Research on the prediction of foundation settlement by BP neural network

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Abstract. To accurately predict the change of foundation settlement after surcharge preloading treatment, taking the surcharge preloading engineering area of an airport as an example, a foundation settlement prediction model based on BP neural network is constructed. Using two sets of field measured settlement data as the data basis, the model is trained and predicted, and its prediction performance is evaluated. The research results show that BP neural network has good performance in predicting foundation settlement, with a prediction accuracy of more than 98%. It is a relatively ideal prediction method. The research results can provide theoretical support for settlement prediction after foundation treatment.

Keywords: BP neural network; foundation treatment; foundation settlement; settlement prediction.

1. Introduction

In recent years, in order to overcome the limitations of curve fitting methods and obtain higher-quality prediction results, researchers have tried to introduce data-driven methods represented by machine learning, such as Generalized Regression Neural Network (GRNN), Long Short-Term Memory (LSTM) neural network, Random Forest model (RF), and Support Vector Machine (SVM). Among them, the BP neural network model has attracted much attention in prediction and has been widely and successfully applied in various aspects of different fields [1-12].

In the field of civil engineering, many scholars have successfully predicted in aspects such as shield tunneling [13-14], soil strength [15], and rock burst [16] by using the BP neural network. However, in the aspect of surcharge preloading settlement prediction, the BP neural network model has not been fully utilized. Compared with the traditional curve fitting method that can only predict future settlements based on existing settlements, the BP neural network model can reduce errors through powerful computing capabilities and continuous alternation and repetition. In view of this, this paper constructs a BP neural network model to predict the partial surcharge preloading settlement in the reclaimed area of an airport. This paper uses the BP neural network model and traditional curve fitting method to predict and quantitatively evaluate surcharge preloading settlement, in order to provide a theoretical basis for the construction of settlement prediction under foundation engineering treated by surcharge preloading.

2. BP neural network

The BP neural network was studied and designed by Rumelhart, McClelland, etc. [17]. It is a multi-layer feedforward neural network trained according to the error backpropagation algorithm and is one of the most widely used neural network models [18].

The main structure of the BP neural network is composed of an input layer x, a hidden layer h, and an output layer y. The input layer and output layer have only one layer, while the hidden layer can have one or more layers. Each layer is linked by several neurons (nodes). The output value of each node is comprehensively determined by the input value, connection weight, and threshold. This algorithm integrates forward propagation of information and backward propagation of errors. In the forward propagation process, after the input value is processed by the hidden layer, it is output from the output layer. After function operation, the output value is compared with the expected value. If there is an error, further through error backpropagation, starting from the output layer and reversely correcting the connection weights layer by layer to the hidden layer. This process is error backpropagation. Its operation process is the continuous alternation of forward propagation and backward propagation. As the error between the computer operation output value and the real value continues to shrink, the correctness rate of the network's response to the input pattern also continues to rise. This cycle continues until the error meets the conditions, and the data passes through the entire operation process, the model training ends [19]. Figure 1 shows the structure diagram of a typical three-layer BP neural network.

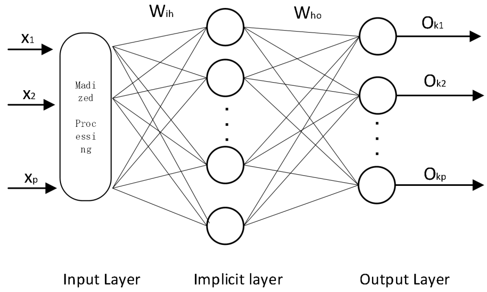


Figure. 1 Typical three-layer BP neural network.

The main calculation process of a typical three-layer BP neural network is as follows:

(1) Network initialization

Assign random numbers within the interval (-1, 1) to the connection weights Wih and Who between layers, and set the error function e. That is, the connection weight between the input layer and the hidden layer: $W_{ih} \in (-1,1)$, and the connection weight between the hidden layer and the output layer: $W_{ho} \in (-1,1)$.

(2) Randomly select training data

Randomly select some corresponding input values and expected output values and put them into the program together, and perform data preprocessing, that is, normalization processing. The input vector:xk=(xk1,xk2,⋯,xkp); expected output vector:dk=(d1,d2,⋯,dp).

(3) Hidden layer calculation

The input values and expected output values after normalization processing become the input vector hi=(hi1,hi2,⋯,hip) of the hidden layer. After being operated by the initialized network model, the output vector ho=(ho1,ho2,⋯,hop) of the hidden layer is obtained.

(4) Output layer output

The hidden layer vector ho is operated to obtain the output layer output vector Ok=(Ok1,Ok2,⋯,Okp). The accuracy of Ok directly affects whether the model needs to perform the next round of error backpropagation to improve the model accuracy.

$$O_k = \frac{1}{2}\sum_{h=1}^{l} h_o W_{ho} + a_j$$

l is the number of nodes in the hidden layer, and aj is the bias from the input layer to the hidden layer.

Error calculation

Calculate the variance E between the output Ok of the output layer and the expected output dk, and judge whether this round of operation meets the error requirements. If not, correct the weights in the next step according to the error backpropagation.

$$E = \frac{1}{2}\sum_{k=1}^{m} (d_k - O_k)^2$$

m is the number of nodes in the output layer

Correct the weights

By updating the weight values and bias values of each node in each layer from the input layer to the hidden layer and from the hidden layer to the output layer, and starting to alternate and repeat from the selection of training data again, the output value of the model gradually approaches the expected output value.

3. Engineering Overview

3.1 Project status

Some areas of an airport are formed by land reclamation. The sand filling area uses offshore sand and some nearshore sand for dredger fill land reclamation. To enhance the bearing capacity of the foundation, methods such as surcharge preloading and vacuum preloading are used for foundation treatment. This paper selects a surcharge preloading foundation treatment area and conducts automatic monitoring on it, and analyzes the monitoring data of surface settlement during the treatment process. The foundation treatment object of this test area is mainly silt soft soil. According to the site investigation results, the rock and soil layers in the field are complex. The upper strata of the site consist of various soil types such as dredger fill sand, silt, clay, granite, etc., and the base is granite intruded in the early stage of Yanshanian period. The detailed geology is shown in Figure 2, and the relevant parameters of the physical and mechanical aspects of its main soil layers are shown in Table 1.

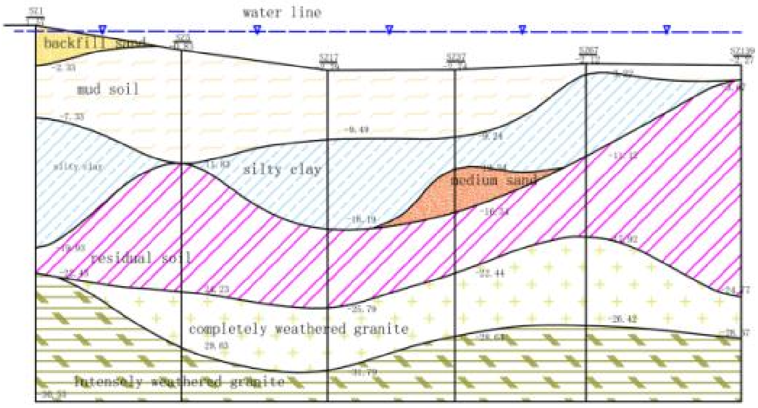


Figure. 2 Typical geological profile of a surcharge preloading soft foundation treatment area

Table 1. Physical and mechanical parameters of each soil layer in the sand filling area

Soil layer name	Unit weight γ (kN/m^3)	Natural void ratio e_0	Compression modulus E_s(MPa)	Cohesion c(kPa)	Angle of internal friction φ(°)	Vertical permeability coefficient K_v(cm/s)	Horizontal permeability coefficient K_h(cm/s)
Dredger fill sand	18.0	0.7	4.0	16	26	3.5×10^{-2}	4.5×10^{-2}
Silt (mixed with sand)	16.3	1.68	1.9	10.2	4.1	1.0×10^{-8}	1.0×10^{-8}
Silty clay	18.6	0.86	4.7	26.7	19.7	4.3×10^{-5}	5.3×10^{-5}
Medium sand	18.2		6.0			1×10^{-2}	2×10^{-2}
Residual soil	18.4	0.82	5.3	26	20.8	6.5×10^{-5}	6.4×10^{-5}

3.2 Data collection

Select the measured settlement and time series of blocks DK1-33 and DK1-35 as the initial training data set. The expected output is settlement. The number of samples of DK1-33 and DK1-35 are 5383 groups and 5475 groups respectively. Due to unexpected situations such as power outages, poor signals or delays encountered during on-site monitoring, interpolation methods are used to supplement the missing data. The training sample data is shown in Table 2 (only some samples are listed to reduce the length).

Table 2. Partial model training samples

DK1-33		DK1-35	
Time	Settlement	Time	Settlement
2022-07-13 19:29:29	-0.610	2022-07-14 09:46:46	-0.019
2022-07-21 12:01:01	-40.433	2022-08-01 02:41:41	-43.149
2022-08-06 05:38:38	-83.881	2022-08-10 13:27:27	-97.968
2022-08-20 03:46:46	-293.176	2022-08-30 19:01:01	-215.361
2022-09-02 21:31:31	-381.984	2022-09-09 05:20:20	-239.122
2022-09-17 22:04:04	-458.989	2022-09-30 06:04:04	-351.231
2022-10-03 08:59:59	-566.806	2022-10-21 17:46:46	-481.566
2022-10-22 01:10:10	-620.176	2022-11-01 05:34:34	-499.382
2022-11-07 03:45:45	-686.266	2022-11-24 21:05:05	-524.266
2022-11-29 22:04:04	-733.452	2022-12-07 16:59:59	-532.201
2022-12-14 12:35:35	-746.022	2022-12-23 02:21:21	-539.222
2023-01-01 05:47:47	-754.188	2023-01-04 05:04:04	-543.675
2023-01-24 18:22:22	-756.883	2023-01-26 21:00:00	-561.889

In order to reduce the adverse effects caused by singular sample data, shorten the training time and reduce errors, the relevant data of the initial data set is uniformly normalized. After normalization, the data is constantly between the [0, 1] region.

4. Data Analysis

4.1 Error analysis

As can be seen from Figure 3, as the number of training increases, the error of settlement prediction at the two measuring points becomes smaller and smaller until it stabilizes after 800 times. Among them, in the interval of 0-100 for the number of training times, the convergence speed of the error is the fastest, indicating that at this stage, the model accelerates the convergence speed of the model through the joint action of forward propagation and backward propagation. As the number of training increases, when the number of training reaches 1000 times and then reaches an extremely high accuracy, the error values are all less than 10^{-5}, indicating that the quality of each parameter obtained by training this model is relatively high and fully meets the prediction requirements.

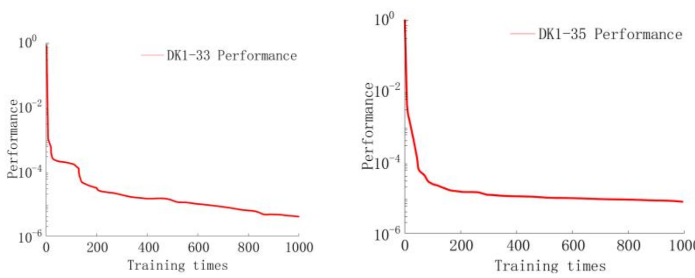
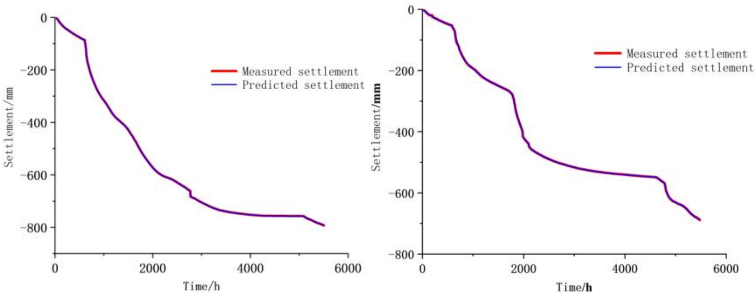


Figure. 3 Error between predicted value and measured value under different training times

4.2 Prediction result

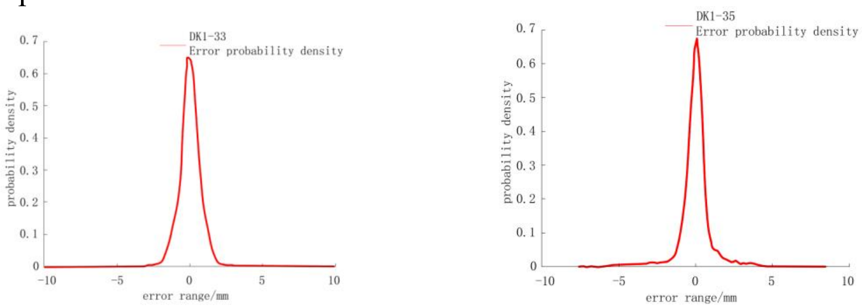
The respective data sets of the two experimental areas are compared, that is, the settlement amount predicted by the trained model and the measured settlement amount ,to judge the superiority and inferiority of model training. Figure 4 shows the comparison of the measured settlement curve and the predicted settlement curve of different test areas. It can be seen that the measured settlement and the predicted settlement are basically in a coincident state, indicating that the prediction effect is extremely good. Taking the absolute error between the predicted value and the measured value equal to 5% as the standard, meeting the standard is correct prediction. Conversely, if the absolute error exceeds 5% of the measured data, it is a prediction error. It can be concluded that the prediction accuracy rate of DK1-33 is 98.87%, and the prediction accuracy rate of DK1-35 is 96.68%. Both sets of data reach more than 96%. Similarly, if the prediction error is equal to 20% as the standard, the prediction accuracy rate of the two sets of data can be as high as more than 99.7%. The above data shows that in terms of predicting settlement, the BP neural network has excellent performance and can generally meet the needs of settlement monitoring on construction sites.



(a) DK1-33 (b) DK1-35

Figure. 4 Comparison of the original data curve and the predicted curve of different test areas

Figure 5 shows the error probability distribution curves of the predicted values and measured values of settlement in different blocks. According to Figure 5, the error probability density distribution diagrams of the two are highly concentrated and are all concentrated within ±3 mm. Among them, the proportion of error probability density within 3 mm in block DK1-33 is 99.56%, and the proportion of error probability density within 3 mm in block DK1-35 is 96.53%. This shows that the BP neural network is suitable for prediction based on field-monitored measured data and can achieve good prediction results.



(a) DK1-33 (b) DK1-35

Figure. 5 Probability density of errors between predicted values and measured values in different test areas

5. Conclusion

Based on the existing foundation treated by surcharge preloading, this paper proposes a method of predicting monitoring data through training by the BP neural network model. Verified by an engineering example of on-site monitoring at an airport, the following conclusions are drawn:

The BP neural network can achieve a very good prediction effect on the measured data of on-site monitoring. Based on an error of 5%, the accuracy rate can reach more than 96%. And when the number of training times is 1000, the model is more stable. In conclusion, the BP neural network is suitable for data prediction of on-site monitoring when the foundation is treated by surcharge preloading.

The surface settlement predicted in this paper is based on the foundation treatment of surcharge preloading and predicts the existing settlement and time. For different foundation treatment methods, theoretically, the BP neural network can also be used to predict the settlement after foundation treatment. How to apply this model to any foundation treatment monitoring project is a question worthy of in-depth study. On the other hand, when considering the combined influence of multiple factors at the same time, the prediction effect and performance of the BP neural network remain to be discussed.

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