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Retraction

Retracted: Field Test and Data Simulation of Foundation Pit Support System Based on BP Neural Network

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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.

References

[1] F. Chen and H. Wang, "Field Test and Data Simulation of Foundation Pit Support System Based on BP Neural Network," *Mobile Information Systems*, vol. 2022, Article ID 1838009, 9 pages, 2022.

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Research Article

Field Test and Data Simulation of Foundation Pit Support System Based on BP Neural Network

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In view of the neural network problem, a field test and data simulation study of the root pit support system is proposed. First, in some difficult cases, the BP algorithm is usually due to the low level of training, thus changing the tuition and fees. Second, the BP algorithm can mix heavy objects with special effects, but the gradient process will generate local minima, so the minimum error cannot be guaranteed. The experimental response and simulation data of the BP neural network foundation pit support system is analyzed, and all experimental data are recorded. Finally, from an empirical point of view, the results brought by the field test of the central support system are determined and ultimately, promote the development of human life. The genetics-based estimation algorithm reproduces the neural network, the estimation time is 10 s, the prediction error root floats between −0.05–0.05 mm, the maximum correlation near error is 0.36%, and the approximate IA value is higher than 0.9.

1. Introduction

Early research on neural devices dates back to the 1940s. The following is a history of the development of the neural network designed, and brief acquaintances are briefed on the specific points of the conclusive research results at the appropriate time. In 1943, psychologist W. McColloch and mathematical logician W. Bates developed a mathematical model of neurons, starting with the analysis and writing of neurons. This project is from theoretical discussions to the first position of neural network research in engineering practice. During that time, many organizations around the world followed the development of sensors that are essential for research in word recognition, speech recognition, sonar signal recognition, learning, and memory. Many people mistakenly believe that digital computers can solve all kinds of problems of intelligence, design knowledge, experts, etc., without focusing on the future work of technology. The second is that the electron level returns to that period. The main components are tubes or transistors.

In the history of artificial neural network development, no efficient algorithm has been found to change the connection weight of the hidden layer for a long time. Before the introduction of the error back propagation algorithm (BP algorithm), the weight adjustment problem of multilayer neural network was successfully solved with continuous nonlinear functions. Learning BP neural network (back diffusion), that is, the process of error reverse diffusion algorithm, is composed of information-forward propagation and error back propagation [1]. In your question, please first find some properties of the specific problem and corresponding evaluation data used for neural network training. Although BP network is widely used, it mainly has some shortcomings and shortcomings, including the following aspects. This problem can be solved with additional momentum. Third, there is no theoretical guidance on the choice of the network's hidden layers and the number of units. Generally, this is based on repeated experience and experience. Therefore, the network is often redundant, and the burden of online learning will also increase.

Csatho (1994) applied the full Lagrangian description method of finite deformation theory, carried out numerical simulation analysis of foundation pit engineering, and proposed that the depth of the foundation pit exceeds 10 m, and if the geometric nonlinearity is not considered, it will lead to large calculation errors and even wrong results [2]. According to the concept of nonlinear rheology, He and Zheng established a finite element analytical quadratic initial strain method for nonlinear rheology, it is concluded that the calculation of the lateral displacement of the supporting structure will become smaller if the nonlinear rheology of soft soil is not considered [3]. Wang et al. (1998) proposed the idea of dynamic construction inversion analysis, that is, the dynamic construction factors of gradual excavation and road-by-lane support are introduced in the conventional inverse analysis process, in order to obtain the actual construction situation simulated by the simulation, this provides a reliable guarantee for the deformation prediction in the following construction stages [4]. Yan and Xun (1999) from the point of view of rheology, put forward the relevant calculation formula of the coupling of Earth pressure, displacement and time, and it has certain practical scientific significance for further discussing the calculation method of Earth pressure [5]. Feng (2000) carried out the research and analysis on the problem that the measured internal force ratio of the supporting structure of foundation pit engineering is small, and the calculated value using classical soil mechanics theory is small, and some possible influencing factors are pointed out. For the long-term debated issue of "water and soil calculation" and "water and soil separate calculation," it is pointed out that "water and soil cost-effective" may have a certain microscopic basis, which will be a subject to be further studied [6]. Xie et al. (1988) used the centrifugal model experimental technical scheme, by setting a liquid to flow out from the base, the process of soil excavation was simulated, and a large number of continuous experimental observations were carried out, and some useful conclusions were drawn [7]. Mori et al. (1993) analyzed the effect of seepage on the soil pressure by using the finite element technique, and its distribution law, lateral displacement of retaining wall, and soil settlement behind the wall have important influences [8]. Lam et al. (1999) analyzed the effects of soil strength anisotropy, heterogeneity, and retaining wall depth on the stability of foundation pit construction based on the upper-bound theory, and compared them with the results of numerical analysis methods and explained its advantages and disadvantages [9].

Based on the current study, the authors published a study on the experimental and data simulation of the root pit support system. According to the actual situation of the project, an effective on-site management plan is formulated. Through the analysis of the situation and analysis of the data, the internal strength and support of the group obtained during the construction of the foundation pit will change correctly. The data shows that during the excavation of the foundation pit, the Earth pressure changes. Regular low cost and the support can be fully controlled. At the same time, the observation results can be compared with the simulation results analysis to confirm the accuracy and precision of the simulation results.

2. Field Test and Data Simulation of Foundation Pit Support System Based on BP Neural Network

2.1. The Purpose and Significance of This Study. In order to ensure the safety of foundation engineering construction and the safety of the surrounding environment, it is necessary to estimate and monitor the strain (or large deformation) during deep foundation system support and foundation pit excavation, and use the prediction and evaluation results to bring construction safety and success. Due to many uncertainties such as strong foundation construction environment, clear timing, lack of design experience, the design and construction of base projects conceal safety features or have no engineering costs. Especially in the central pit project in the prosperous part of the city, its complex construction conditions, intricate underground pipelines, and strict regulations on the environment (such as settlement and lateral movement around the house) support a set of analysis theories. With confidence, in order to simulate and identify the design and construction of the foundation works, by analyzing the results, we can understand the weak links of the foundation pit works, strengthen the protection and measurement of the stress, and let the center pit work, building security and economy [10].

2.2. The Content of the Author's Research. The development history of foundation pit engineering and the theory of foundation pit engineering design is systematically expounded and pointed out the significance of numerical analysis method in the theory of foundation pit engineering design, combined with the previous research and analysis results of other scholars, using the finite difference numerical analysis method. The numerical simulation analysis of the foundation pit engineering of the No. 2 Heavy Plant was carried out, and the analysis results and the experimental results show that the simulation analysis can truly reflect the dynamic balance process of foundation pit engineering during construction and excavation, as well as the stress-strain laws of various enclosure structures in this balance process. The details are as follows:

(1) An overview of the reasons for the generation of foundation pit engineering and the research history of foundation pit engineering design theory points out the function and significance of numerical analysis method in the simulation analysis of foundation pit engineering.

(2) The study describes the design of the on-site measurement scheme of the foundation pit project, and the monitoring instruments are arranged at selected points on the enclosure system structure to monitor the data during the construction period through the actual engineering field measurement plan of the circular deep foundation pit of the No. 2 plant. The deformation law (displacement change curve, stress field curve) of the maintenance system structure of

the foundation pit project is further analyzed and studied.

(3) Using the finite difference program FLAC3D to carry out numerical analysis and simulation of the circular deep foundation pit of the Erzhong Factory, comprehensively consider various external factors, different construction schemes, and the stress-strain (displacement) law of the maintenance system structure under the premise of construction steps, and play a real-time guiding role in construction.

(4) Through the structural comparison between field measurement and numerical simulation analysis, the difference between the two results is analyzed, and the common deformation mechanism of the envelope structure is sought, and suggestions and prospects are put forward for further research in the future.

2.3. Foundation Pit Support Structure System. The deep foundation pit of the 35-m quenching device adopts the row pile occlusal enclosure system [11]. The inner side of the foundation pit is supported by steel inner support ring beams and in order to achieve the reduction of foundation pit excavation for the purpose of the lateral displacement of the retaining piles and the soil behind the piles, the entire foundation pit-supporting structure is the row pile wall-+inner support. The row pile wall adopts the combination of continuous row piles and high-pressure rotary jet piles to form an underground continuous structural system, and the architecture has great stiffness and can double as a water stop.

The row pile wall is made up of 58 row piles that overlap each other on the plane in the shape of the word "pin," the pile body is 40.5 m long, and the pile bottom is embedded 3 m below the bottom of the foundation pit. The row of piles is formed by high-pressure impact-forming holes and underwater pouring. The construction sequence is to impact the holes at intervals (punch one by one), then lower the prerolled steel cages into the holes, correct the position of the steel cages, and finally pour C30 commercial concrete, after the concrete reaches a certain strength (considering the weather during the construction period, usually about 75%–85% of the design strength in one day), then impact holes at the interval of the hole-forming piles. The construction process is the same as before, since the outer row piles and the inner row piles are tightly engaged, and a high-pressure rotary jet pile with a diameter of 500 mm is made between the outer row and the inner row of piles, form a water-stop curtain [12].

A crown beam is set on the top of the pile, with a width of 1.8 m and a height of 1.0 m. The inner support adopts annular box girder, with a total of 5 levels, and each level of support is constructed and welded on-site by six sections of ring beams. The depths of the inner supports are 7.8 m, 13.6 m, 19.4 m, 24.4 m, and 31 m, respectively (all calculated from the ground). Among them, the design dimensions of the tertiary support at the depths of 7.8 m, 13.6 m, and 19.4 m are $400 \times 300 \times 14 \times 14$ (width × height × wall thickness × wall thickness, all in millimeters), 24.4 m, 3l m depth inner support design size is $600 \times 550 \times 16 \times 16$ (same as above).

3. Protocols for Experiments and Research Questions

3.1. Factors Affecting the Deformation of the Foundation Pit Envelope. The main factors affecting the deformation of the envelope structure include engineering, geological, and hydrogeological conditions of foundation pit; support type and structural design parameters; plane size and excavation depth of foundation pit; and the construction process and the surrounding environment of the site [13]. The impact of the construction period; ground overload and vibration loads; supporting conditions; stiffness of the enclosure structure; depth of the enclosure below the pit bottom; soil layer strength (including soil cohesion c, internal friction angle, etc.); and the influence of groundwater, etc.

3.2. Determination of Network Structure. The deformation of the enclosure structure of the foundation pit is the result of the comprehensive action of various influencing factors [14]. Combined with the actual situation, four representative indicators, including construction period (T), excavation depth (D), groundwater level (W), and current temperature (C) are selected from various factors as the input of the network. The deformation S at a certain height of the CX15 measuring point is selected as the output of the network [15]. Take a hidden layer, the number of nodes is 10 (it is $(2n+2)$, the number of neurons in the input layer n, among the various factors affecting the deformation of the envelope structure, the engineering geological and hydrogeological conditions of the foundation, the type of support and the structural design parameters, the ground overload and vibration load, the soil layer strength (including the c, value of the soil, etc.) have an equal impact on the observed deformation of each sample; therefore, its influence on the deformation results is not considered when selecting the influencing factors. In order to determine whether the deformation (S) at the height of 17.5 m at the CX15 measuring point has an objective correlation with the construction period (T), excavation depth (D) [16], groundwater level (W), and air temperature on the day (C), correlation analysis was performed on them, respectively, and the larger the correlation coefficient $R2$, the greater the correlation between the two sets of statistical data. As can be seen, the temperature (C) of the day has a great influence on the deformation (S) at the height of 17.5 m at the CX15 measuring point, while the construction period (T), the excavation depth (D), and the groundwater level (W) have a great influence on it, obviously [17].

3.3. Network Training and Testing. Taking the collected 15 different working conditions, the wall deformation monitoring value of the CX15 measuring point sample of the neural network, the NNBP1.0 program developed by Visual C++ is used to study and test the situation. When the network iterates to 10,000 times or the objective function εAV is less than the predetermined $\varepsilon = 1\ 0 \times 10^{-6}$, get out of the loop, the training is over. From the comparison between the actual output and the expected output of the learned training samples, the maximum difference is 0.93%, and the average error is 0.17% [18]. It can be seen from the table that the values are very close, indicating that the fitting accuracy of the modulus is relatively high. The BP network realizes the dimensionality reduction mapping from the input p-euclidean space to the output dimensional Euclidean space; therefore, it can be used in nonlinear classification, preprocessing, etc., and as a function calculator, it can approximate any nonlinear function with arbitrary precision [19].

The field test and data simulation of foundation pit support system based on BP neural network are shown in Figure 1.

It can be seen from the figure that the optimal support scheme includes safety, economy, feasibility, safety including the safety of the strength of the envelope itself, the stability of the maintenance structure, the safety of the construction around the pit, and the safety of the underground pipeline [20]. Economics include construction cost and construction period, and feasibility includes site conditions, construction convenience, and foundation pit scale.

Field test and data simulation of foundation pit support system is based on BP neural network, as shown in Figure 2.

Specifically, it includes inputting the relative superiority of each program objective, determining the initial weight vector of the indicators, calculating the hidden layer 32., $C = 26$ kPa; silty clay = 14., $C = 36$ kPa; fine sand = 32 [21]. Apply the principle of qualitative ranking and quantitative calculation of the importance of the index set and determine the initial weight vector of the three subsystems in the model as $W = (Wl, w2, w3)$ = (safety, economy, feasibility) = (0.40, 0.18, 0.42) [22].

The specific formula and algorithm of the field test and data simulation of the foundation pit support system of the BP neural network are the folowing:

(1) For the first hidden layer, the input of node $k1$ is ml and –; = . In the formula, $m1$-the number of nodes in the first layer are included in the second layer. The output is as shown in (1):

$$l_{kJ} = \sum_{i=1}^{m1} \text{wikir}_{ij}. \tag{1}$$

(2) For hidden layer 2, the input of node $k2$ is as shown in (2):

$$\mu kJ = \frac{1}{1 + \sum_{i=1}^{m1} wikir_{ij} - 1}. \tag{2}$$

(3) The number of layer 2 nodes included in layer 3. The output is as shown in (3):

$$I_{KJ} = \sum_{i=2}^{m2} \omega\text{ikrir}_{ij}. \tag{3}$$

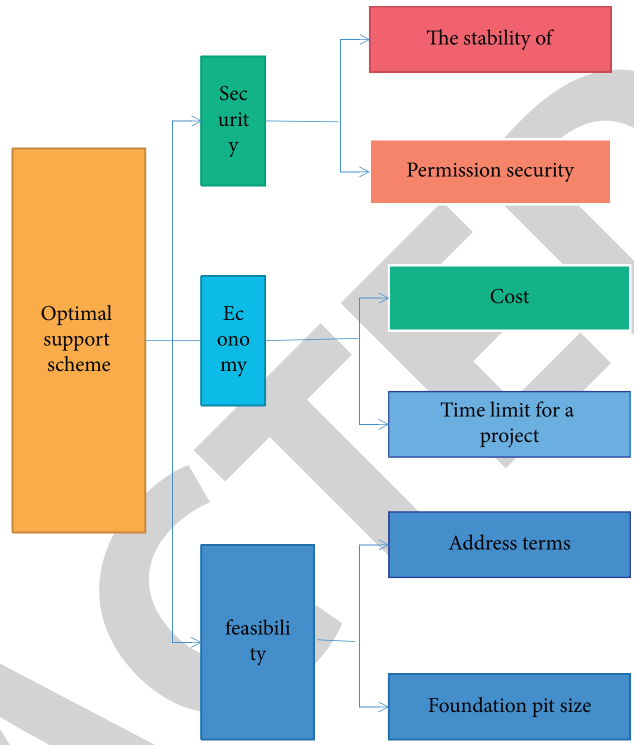

Figure 1: Structure diagram of the field test and data simulation model of the supporting system of the network foundation pit.

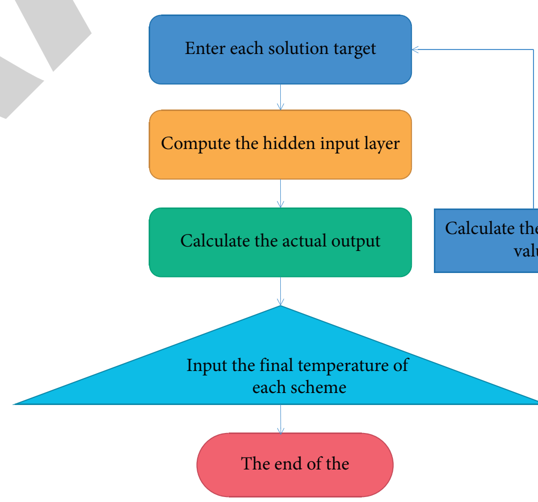

Figure 2: The program block diagram of scheme optimization and feedback calculation.

(4) For the output layer, there is only one node P, and the input is as shown in (4):

$$ųkJ = \frac{2}{1 + \sum_{i=1}^{m1} \text{wikir}_{ij} - 1}. \tag{4}$$

(5) z *is* the number of nodes in layer 3. The output is as shown in (5):

$$ųkJ = \frac{1}{1 + \sum_{i=1}^{m1} \text{wikir}_{ij} - 1} = \frac{2}{1 + \sum_{i=1}^{m1} \omega\text{ikir}_{ij} - 1}. \tag{5}$$

(6) In the above formulas, is the connection weight between nodes i and l. That is the connection weight season between nodes l and $k2$; households are the connection weights between nodes 2 and P, which are required to satisfy formulas (6) and (7):

$$\sum_{i=1}^{m1} \text{wiki}r_{ij} = 1, \tag{6}$$

$$\omega_{iK1} = 0, \sum_{k2=1}^{L} \omega k1k2 = 1. \tag{7}$$

(7) In order to make the scheme optimal, the square error between the actual output of the network and the expected output M of the scheme should be minimized, that is, Ma = Gao (a M(ut/)) is the smallest, this can be achieved by adjusting the connection weights in the network. Applying the gradient descent method, the adjustment amount of the connection weight is shown in (8) and (9):

$$\omega_{\mathrm{k1k2}} = 0; \tag{8}$$

$$\sum_{k=2}^{l} \text{wiki} = 1, \omega_{K1p} = 0. \tag{9}$$

(8) Through the derivation of the implicit function, the weight adjustment formula of the hidden layer node and the output layer node P is as shown in formula (10):

$$l_{pj} = \sum_{k_2=1}^{L} \omega \text{kpki}. \tag{10}$$

(9) In the same way, the weight adjustment formula of the input layer node i and the hidden layer node is as shown in formula (11):

$$E_j = \frac{1}{2}\left\{\text{ụ}_{pj} = M\left(\text{ụ}_{pj}\right)\right.. \tag{11}$$

(10) For different support schemes, the final output of the network, that is, the relative superiority degree can be obtained according to the above steps. The largest one is the selected deep foundation pit support scheme [23]. The program optimization and feedback calculation procedure are shown in formula (12):

$$\Delta\omega_{k1p} = -\eta \frac{\omega Ej}{\omega kp}. \tag{12}$$

3.4. Experimental Methods to Validate the Scheme. The BP neural network technology is used to predict and simulate the possible deformation of the matrix in the future, do a good job in the support and repair period, reduce the difficulty of support and repair, and escort the safety of the root pit. An analyzes of the time domain (Time series only) features, spatial domain (adjacent points only) features, time domain and spatial domain processing integrated features that have been simulated and studied many times based on engineering examples.,and which are used to estimate the horizontal, vertical, and deformation of the Zhoushan base survey point, and compared with the support vector machine regression (SVR) and random forest regression (RF) methods [24]have been carried out. The multidimensional experience that the simulation results shows and the prediction algorithm are based on the genetic reproduction neural network. The estimated time is 10 s, the prediction error is floating at −0.05–0.05 mm, the maximum relative error is 0.36%, and the approximate IA value is higher than 0.9. This method not only provides support for the protection management security model but also for the central health management systems that offer new perspectives.

3.5. Experimental Results. Starting with the simplest predictions, the analysis estimates that the CX15 measures horizontal displacement at a depth of 17.5 m. The first 12 sets of data among the 15 sets of data were selected as standard learning materials, and the last three sets of data were selected as standardized tests [25]. Courses and training materials are listed in Table 1:

According to Table 1, it can be seen that the NNBP1.0 program developed using Visual C++, and the training samples need to be normalized. After the first set of data to be trained is input into the NNBP1.0 program, the training can be carried out. After the learning and training is completed, a neural network corresponding to the learning and training samples is formed. Next, let the trained neural network predict the last three sets of data, and the normalized result of the predicted horizontal displacement of the building envelope is 0.788279884, 0.863980 662, 0.968068530, and then denormalized to get the final result: 20.4 mm on March 21; 22.0 mm on March 25; 24.2 mm on March 28, and the measured values are the following: 20.4 mm on March 21; 22.3 mm on March 2; and 24.9 mm on March 28. It can be seen that the predicted value is very close to the actual value.

When estimating and analyzing the above data, the first 10 groups, 11 groups, 12 groups, 13 groups, and 14 groups were used to model the courses, and the latter data were estimated. The results are shown in Table 2:

It can be seen from Table 2 that, it is completely feasible to use the neural network method established above to make short-term prediction of the deformation of the foundation pit envelope, and very effective. However, relatively speaking, the longer-term forecast values have larger errors. At the same time, it also shows that although the neural network method can effectively carry out deformation prediction, the on-site monitoring work still needs to be carried out.

The hidden layer of the neural network for predicting horizontal displacement and predicting settlement is set to 5 to 14, and the error standard deviation of the output value is shown in Figure 3:

It can be seen from Figure 3 that when the hidden layer of the neural network for predicting horizontal displacement

Table 1: Study sample data table.

Carpentry	Construction date	Excavation depth	Groundwater level	Temperature of the day	Key points	Length	Width	Area
1	11–12	9.4	9.1	8.4	7.5	20	10	6.6
2	1–2	15.41	14.35	14.47	15.39	3.12	5.21	4.11

Table 2: Training result prediction sample table.

Carpentry	Construction date	Excavation depth	Groundwater level	Temperature of the day	Actual measurement *A*	Actual measurement *B*	Actual measurement *C*	Actual measurement *D*
1	11–12	9.4	9.12	8.444	7.55	205	105	6.6565
2	1–2	15.41	14.351	14.47	15.39	3.1244	5.214	4.114

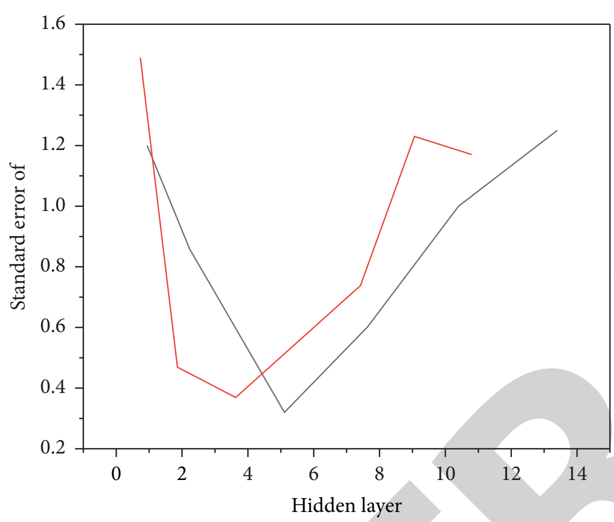

Figure 3: The variation curve of error standard deviation with the number of hidden layers.

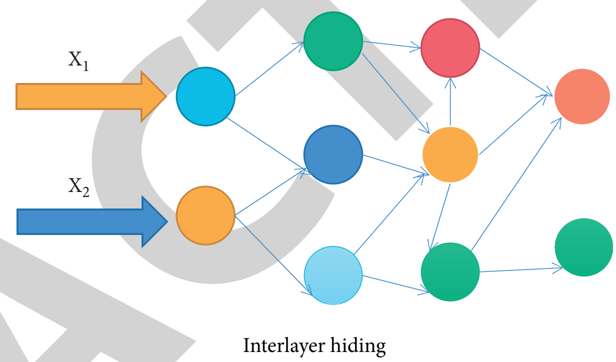

Figure 4: BP network structure diagram.

is set to 7, the error standard deviation of the output value is the smallest, while for the neural network for predicting settlement, when the number of hidden layers is 9, the output value is the most accurate. Therefore, the number of hidden layers of the two is set to 7 and 9, respectively.

BP network is a multilayer feed-forward neural network, including access process, encryption (intermediate) process, and release process, where the encryption process can be one or more sets. Generally speaking, our BP layer neural network can easily solve most problems. The layers of the BP network are fully connected, and the neurons in each layer are not interconnected. As shown in Figure 4:

As can be seen from Figure 4, 1 is a four-layer BP network, in which the hidden layer (middle layer) is two layers, the number of neurons in this layer is 3, and the number of input and output neurons is 2. After normalizing the BP network, each neuron responds to the input, and the signal propagates through the input layer, from the hidden layer (intermediate layer) to the output layer, and according to the principle of reduction, the difference between the expected output and the actual output, through the release process, from the intermediate process, and finally back to the input layer, adjust the weight of each connection layer by layer, and this algorithm is called error recovery after propagation. The algorithm, or BP algorithm for short, continues to improve the accuracy of the network's response to the input as the repetition error continues.

The hidden layer of the BP network uses different numbers of neurons; the output layer uses different transfer functions and different training functions, and the following series of experimental results are obtained, as shown in Table 3:

The transfer function of the output layer is Purelin, the training function is trainingdx, and the target error is less than 0.0002. It can be seen from Figure 4 that under the same conditions, for the discussed problem, the output layer transfer function tansig and pure lin have little effect on the overall network.

If the accuracy of the target error is not very high, the number of neurons in the hidden layer of the BP network is 8, which is the most suitable, and the network structure is relatively simple, and the convergence speed is also fast. As shown in Table 4:

It can be seen from Table 4 that the transfer function of the output layer is tansig, and the training function is tra ingdx. If the accuracy of the target error is high, for the problems discussed, the number of neurons in the hidden layer is 16 which is the most suitable, and the approximation error *E* is small, and the convergence speed is much faster.

According to the above series of experiments, as well as the training speed, computation, and memory requirements of various algorithms, the number of hidden layer neurons in the BP network net we designed is set to 16, as shown in Table 5:

Table 3: Test result table.

Sample	Number of hidden nerves	Excavation depth	Groundwater level	Temperature of the day	Hidden number *A*	Hidden number *B*	Hidden number *C*	Hidden number *D*
1	1155	9.554	9.22	8.22	7.55	205	1.22	6.6566
2	555	15.41	14.351	14.47	15.5	3.124	5.23	4.44

Table 4: Test result table.

Sample	Number of hidden nerves	Excavation depth	Groundwater level	Temperature of the day	Hidden number *A*	Hidden number *B*	Hidden number *C*	Hidden number *D*
1	11–12	9.41	9.14	8.48	7.55	205	1.22	6.6566
2	1–2	15.41	14.351	14.47	15.39	3.12455	5.214	4.114

Table 5: Test result table.

Sample	Training function	Excavation depth	Groundwater level	Temperature of the day	Convergence steps *A*	Convergence steps *B*	Convergence steps *C*	Convergence steps *D*
1	Trainmp	9.554	9.22	8.22	7.55	205	1.22	6.6566
2	Tiaminp	15.41	14.351	14.47	15.5	3.124	5.23	4.44

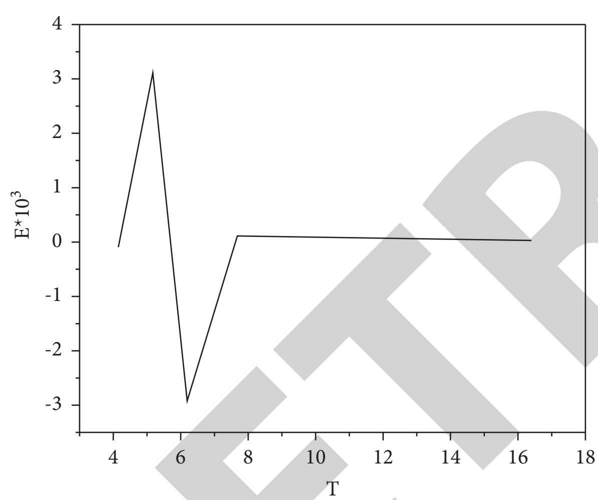

Figure 5: Error change in the network training process.

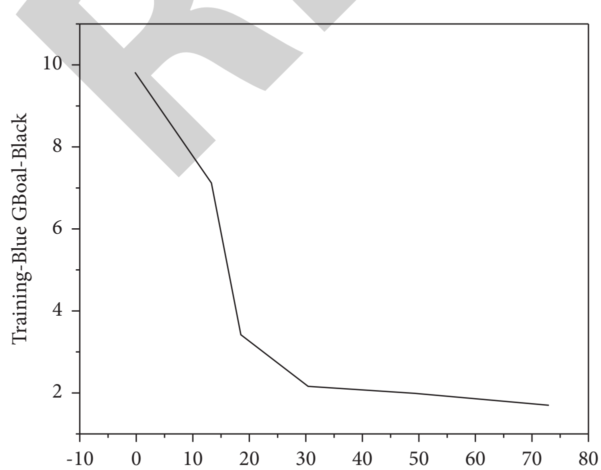

Figure 6: Error curve of BP network net.

It can be seen from Table 5 that the transfer function of the output layer is tansig, the target error is less than 0.00002, and the number of neurons in the hidden layer is 16.

It can be seen from Figures 5 and 6 that tra ingd, tra ingda, and traingdm are poor training functions with long convergence time and large approximation error *E*, while the training functions tra inrp, tra incg, ftra incgp, tra incgb, tra inscg, trainbfg, and tra inoss have average performance, trainlm is a better training function, the convergence time is very short, and the approximation error *E* is very small.

4. Conclusion

First, the characteristics of deep foundation pit engineering and artificial neural network deformation prediction are summarized in detail. Research status of measurement application is evaluated. On the basis of expounding and analyzing the general principle of neural network, artificial neural is summarized. The advantages of artificial neural network are analyzed. Second, a more comprehensive analysis is carried out, and summarized the main factors affecting the deformation of deep foundation pit retaining, and established the deep foundation pit retaining with analytic hierarchy process. Evaluation index system and list of the quantitative standards of the evaluation system are carried out, and then some are picked up. Taking a deep foundation pit as an example, the horizontal displacement data of deep soil with different monitoring dates were obtained from the survey holes. As the training sample data of this paper, the factors affecting the deformation of deep foundation pit retaining are selected based on the construction. The evaluation index system and quantitative standard were assigned values, respectively, which were taken as the input layer neurons of the network to. The horizontal displacements of the soil in different depths were used as the output layer neurons of the network, and Matlab was used along with Toolbox and writing applications with momentum gradient descent was constantly debugging the parameters of the neural network. Finally, 48 network models are determined to predict the horizontal displacement of the soil at the different depths and verified the validity of each model.

Starting from the unpredictability of the BP neural network, the first three data monitoring of the horizontal displacement and stability of the center pit roof of a building structure in Foshan and the horizontal displacement and convenience of the 16-dollar measurement point estimated accordingly at the S03 measurement point are analyzed. First the data was prerecorded, and then the BP neural network for identification, training, and testing was used, and finally short-term determination of horizontal and vertical coefficients were achieved.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest with any financial organizations regarding the material reported in this article.

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