled housing cost prediction. The design of the network structure is a very important task when using the extreme learning machine for assembled house cost prediction. The so-called design of the network structure is first to solve the problem of the number of input nodes, hidden layer nodes, and output nodes in the network structure [6]. Up to now, there is not a perfect and exact theory to guide how to determine the number of hidden layer nodes in the network structure. Whether the design of the network model is reasonable is directly related to the convergence state of the network model, and choosing a suitable network model structure can significantly enhance the training ability of the samples and improve the accuracy of the cost prediction of assembled houses.

4.2. ELM Parameter Optimization Based on PSO Algorithm. Through the preliminary study of the limit learning machine and the particle swarm algorithm above, two aspects need to be considered in the optimization process of the limit learning machine using the particle swarm algorithm.

4.2.1. Input Weights and Hidden Layer Bias Values. The input weights and hidden layer bias values of the ELM are optimized by the PSO algorithm, and the input weights and hidden layer bias values are used as the particles in the PSO algorithm, and the length D of the particles is denoted as

$$\begin{aligned} D &= K(n+1), \\ \theta^m &= [\omega_{11}^m, \omega_{11}^m, \ldots, \omega_{11}^m, \omega_{21}^m, \omega_{21}^m, \ldots, \omega_{2k}^m, \ldots, \omega_{n1}^m, \\ &\quad \omega_{n2}^m, \omega_{nk}^m, \ldots b_1^m, b_2^m, \ldots b_k^m], \end{aligned} \tag{1}$$

where K is the number of nodes in the hidden layer, n is the number of samples in the input layer, ω_{ij}^m, b_j^m is the random number in $[-1, 1]$.

4.2.2. Adaptation Function. The fitness is a measure to evaluate the position of the particle and also indirectly portrays the generalization performance of the limit learning machine. The input weight matrix and bias value of the limit learning machine can be used to derive the output weight matrix, that is, to derive the prediction value, and to judge whether the prediction value meets the accuracy requirement, which is often expressed in the following mean square error equation:

$$f = \frac{1}{n}\sum_{i=1}^{n}\left(y_j - \hat{y}_j\right)^2, \tag{2}$$

where y_j denotes the actual output value of the jth sample and $\hat{y}_j$ denotes the predicted value obtained by the limit learning machine.

4.3. PSO-ELM Based Cost Forecasting Steps for Assembled Housing. In the process of limit learning machine prediction, the input weights and bias values are searched in a certain range with the help of the particle swarm algorithm, and the mean square error equation is used as the fitness function of the particle swarm algorithm while minimizing f in equation (2), at which time particle θ^m is the optimal input vector and bias value of the limit learning machine. The steps for optimizing the cost prediction of assembled houses using the particle swarm algorithm for the limit learning machine are as follows.

Step 1: collect sample data of assembled housing costs, divide them into training samples and validation samples, and form a sample matrix

Step 2: establish the limit learning machine network structure model and determine the parameters of the network model

Step 3: random training to obtain the weights and hidden layer node bias values, using the input weights and bias value range as the particle velocity and position seeking a range

Step 4: initialize various parameters in the particle swarm algorithm, such as the maximum number of iterations, population size, acceleration constant, inertia weight, and particle dimension

Step 5: combine the training samples to obtain the fitness of the particle and compare it with its own optimal fitness and the global optimal fitness to obtain the individual optimal position P_{best} and the global optimal position G_{best}

Step 6: iterate and keep updating the velocity and position of the particles until the stopping condition (maximum number of iterations or minimum fitness value) is met, exit, and decode them as the input weights and hidden layer node bias values of the limit learning machine

Step 7: assign the output optimal parameters to the extreme learning machine prediction model, train the training samples with this model, and after training, input the validation sample data for prediction

The prediction flowchart based on PSO optimized ELM is shown in Figure 1.

5. Cost Forecast for Assembled Housing

5.1. Model Training and Simulation. After the data normalization process is completed, the data samples to be used for cost prediction are divided into two parts: training data and test data. The first 30 groups of the sample data are taken as training samples, and the remaining 5 groups are taken as test samples. In the training sample, the training sample is divided into two parts: p_ train and t_ train. p_ train record 11 cost prediction indexes of floor area, structure type, number of floors, and height of floors in the first 30 groups of samples, and t_ train records one-sided cost data. In the test sample, t_ text records 11 cost predictors such as floor area, structure type, number of floors, and number of stories in the test sample. In order to be able to better verify the superiority of the extreme learning machine optimized by particle swarm algorithm, three machine learning algorithms, BP neural network, ELM, and PSO-ELM, are used in the MATLAB platform to model and simulate the cost of assembled houses respectively.

5.1.1. ELM Model. To establish the standard ELM model, first of all, we need to program in MATLAB2018a platform to get the ELM algorithm program [24]. The best performance of the Sigmoid was found through simulation analysis of the excitation function in the same number of hidden layers and regularization [8]. Therefore, in this paper, the Sigmoid function is chosen as the excitation function for the simulation prediction. After the two parameters are determined, the prediction results are plotted using the plot plotting function, and the obtained prediction results are shown in Figure 2.

5.1.2. PSO-ELM Model. Before optimizing the input weights w_i and bias values b_i in the ELM model using the PSO algorithm, the parameters of the particle swarm algorithm need to be set in conjunction with the study of the parameters of the particle swarm algorithm in Chapter 4, with the population size sizpop = 20, the maximum number of iterations maxgen = 200, the inertia weight $\omega = 1$, the acceleration constant $c_1 = c_2 = 1.5$, and the mean square error of the training sample as the fitness value of the particles. After the parameters of the particle swarm algorithm are set, the PSO-ELM model is established, and the unilateral cost of the test sample is obtained as shown in Figure 3.

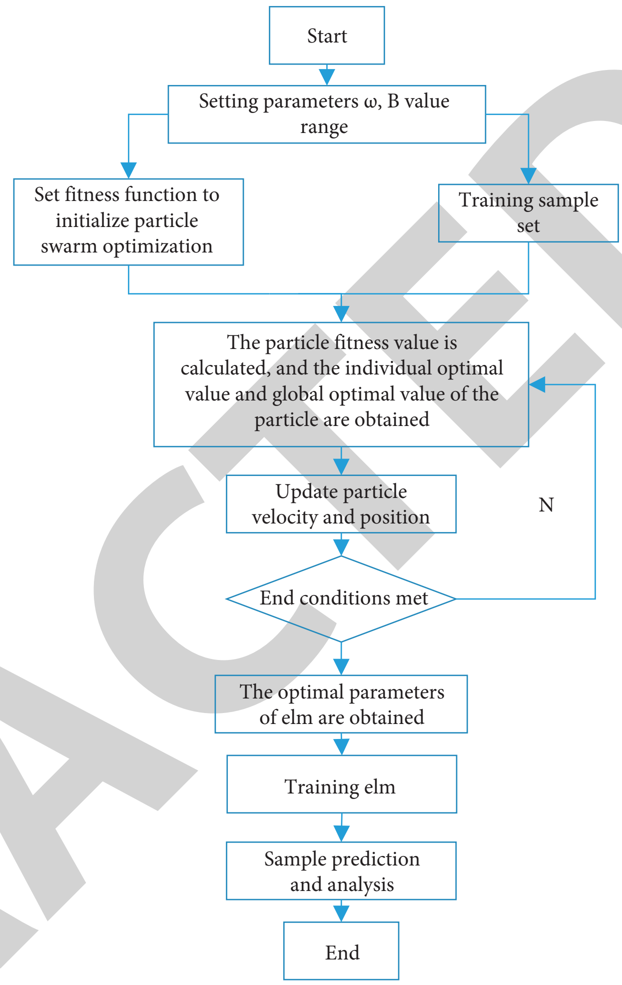

Figure 1: Flowchart of PSO-based optimized ELM prediction.

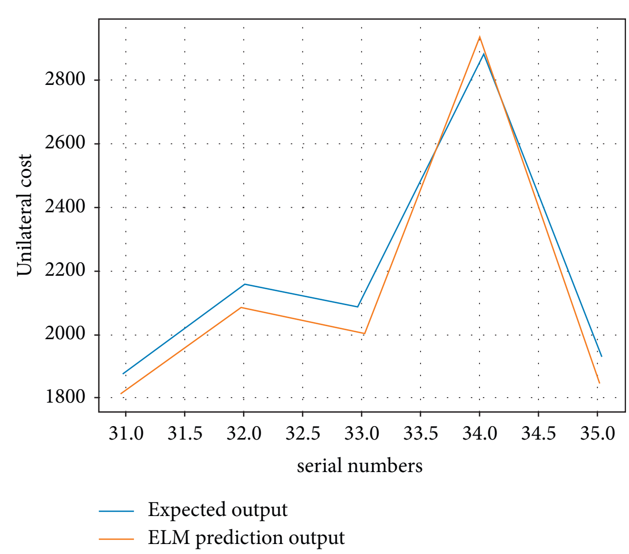

Figure 2: Comparison of prediction curves of ELM model.

5.1.3. BP Neural Network Model. When using the BP neural network model for cost prediction, it is necessary to first create a neural network using the function newff (), and the

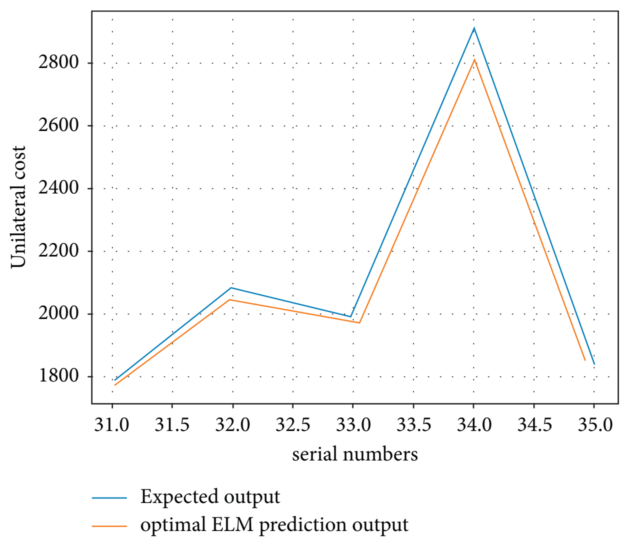

Figure 3: Comparison of prediction curves of PSO-ELM model.

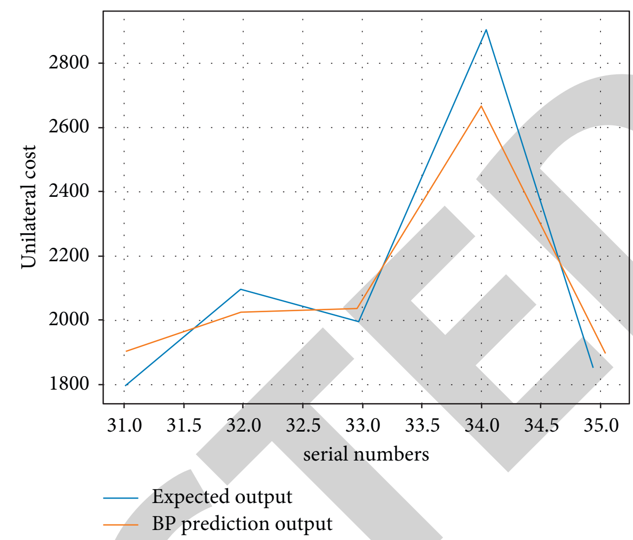

Figure 4: Comparison of prediction curves of BP neural network models.

excitation function on the neurons is chosen logsig () function. The number of nodes in the hidden layer can be initially determined by using the formula $m = 2n + 1$, based on which the number of nodes can be increased or decreased according to the training error. The number of hidden layers is determined as 25, the maximum number of iterations is set as 1000, the learning rate is 0.1, and the momentum factor is 0.01. Finally, the trained neural network is used to predict the test sample, the plot() function is called to draw the prediction image, and the prediction image of the test sample is shown in Figure 4.

5.2. Analysis of Prediction Results. The prediction effect of the three prediction models, ELM, PSO-ELM, and BP neural network, is put under the same coordinates, and their prediction curves are compared as shown in Figure 5. Although the prediction curve comparison graph can reflect the prediction trend of each method, it cannot reflect the prediction effect of the three prediction methods on the cost of assembled houses quantitatively well, so this paper selects the relative error ∂, the average absolute relative error MAPE, and the running time to reflect the effect of cost prediction, and the specific results are shown in Table 1. Among them,

$$\partial = \frac{y_i - \hat{y}_i}{y_i},$$
$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}|\partial| \times 100\%, \tag{3}$$

where y_i represents the actual cost of the i-th sample, $\hat{y}_i$ represents the predicted cost of the i-th sample, n represents the number of samples tested, ∂, and the magnitude of MAPE reflects the predictive power of the prediction model, with smaller values indicating stronger predictive power of the model and vice versa.

From Table 1, we can see that the average absolute relative error of all three prediction models is less than 10%

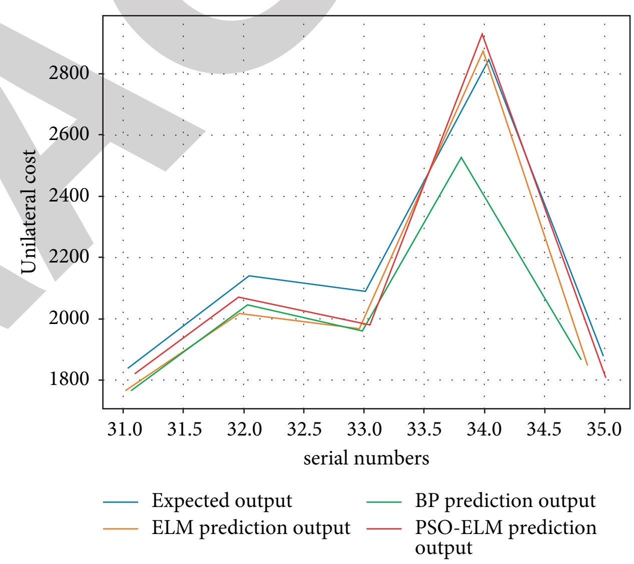

Figure 5: Comparison of prediction curves of ELM, PSO-ELM, and BP neural network models.

(the error range of investment estimation is ±10%), which indicates that the cost prediction using these three methods is successful and can be applied to the cost prediction of assembled houses. The main reason is that the BP neural network model requires a large number of samples for cost prediction to achieve high prediction accuracy, which makes it more difficult to collect data for the developing assembled housing projects. The optimized ELM prediction accuracy was significantly improved, indicating that it is practical to optimize the extreme learning machine using the particle swarm algorithm. The running time of the BP neural network-based prediction model is 9.83 s, that of the ELM-based prediction model is 1.83 s, and that of the PSO-ELM-based model is 3.56 s. The running times of all three are very fast.

Table 1: Comparison of prediction effects of different models.

Number	Actual value (yuan/m^2)	Estimate (yuan/m^2)			Relative error (%)		
		ELM	PSO-ELM	BP	ELM	PSO-ELM	BP
31	1811.59	1898.35	1824.58	1923.25	4.85	0.56	6.65
32	2135.09	2189.48	2100.01	20064.84	2.58	−1.65	−3.35
33	2035.75	2125.09	2043.78	2072.82	4.50	0.48	1.93
34	3028.89	2978.12	2918.89	27.58.05	−1.65	−3.63	−8.95
35	1868.54	1942.92	1879.53	1951.78	3.94	0.55	4.42
MAPE (%)	—	—	—	—	3.48	1.37	5.04
Running time (s)	—	—	—	—	1.39	3.67	9.81

The prediction time of the PSO-ELM model is slower than that of the ELM model, but the prediction accuracy of the former is higher. The standard limit learning machine does not require iteration in the prediction process, and the input weights and bias values are given randomly, and its operation speed becomes very fast, but the PSO-ELM model uses the particle swarm algorithm to optimize the randomly given input weights and bias values by iterating continuously until the best parameters are obtained, which reduces the instability of the standard limit learning prediction. Through the analysis of the performance of the three prediction models, this paper selects the PSO-ELM model as a better guide for the cost prediction of assembled houses with better results.

6. Conclusions

This paper considers that the response to safety accidents in assembly building construction is no longer limited to the traditional safety and civilization construction measures specified in the scope, but also from the production of components, logistics and transportation, on-site assembly multispace, to achieve the optimal allocation of safety inputs under the conditions of resource constraints. Strong conditions are provided for the maintenance and renewal of assembled residential buildings. The method of this paper on the safety performance of components is the focus of more attention to respond to safety accidents in assembly building construction, should enhance the frequency of safety inspection before the delivery of components and the use of the whole process of safety state identification technology accounted for, to ensure the stable articulation of the safety performance of each space components to lay a solid foundation for the later maintenance.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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