Research Article

Prediction of the Normalized COVID-19 Epidemic Prevention Costs of Construction Projects Based on an Optimized Neural Network

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During the COVID-19 epidemic, the Chinese central government adopted a dynamic clearing prevention and control strategy. Meanwhile, most local governments issued policies to incorporate normal epidemic prevention costs into the costs of construction projects. However, there are few provisions on how to determine the calculation standards for these costs. To accurately predict the normalized epidemic prevention costs of construction projects from different aspects, the relevant factors that affect epidemic prevention costs are investigated and an optimized neural network prediction method that can effectively eliminate abnormal data with a too large deviation is proposed. The results show that compared with the traditional backpropagation (BP) neural network and BP neural networks optimized by genetic algorithm, the error of the optimized neural network achieves a smaller error in predicting the normalized epidemic prevention costs of construction projects (the average error of the traditional BP neural networks is 6%). Meanwhile, among the factors that affect epidemic prevention costs, total investment, project category, and construction scale have the greatest impact. Based on the research results, this paper proposes pricing suggestions and corresponding management solutions for the epidemic prevention costs of construction projects, which will be helpful to project managers.

1. Introduction

Normalized control in the post-pandemic era is an inevitable trend because the global coronavirus disease 2019 (COVID-19) epidemic situation remains unclear [1]. To date, there are a limited number of antiviral agents or vaccines for the treatment of COVID-19 [2]. To prevent the spread of the COVID-19 epidemic, the governments of different countries implemented a series of strategies to address national conditions [3]. In accordance with the overall decision-making and deployment requirements of the Chinese central government, the current general strategy is to "Prevent input from the outside and rebound from the inside," and the general policy is to achieve "Dynamic zero COVID-19."

Based on this, regular epidemic prevention and control strategies are carried out. As a result, this policy will inevitably increase the cost of engineering projects [4]. This paper aims to provide a method to predict the cost of epidemic prevention under the guidance of a dynamic zero-clearing policy. For this study, a total of 61 data sets were obtained by investigating the factors that influence projects' regular epidemic prevention costs, and they were based on actual case data and project site investigation data (real engineering project data). Then, prediction results were obtained using neural networks in machine learning to process the relevant data. Some studies use a genetic algorithm (GA) to optimize a back propagation (BP) neural network since the common BP neural network can easily

lead to a partially optimum solution. The effect of this method is good. However, in the prediction of the normal epidemic prevention costs of construction projects, the on-site prevention and control efforts of various projects are not completely consistent. Additionally, epidemic severity, epidemic prevention policy, and the internal and external environment of the project area affect the costs of epidemic prevention. Considering the above reasons, an optimized neural network is used in this study. Compared with the ordinary BP neural network optimized by a genetic algorithm, the proposed optimized method can effectively eliminate data with a large deviation and then obtain more accurate prediction results. Through verification, it is found that the error of the optimized neural network is much smaller than that of the BP and ordinary BP neural networks optimized by other algorithms. In addition, total project investment, project category, and construction scales are the three most sensitive factors that affect epidemic prevention costs. This paper provides a reliable method to predict the costs of epidemic prevention for domestic construction projects under the background of dynamic zero clearance and proposes reasonable and feasible suggestions on cost collection.

The paper is organized as follows: Section 2 summarizes the relevant work, to accurately predict the normalized epidemic prevention costs of construction projects influenced by several aspects, the relevant factors that affect epidemic prevention costs are investigated in Section 3, and an optimized neural network prediction method that can effectively eliminate abnormal data with a too large deviation is proposed in Section 4. The prediction method proposed in this paper is tested through real project cases obtained by investigation in Section 5. Section 6 discusses the applicability and precautions of the proposed method. Finally, Section 7 concludes this paper.

2. Related Works

2.1. The Impact of COVID-19 on the Construction Industry. Some studies have investigated the impact of COVID-19 on the construction industry in Ghana, the United States, the United Arab Emirates, and the UK [5–8]. In terms of the construction industry, many migrant workers live on construction sites, and they usually have the characteristics of high mobility and high intensity [9]. Considering this, they are identified as a typical susceptible population, and if the epidemic spreads among them, the situation will be difficult to control. Epidemic prevention and control is one of the core social responsibilities of construction enterprises under such circumstances [10], and the Occupational Safety and Health Administration (OSHA) provides guidance for construction employers and workers [11]. Thus, regular epidemic prevention and control costs must be considered. Health and safety (H&S) technologies have received increasing attention. The construction industry continues to adapt to the changing COVID-19 landscape, and H&S guidelines have been recommended to minimize the spread of the virus and enable construction sites to return to normal conditions [12]. According to the "Guidelines for the regular prevention and control of COVID-19 in housing construction and municipal infrastructure construction sites" (Quality Letter (2020) No. 489) [13], published by the General Office of the Ministry of Housing and Urban-Rural Development (MOHURD), the cost of epidemic prevention arising from normalized epidemic prevention and control can be included in construction costs. Meanwhile, according to the statistics, a total of 31 provinces, municipalities, and autonomous regions across China have promulgated policies to adjust project pricing during epidemic prevention and control. These policy documents clearly state that epidemic prevention costs can be included in project costs. However, different provinces differ greatly in their calculation and collection of these costs. Project managers often rely on personal judgment or experience to evaluate the cost because the industry has not yet established a recognized calculation method and charge rate. There are also few studies on COVID-19 quarantine costs in academia. In the existing literature, there is no quantitative study on the collection or prediction of normal epidemic prevention costs for construction projects. In China, it was only mentioned in a study by Wang Feng's team in 2000, which explained that the cost of epidemic prevention has a strong relationship with the number of people in epidemic prevention stations [14]. Few international studies have mentioned these issues (which may be related to foreign quarantine measures). However, theoretical research on this aspect is urgently needed to support engineering practices. The study results can guide project managers to measure early-stage budgets or process settlement and final settlement.

2.2. Main Forecasting Methods and Their Applications. Software computing methods conquered other classical models in the short-term estimation of pandemics [15, 16]. Mangoni and Pistilli developed a generalized SEIR model to make predictions on the COVID-19 outbreak using the Italian data [17]. Based on this, neural networks and deep learning are classical methods in the prediction field, and various scientists have tried to make predictions using different methodologies. Different neural network prediction methods or models are widely used in the prediction of COVID-19 events [18–24]. The deep learning methods have shown promise in healthcare prediction challenges involving electrocardiogram data [25]. An artificial neural network with rectifying linear unit-based technique was implemented to predict the number of deaths, recovered, and confirmed cases of COVID-19 in Pakistan [26]. Wieczorek et al. constructed a neural network model for predicting the COVID-19 outbreak and reported an accuracy of above 99% in some countries [27]. Xu et al. introduced a new method based on a deep learning system to screen coronavirus COVID-19 pneumonia, and they aimed to develop an early examination model to recognize COVID-19 pneumonia from Influenza-A viral pneumonia and health conditions with lung section images [28]. Sabir et al. evaluated the mathematical system for the novel COVID-19 dynamics using the neuro-swarm heuristic solvers via artificial intelligent algorithms [29], and they presented numerical

simulations of the influenza disease nonlinear system (IDNS) using the stochastic artificial neural networks (ANNs) supported by Levenberg-Marquardt back propagation (LMB) [30]. Based on the dynamics of COVID-19, they presented a novel design of intelligent solvers with a neuro-swarm heuristic integrated with an interior-point algorithm (IPA) for numerical investigations of the nonlinear fractal system [31]. Zeroual et al. conducted a comparison of some learning methods to predict the number of new cases and recovered cases [32].

3. Identification of Influencing Factors

Epidemic prevention and control fees are specially used for the increased wages of personnel, prevention and control materials, the wages of workers in isolation, commuting vehicles, and other related inputs of temporary facilities, which are similar to other construction costs. Therefore, according to the pricing base and relevant policies combined with brainstorming and expert interviews, this paper aims to reveal the factors that affect the costs of normalized COVID-19 epidemic prevention.

The composition of regular COVID-19 epidemic prevention costs is closely related to specific projects, and the influencing factors of different projects also vary. However, due to the lack of relevant research data, the following aspects were considered to identify the factors that affect the costs of COVID-19 prevention. These factors include the pricing base of partial costs in project investment estimation, industry management policy, brainstorming of the research group, and rounds of expert consultation.

3.1. Pricing Base. In the entire life cycle of a project, different stages have different precision requirements for the project costs. Investment estimation is generally adopted in the early decision-making stage of a project. Limited by the depth of the scheme design, the calculation of investment estimation mainly adopts the method of charging a base fee multiplied by a rate and includes survey and design expenses and a construction premium. Tiered pricing is another method that includes a project supervision fee and a bidding agency fee. The base rates of these charges generally include the project cost, construction and installation cost, total land area, and construction building area.

3.2. Industry Management Policy. Among the policies at the national and local levels, many suggestions are given for the collection of regular COVID-19 epidemic prevention expenses. After categorizing these policies, the relevant influencing factors were determined and are presented in Table 1.

3.3. Brainstorming and Expert Consultation. Members of the research group performed several rounds of brainstorming and interviewed front-line engineering management experts. The factors that affect the costs of regular COVID-19 prevention identified in the first two groups were refined and supplemented by the four categories listed as follows: the first category is the project itself, such as project types, the content of construction, site area, and construction period. The second category is related to the implementation of a specific subject situation, the registration of qualifications, the number of individuals in the management team, the number of workers, and so on. The third category is related to the pressures of the COVID-19 outbreak, such as local epidemic infection numbers during the construction period and the overall domestic epidemic situation. Under high outbreak pressures, the construction costs will increase because of the inactive labor market. That is, workers are forced to stay at home and cannot go to the construction site [33]. The fourth category is related to management measures (e.g., ensuring a smart construction site situation), regular epidemic prevention and control efforts (e.g., checking body temperature, wearing a face mask, and keeping a safe social distance) [34], and using technologies (e.g., information technology solutions, video-conferencing apps, and wearable sensing devices) [35, 36].

Many more factors affect the cost of COVID-19 prevention, including national culture [37], governmental efforts and a positive public response [38], and public employment services and labor market policy responses [39–42]. Combining the findings presented in the above three groups, 12 factors that affect the costs of COVID-19 prevention on two levels were determined (Table 2).

4. Construction of an Optimized Neural Network

4.1. Ideas for Optimization. Neural networks, especially a BP neural network, have advantages in prediction and can improve the judgment and prediction accuracy of a model [43]. However, a single BP neural network can easily produce a local optimum solution during the network training process [42]. To overcome this defect, some scholars have used a genetic algorithm to optimize their method. The genetic algorithm was proposed by Professor John Holland in 1960, and it provides a solution for optimizing and searching. Its principle is to imitate the survival of the fittest in natural populations [44]. Empirical analyses have found that a BP neural network optimized by the genetic algorithm has a higher evaluation accuracy and stronger generalization ability than the traditional BP neural network, thus being more suitable for evaluation and prediction research [45, 46]. However, in specific application scenarios, although using a genetic algorithm to optimize the BP neural network can overcome the local optimum defect, and the R^2 in the training process is more stable [47], the ordinary BP neural networks optimized by other algorithms suffer from a certain degree of overfitting [48]; thus, the erroneous data in the sample cannot be eliminated, resulting in a better learning effect but poor prediction ability. Considering the particularity of the epidemic prevention scheme of each construction project, there are subjective factors in the cost prediction, and the physical relationship between the factors is weak. In this study, a model based on an optimized neural network was constructed according to the related literature

TABLE 1: The factors that affect the costs of the regular prevention of COVID-19 (policy aspects).

Influence factor	Source of policy
Project type	"Guidelines for the regular prevention and control of COVID-19 in housing construction and municipal infrastructure construction sites" (MOHURD)
Total investment	"Guidelines for the regular prevention and control of COVID-19 in housing construction and municipal infrastructure construction sites" (MOHURD)
Construction scale	"Guidelines for the regular prevention and control of COVID-19 in housing construction and municipal infrastructure construction sites" (MOHURD)
Construction period	"Guidance on contract implementation and price adjustment of housing and municipal works under the impact of COVID-19"
Number of individuals in the management team	"Notice on pricing adjustment of construction projects during normal epidemic prevention and control in Hubei province" "Guidance on further management of construction contracts during the prevention and control of COVID-19 in Sichuan province"
Number of workers	"Notice on pricing adjustment of construction projects during normal epidemic prevention and control in Hubei province" "Guidance on further management of construction contracts during the prevention and control of COVID-19 in Sichuan province"

TABLE 2: List of factors that affect the costs of COVID-19 prevention.

Primary influencing factor	Secondary influencing factor
Project itself	Project type Construction scale Construction content Total investment Construction period
Implementing a specific subject situation	Registration of qualification Number of individuals in the management team The number of workers
COVID-19 outbreak pressures	Local epidemic outbreak numbers during the construction period Overall domestic epidemic situation
Management measures	Smart construction site situation Regular epidemic prevention and control efforts

[49]. The model first optimizes the collected sample values to exclude invalid data that are greatly affected by subjective factors and then imports the remaining data into the neural network. The specific research process of this model is shown in Figure 1:

(i) Data collection, screening, analysis, and normalization processing: appropriate parameters are selected to quantitatively characterize the above influencing factors. Several groups of effective data for modeling and analysis are obtained by screening and judging, and normalized processing is carried out.

(ii) Invalid data elimination: considering that the overfitting phenomenon is easy to occur in the construction process of the traditional neural network, which leads to a poor prediction accuracy of the output model. This modeling process will optimize the normalized sample values in the previous step and eliminate invalid data that are greatly affected by subjective factors to improve the prediction accuracy. The optimization steps are as follows: (A) divide the sample values collected in the previous step into a training set and a prediction set and build a BP neural network prediction model; (B) calculate the deviation between the predicted results and the actual results of all sample values and take the corresponding samples with the top 5% of the error order as invalid samples and eliminate them, thus obtaining the samples to construct the neural network.

(iii) Take the samples extracted from Step ii as objects, divide them into a training set and a prediction set, and build a prediction model based on the neural network. See Section 5.3 for specific parameters of the neural network. See Section 4.2 for the prediction process of the optimized neural network.

4.2. Optimization Process. Each method has its scope and limitations. The traditional BP neural network has the problems of a slow convergence speed and easily producing local optimum solutions. Therefore, optimization methods have been investigated. A genetic algorithm has been used to improve the BP neural network, and the sample value optimization operation is added before the model is run.
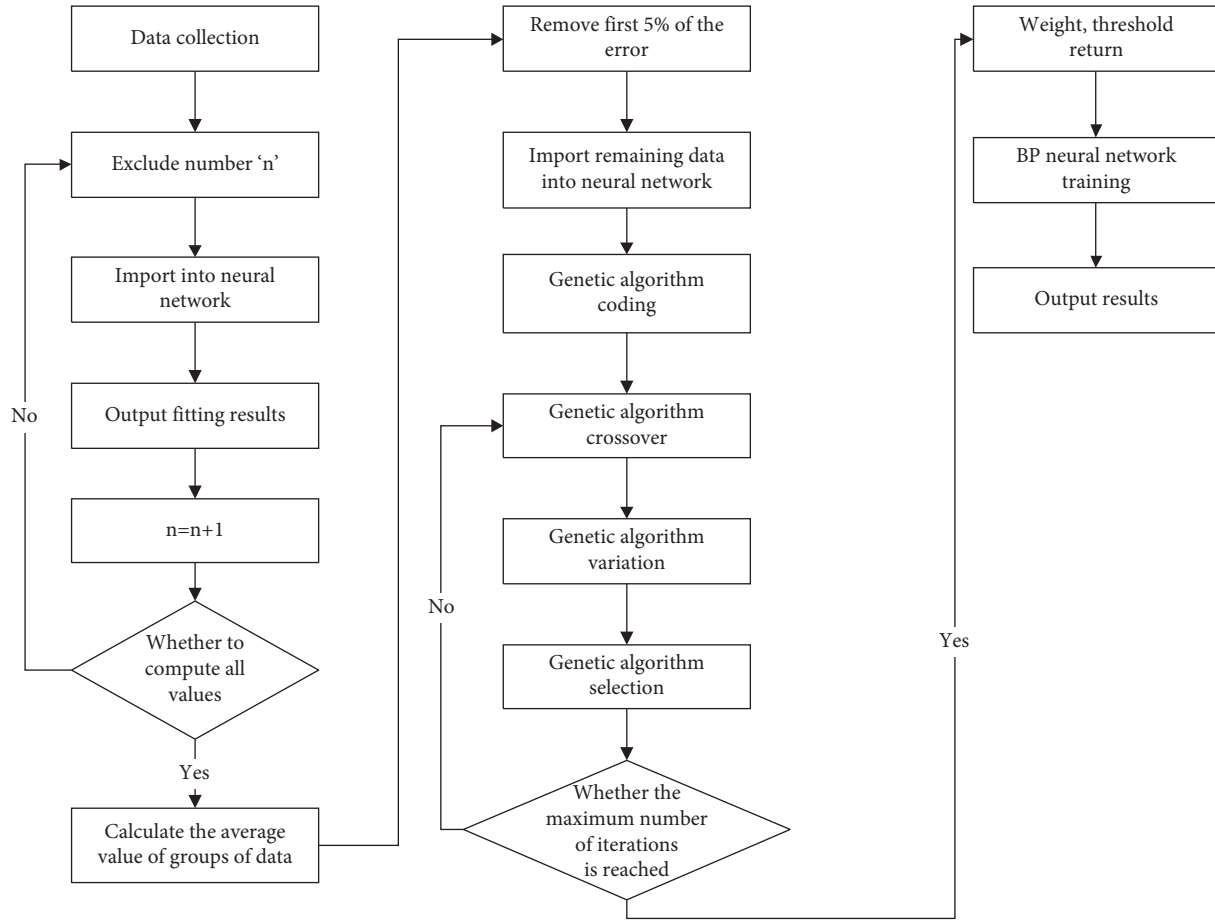
FIGURE 1: The research process of the proposed model.

Specifically, it is assumed that there are n learning samples, each of which contains k factors. From the first to the n-th sample, the samples are removed to form a new sample set. N sample sets are extracted in total, and each sample set contains n-1 samples. Then, the n sets of data are imported into the BP neural network for training, and the average error of the n sets of data is calculated. The above operation is repeated $0.2n$ times (rounding), and the error is accumulated. The learning samples with the first 5% cumulative error are eliminated, and only 95% of the remaining valid data are retained.

The key steps in the application of the neural network method are selection, crossover, and mutation, and the specific operation steps are as follows in Algorithm 1.

4.2.1. Chromosome Determination.
The genetic algorithm is adopted to optimize the BP neural network. First, the chromosome length is determined, and the initial population is constructed by randomly generating chromosomes. The chromosome includes the two parameters of weight and threshold, and the calculation of length is shownas follows:

$$S = RS_1 + S_1 S_2 + S_1 + S_2, \tag{1}$$

where R represents the number of factors, S_1 represents the amount of input data, and S_2 represents the amount of output data.

4.2.2. Selection.
The error calculated by weight and threshold is the most important index to measure the quality of the BP neural network, and the genetic algorithm is used in the initial error backhaul process. The algorithm selects suitable individuals for the next generation by calculating the fitness of different individuals, and the fitness function is shown as follows:

$$F_i = \left(\frac{\max(f) - f_i + 1}{\max(f) - \min(f) + 0.0001} \right)^2, \tag{2}$$

where $\max(f)$ represents the maximum value of the fitness function in the population and $\min(f)$ represents the minimum value of the fitness function. The gap of the fitness function calculated by formula (2) is much larger than that constructed by the reciprocal of the fitness. Therefore, in the latter iteration, weak-dominant individuals are easier to be saved. The choice is based on roulette, that is, the smaller the error is, the easier the individual to be saved.

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Input: Data collected D (a, b)
Output: Trained models
h = generate h groups of different choices
u = number of outliers deleted
m = first deleted outlier sequence number
Step 1: Data normalization processing
Step 2: Training of models with normalized data
for g = 1 to h
    for every D (g, m)
        do
            delete the m-th data
            data D (g,:) import into neural network
        Output: Output fitting results
        m = m+1
        while (Calculate all values)
end
Step 3: Calculate the average avg of h groups of data
Step 4: Pick out the top 5% and remove
Step 5: Import remaining data into neural network
Step 6: Execute genetic algorithm
Genetic algorithm coding
    do
        Genetic algorithm crossover
        Genetic algorithm variation
        Genetic algorithm selection
    While (the maximum number of iteration is reached!)
Output: weight and threshold
Step 7: training BP neural network
Output: final result
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ALGORITHM 1: Algorithm of the proposed model.

4.2.3. Crossover. Similar to biogenetics, the crossover of the genetic algorithm is achieved by selecting two individual codes of population. The algorithm needs to set a crossover probability. When the random value is less than the crossover probability, the crossover operation will be performed. The specific method consists of selecting one of the chromosomes in the paternal line and determining its position in the maternal chromosome. Then, one position is selected in the maternal chromosome, and its position is determined in the paternal chromosome. The two are exchanged until all the exchanges are completed. A crossover probability of 0.7 was selected in this study.

4.2.4. Mutation. The mutation operation was performed to explore the solution domain. If there is no mutation in the population, it will produce certain inertia, premature convergence, and stop developing, which offers a better direction. The mutation operation consists of the following steps. This study set the mutation probability, executed the mutation operation when the random number was lower than the mutation probability, randomly generated a two-digit number, found the position of the two-digit number in the chromosome, and then exchanged them. The mutation probability was selected as 0.1 in this study.

4.2.5. Backhaul Neural Networks. When the genetic algorithm is finished, its result cannot be directly used due to the limitation of its coding accuracy. The threshold and weight are returned to the BP neural network to continue training until the training goal is achieved.

4.3. Sensitivity Analysis. According to the properties of forwarding transmission and the reverse adjustment of the BP neural network, combined with the algorithm of the BP neural network, the weight coefficient between the output neurons can be obtained, and then the most significant factor that affects epidemic prevention costs can be determined. Since the weight coefficient does not directly reflect the size of the influencing factor, to obtain the relationship between the input and output vectors, it is necessary to analyze the weight of the output results. Based on neural network weights, formulas (3)–(5) are used to obtain the absolute influence coefficient of different factors, that is, the sensitivity of the different factors:

(i) Correlation significance coefficient:

$$r_{ij} = \sum_{k=1}^{p} W_{ki} \frac{1 - e^{-x}}{1 + e^{-x}}, x = w_{ij}. \tag{3}$$

(ii) Correlation coefficient:

$$R_{ij} = \left| \frac{1 - e^{-y}}{1 + e^{-y}} \right|, \quad y = r_{ij}. \tag{4}$$

(iii) Absolute influence coefficient:

$$S_{ij} = \frac{R_{ij}}{\sum_{i=1}^{m} R_{ij}}, \tag{5}$$

where i is the input vector, j is the output vector, and k is the hidden layer neuron. The weight coefficient between the input and hidden layers and the weight coefficient between the hidden and output layers are represented as well.

5. Authentic Proof Analysis

5.1. Selection and Record of Input Variables. The 12 influencing factors mentioned in Table 2 cannot be completely used as the input variables of the neural network due to the difficulties in obtaining some data. According to the analysis of the research team, the three factors, namely the project construction content, the overall domestic epidemic situation, and the normalized epidemic prevention and control efforts, are not suitable for use as input variables. Especially in the early decision-making stage of the project, the overall domestic epidemic situation and the normalized prevention and control of the epidemic situation cannot be determined and should be abandoned. Each index remains unchanged, and the units and recording methods of the relevant influencing factors are shown in Table 3.

5.2. Descriptive Statistic. This study received data for more than 100 projects. After repeated screening and judgment, 61 items of valid data were obtained. The 61 samples were observed, and it was found that the item distribution was uniform, which met the requirements of the subsequent prediction model. The project types include buildings, municipal engineering, landscape greening engineering, and decoration engineering distributed in urban and rural areas. After the processing of standardized data, the proportion of epidemic prevention costs was calculated by dividing the epidemic prevention costs by the total investment, and some descriptive statistics were obtained according to project type, as shown in Table 4. Among the 61 items of valid data that were collected, there were four types of projects, of which only two were landscape projects. It is of little significance to calculating the confidence interval, so only the confidence interval of housing, municipal, and decorative projects was calculated. Through observation, it was found that the epidemic prevention costs of decoration projects account for the largest proportion of the total investment, and the epidemic prevention costs of municipal projects account for the smallest proportion of the total investment.

5.3. Programing. MATLAB 2019b software (Math Works. Inc, Commonwealth of Massachusetts, the United States of America) was used to implement the above-mentioned optimized neural network, and the data were imported into the neural network. The relevant parameters were set as follows: the first line is "net. train Param. show = 9"; the second line is "net.trainParam.epochs = 1000"; the third line is "net.trainParam.goal = $1e - 28$"; the fourth line is "net.trainParam.lr = 0.1." Specifically, the first line represents the number of fitting times, which indicates that the iteration will stop if convergence is not achieved nine times; the second line in the code represents the maximum number of iterations for the model, which means that the model can be iterated up to 1000 times, but the output does not have to reach the maximum number of iterations; the third line represents the learning target set by the model. The accuracy set here is 10^{-28}, indicating that when the number of iterations of the model exceeds the set value or the accuracy is lower than 10^{-28}, the model will stop training; line 4 represents the learning efficiency, which is set to 0.1. The setting of learning efficiency cannot be too large; otherwise, it will affect the stability of the model.

The number of hidden layers and neurons in the BP neural network directly affects the training accuracy and speed. Usually, the hidden layer is set to 1 layer. There is no unified approach for setting the number of neurons in the hidden layer. Too many neurons in the hidden layer can lead to overfitting, while too few neurons can lead to underfitting [50]. A new empirical formula was used to determine the number of neurons in the hidden layer, which is shown as follows:

$$N = \frac{N_s}{\alpha N_i + \alpha N_o}, \tag{6}$$

where N_i represents the number of neurons in the input layer, N_o is the number of neurons in the output layer, and α is the constant term.

The number of neurons in the hidden layer was determined according to formula (6), where $N_i = 9$, $N_o = 1$, and $N_s = 55$. After repeated tests, when α was set to 0.25, that is, when the number of hidden layers was 22, the obtained training effect was the best.

5.4. Operating Result. The data were imported into the program, the number of samples selected for training was 55, and the number of samples used for testing was six. First, the sample value was optimized and the outliers were eliminated. After removing different data points one by one, six groups of different training results were obtained, as shown in Figure 2. The comparison between the test result and the real value indicates that the program works well and shows good fitting performance.

As shown in Figure 3, there were obvious errors in the 10th, 48th, and 54th groups of data, and those observations are so high. This study analyzed these three data in detail, and the relative error of the 10th group of data is due to the small amount of total investment, while the relative error of the 48th and 54th groups of data is due to the small pressure of epidemic prevention and control in remote areas away from dense crowds.

TABLE 3: Units and recording methods of the input variables.

| Influencing factors	Units	Recording method
Project category	—	Calculate the average cost of epidemic prevention for different factors as a proportion of total investment, recorded by the number in decreasing order
Construction scale	m^2	—
Total investment	Million	—
Construction period	Month	Calculation of construction period beyond January 2020, monthly records
Qualification of construction subject	—	Special levels (4, 3, 2, and 1) to be extrapolated
Number of managers	Person	—
Number of construction workers	Person	—
Number of local outbreaks during the construction period	Time	Record of outbreaks in cities where the project is located
Smart construction site	—	Recorded by logical value 1 not 0
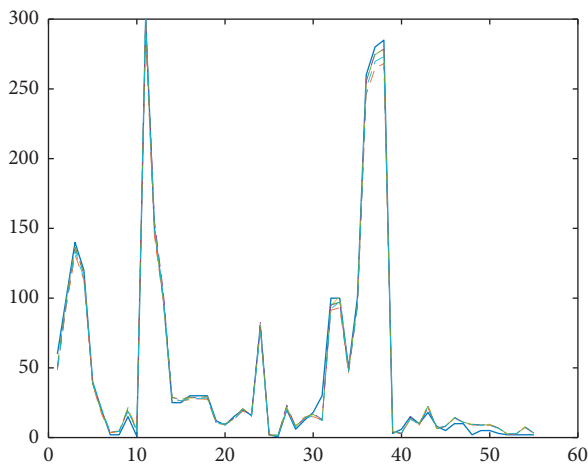
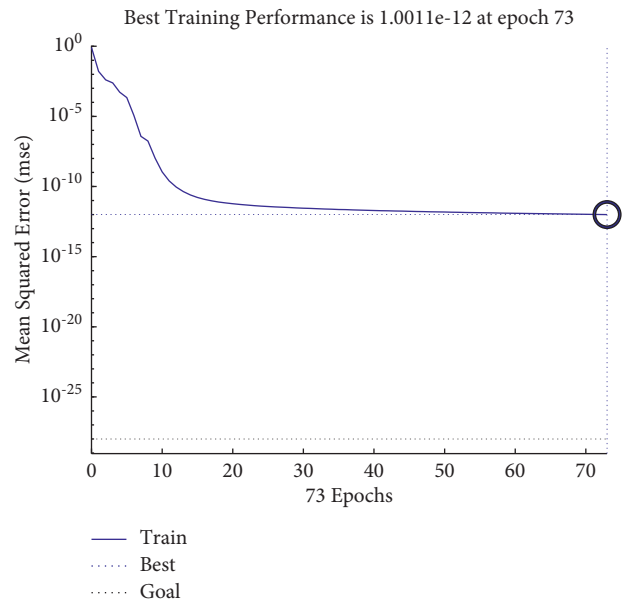FIGURE 2: Comparison of the test results and real values.
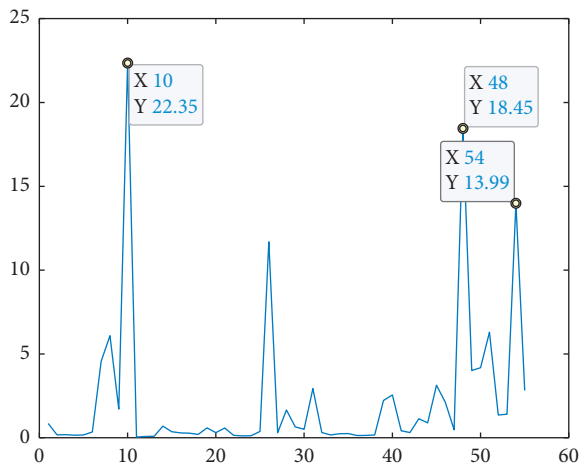

FIGURE 4: Iterative curve.

FIGURE 3: Relative error of different data (X is the sample number, and Y is the relative error).

After elimination, the remaining data were imported into the neural network for learning. The iterative curve is shown in Figure 4. It can be seen from Figure 4 that the model was trained after 73 iterations, and the prediction accuracy of the model was as high as 1.0011×10^{-12}.

Although it did not reach the set learning goal, the error was within the acceptable range. In addition, the slope of the regression function was close to 45°, and the fitting degree was 1, confirming the prediction accuracy of the model.

The six groups of data used for testing were imported into the neural network, and a diagram of the fitting of the model was obtained. The results were compared with those obtained by the BP and BP neural networks optimized by GA. As shown in Figure 5, the optimized neural network performed significantly better than both the BP and ordinary neural networks in the prediction of epidemic prevention costs, and the basic and actual values were consistent. To better reflect the calculation results, the prediction errors of different methods were counted, and the results are presented in Table 5. Although the BP neural networks optimized by GA achieved a better performance than the BP neural network, its average error is larger than that of the BP neural network due to the error of learning samples. However, there is a large gap between the predicted value and the actual value of both the BP and BP neural networks optimized by GA, so it is not a good prediction tool. In
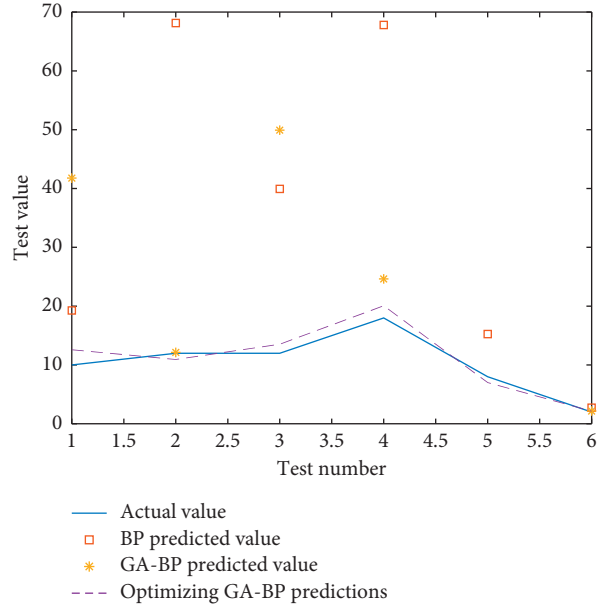
Figure 5: Comparison of the predicted values of the three prediction methods.

Table 4: Statistics of the proportion of epidemic prevention costs.

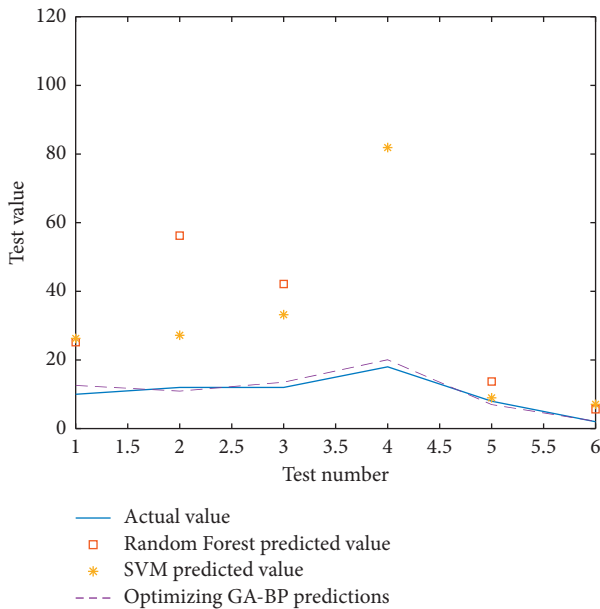| Project types	Number	Average (%)	Upper confidence limit (95%)	Lower confidence limit (95%)
Buildings	36	0.18	0.28%	0.14%
Municipal engineering	12	0.07	0.15%	0.01%
Landscape greening	2	0.24	—	—
Decoration engineering	11	0.29	0.40%	0.11%
Total	61	0.18	0.23%	0.13%

Figure 6: Comparison of the predicted values of the opposed method with the RF and SVM methods.

comparison, the optimized neural network achieved good results in the prediction of epidemic expenses, with an average error of only 13.14%, indicating that it can be used as a prediction tool in the decision-making stage.

There are many other machine learning approaches, including support vector machines (SVM) and random forest (RF) [51–53], each of which has its areas of applicability [54]. To further investigate the optimization performance of the proposed method, it was compared with other machine learning methods, including RF and SVM methods. The same six datasets used for testing were imported into the neural network, and the comparison results are shown in Figure 6. It can be seen from Table 6 that the results are the same as those obtained in the previous comparison, and the optimized neural network has advantages in comparison with SVM (whose average error is 181.09%) and RF (whose average error is 247.42%). Therefore, the proposed method is worthy of further exploration and application.

5.5. Sensitivity Value Calculation. The sensitivity of the influential factors was calculated according to formulas (3)–(5), and the program was repeated five times, through which an average value was obtained. Then, the relevant influencing factors were traced back, and the sensitivity was added to rank the influencing factors of epidemic prevention costs. The results are shown in Table 7. The order of the sensitivity of the influencing factors is the total investment, project category, total construction area, the number of construction workers, construction period, the number of

TABLE 5: Error statistics of three methods (BP, BP neural networks optimized by GA, and the optimized neural network).

Data sequence number	Actual value	BP	Error (%)	BP neural networks optimized by GA	Error (%)	The optimized neural network	Error (%)
56	10	19.2718	92.72%	41.7735	317.74%	12.5919	25.92%
57	12	68.1481	467.90%	12.1349	1.12%	10.9385	8.85%
58	12	39.9396	232.83%	49.9298	316.08%	13.5302	12.75%
59	18	67.8152	276.75%	24.6317	36.84%	20.0691	11.50%
60	8	15.2674	90.84%	60.9559	661.95%	7.0119	12.35%
61	2	2.7418	37.09%	2.1691	8.45%	2.1496	7.48%
Average error			199.69%		223.70%		13.14%

TABLE 6: Error statistics of three methods (RF, SVM, and the optimized neural network).

Data sequence number	Actual value	RF	Error (%)	SVM	Error (%)	The optimized neural network	Error (%)
56	10	25.1888	151.89%	26.2675	162.68%	12.5919	25.92%
57	12	56.2222	368.52%	27.1982	126.65%	10.9385	8.85%
58	12	42.1515	251.26%	33.1918	176.60%	13.5302	12.75%
59	18	100.6665	459.26%	81.8908	354.95%	20.0691	11.50%
60	8	13.7278	71.60%	8.9750	12.19%	7.0119	12.35%
61	2	5.6393	181.97%	7.0694	253.47%	2.1496	7.48%
Average error			247.42%		181.09%		13.14%

TABLE 7: Sensitivity and ranking of factors that affect the epidemic prevention expenses of the normalized COVID-19 epidemic.

Factors	First	Second	Third	Fourth	Fifth	Mean value	Sort
Project category	0.14	0.16	0.15	0.15	0.15	0.15	2
Total investment	0.25	0.25	0.26	0.24	0.24	0.25	1
Construction period	0.09	0.10	0.08	0.10	0.10	0.10	5
Number of outbreaks during the project construction period	0.09	0.09	0.07	0.08	0.08	0.08	7
Number of managers	0.09	0.08	0.09	0.10	0.10	0.09	6
Number of construction workers	0.13	0.13	0.12	0.15	0.15	0.13	4
Construction scale	0.18	0.15	0.12	0.12	0.12	0.14	3
Whether it belongs to a smart site	0.02	0.02	0.07	0.06	0.06	0.05	8
Qualification level of the construction subject	0.02	0.02	0.06	0.00	0.00	0.02	9

managers, the number of outbreaks during the project construction period, and it belongs to the smart site and the qualification level of the construction subject. These results can provide good guidance for subsequent engineering practices. Taking the project decision-making stage as an example, in the process of investment estimation, epidemic prevention costs can be preliminarily determined based on the total investment of the project and be adjusted appropriately in combination with the project category. In the subsequent project implementation stage, when the design scheme is completely determined, the construction organization design is continuously improved, and the labor involved in the construction can be determined, while the investment estimation in the decision-making period can be further corrected based on the number of construction workers involved in the construction. It should be noted that the number of COVID-19 outbreaks during the construction period of the project only ranks in seventh place in terms of the sensitivity of the influencing factors. It is believed that domestic construction sites are currently managed in a closed manner, and there is no serious site aggregation epidemic (except for the site aggregation epidemic of the Qingyun Lanwan Project, Zhonglou District, Changzhou

City, on March 14, 2022, there were no reports of site aggregation epidemics). Therefore, the epidemic prevention and the control of domestic construction projects are better, and the impact of this factor is not significant.

6. Results and Discussion

6.1. Results. The total investment, project type, and total construction area were important factors that affect normalized epidemic prevention costs. After the training and calculation of the optimized artificial neural network method, the factors with high sensitivity were identified as total investment, project type, total construction area, the number of construction workers, and construction period. In engineering practice, the epidemic prevention costs of different types of engineering projects can be preliminarily determined according to the confidence interval.

The construction administrative department may issue different pricing standards. There are differences in the sensitivity of the factors affecting the costs of normalized COVID-19 epidemic prevention. The total investment of the project is an index with a high degree of quantification and strong project attributes. The index or the

construction investment index can be used as the calculation base, the project category as the main adjustment factor, and other factors as reference factors to calculate the cost of epidemic prevention. Taking a citizen center project as an example, 0.14% ~ 0.28% of the total investment of the project can be taken as the value range of epidemic prevention costs, which can be adjusted appropriately considering the impact of public building types and the construction scale.

6.2. Discussion. The epidemic prevention and control fee should be identified as the total price of measure fees. After the Ministry of Housing and Urban-Rural Development issued a document to clarify that epidemic prevention costs arising from the prevention and control of the COVID-19 epidemic can be included in project costs, provinces and municipalities responded positively and issued corresponding policy documents. However, the analysis of the documents revealed that the provisions of different regions are different. Under the current situation of normalized prevention and control, it is suggested that epidemic prevention and control fees should be further identified as a measure fee and added to the total price of measure fees, and relevant documents should be issued regarding the collection and calculation of the total price of measure fees to facilitate the reference, application, and implementation of front-line engineering managers. Meanwhile, the proportion of normalized COVID-19 epidemic prevention expenses should be calculated according to the project type. Under normalized epidemic prevention and control, although local governments have introduced policies and regulations that need to include epidemic prevention costs within engineering costs, they have not specified relevant rates. Through the descriptive statistics applied to 61 items of valid data, the average and confidence interval of the proportion of different types of epidemic prevention costs were calculated according to project types, which is significant for engineering practice.

7. Conclusions

In this paper, an optimized BP neural network prediction model is proposed and applied to predict normalized COVID-19 epidemic prevention costs, and the average prediction error of the optimized neural network was significantly reduced. The general neural network does not eliminate abnormal data, which leads to a good learning effect but increases error rates. Considering a real-life engineering application, a new neural network prediction method optimized with MATLAB was constructed. The collected samples were optimized to eliminate the abnormal data, and then the remaining data were imported into the neural network. In the six groups of the test data, the error was only 13.14%. More data analysis methods should be used to assist the project management decision-making process. Construction project management, especially construction site management, accumulates a large amount of first-hand data, which can guide engineering practice by eliminating

the links and laws between the data. In this study, the optimized neural network prediction model was used to explore the prediction of normalized epidemic prevention costs. The application and comparison of various machine learning methods, such as the optimized artificial neural network with support vector machine and random forest methods, can be further explored to establish a theoretical model that is more suitable for the engineering practice and assist in scientific decision-making in engineering management. In addition, each method has its applicability and advantages and disadvantages. When using specific methods, attention should be paid to the matching between data requirements and method requirements. As far as this method is concerned, construction project managers also need to consider the computational complexity when using this method. In future work, we will explore how to simplify the calculation to serve the project management better.

Data Availability

The case data of this study were obtained from the actual investigation of the research group. The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Huadong Yan was responsible for conceptualization, formal analysis, investigation, and writing of the original draft; Jingchun Feng contributed to project administration; Xu Chen provided software. All authors have read and agreed to the published version of the manuscript.

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