Prediction of Bearing Capacity of Composite Foundation of Vibrating Gravel Pile Based on RBF Neural Network

Wei Wei, Haiyan Xie, Xinxin Mao and He Hu

September 29, 2019

Prediction of Bearing Capacity of Composite Foundation of Vibrating Gravel Pile Based on RBF Neural Network

Wei Wei
School of Science
Dalian Maritime University
Dalian, China
weiw0910@163.com

Haiyan Xie
School of Science
Dalian Maritime University
Dalian, China
winteriscoming@sina.com

Xinxin Mao
School of Science
Dalian Maritime University
Dalian, China
mxx0105@126.com

He Hu
School of Science
Dalian Maritime University
Dalian, China
huhe971007@163.com

***Abstract*—Because many factors related to the bearing capacity of composite foundation of vibrating gravel piles interact with each other, it is difficult to accurately calculate the bearing capacity of foundation. At present, the accurate load test method for bearing capacity of composite foundation requires a lot of manpower and resources and takes a long time, so it may not meet the demand of the real-time detection of on-site construction quality and the progress of project. In this paper, a prediction model of bearing capacity of composite foundation based on RBF neural network is established, and it is compared with the same model based on BP neural network. The prediction results of two models show that the method of predicting the bearing capacity of the composite foundation of the vibrating gravel pile based on RBF neural network is more accurate than that based on BP neural network, and it takes less time to compute. Therefore, RBF neural network provides a new artificial intelligence solution for the rapid design of verification for bearing capacity of composite foundation of vibrating gravel pile.**

***Keywords*—bearing capacity of composite foundation,RBF neural network,BP neural network**

I. Introduction

The soft soil foundation treatment reinforcement technology has developed rapidly in recent years, vibrating gravel pile has been widely used in soft soil foundation treatment of major projects at home and abroad. The bearing capacity of the foundation refers to the load that can be withstood by the unit area of the foundation soil. The maximum load that can be withstood by the unit area of the foundation soil is usually called the ultimate load or ultimate bearing capacity [1]. At present, the static load test can be used to calculate the bearing capacity of the foundation by establishing a Gaussian-based prediction model or establishing a prediction model based on wavelet neural network [2][3][4].

The Gaussian process is a newly developed machine learning method, and it has a good adaptability to deal with complex nonlinear problems. By learning a small number of training samples, this process can establish complex nonlinear mapping relations between bearing capacity of CFG(ement Fly-ash Gravel) pile composite foundation and its influencing factors. Applying this process to engineering examples, the results show that the Gaussian process model is scientifically feasible. This model has high prediction accuracy, strong applicability, adaptive algorithm parameters and easy implementation, so it has a good engineering application prospect.

However, because many factors related to the bearing capacity of composite foundation of vibrating gravel piles interact with each other, it is difficult to find an accurate calculation formula of the bearing capacity. The current design of the calculation of the foundation bearing capacity results in a big discrepancy between the design value and the measured value. At present, the accurate load test method for bearing capacity of composite foundation requires a lot of manpower and resources and takes a long time, so it may not meet the demand of the real-time detection of on-site construction quality and of the progress of project.

It is a good method to build a prediction model based on BP network, but the parameters in it cannot be determined easily when creating a network, and the results of the model are only marginally accurate. Therefore, based on the literature [5], the RBF neural network theory is applied to the model construction of the bearing capacity of composite foundation of vibrating gravel pile to predict its bearing capacity. It can be seen that the RBF neural network can provide a more accurate and faster solution of artificial intelligence for the design and detection of bearing capacity of composite foundation and meet the requirements of real-time detection of on-site construction quality and of engineering progress.

II. Principe Overview Of RBF Neural Network

RBF network is a 3-layer forward network with a single hidden layer: 1) Input layer X: It is composed of signal source nodes, which only plays the role of transmitting data information and does not make any changes on the input information. 2) Hidden layer H: The number of nodes depends on the specific needs. The kernel function (action function) of neurons in the hidden layer is a Gaussian function that performs spatial mapping transformation of input information. 3) Output layer Y: It responds to the input mode. The action function of neurons in the output layer is a linear function. The information outputted by neurons in the hidden layer is linearly weighted. The linearly weighted information is regarded as the output of the whole neural network[6]. In essence, the RBF network can convert the input data from the nonlinear state to linear state, making the data linearly separable [7].

The Gaussian function is usually chosen as the radial basis function,which is

$$\phi(\|x-x^n\|)=e^{-\frac{\|x-x^n\|^2}{2\sigma^2}}\ , \qquad (1)$$

here x^n is the center of the radial basis function.Three layers of RBF network can be defined as follows: the input layer is the connection between the network and the external environment,the hidden layer is the transformation between the input space and the hidden space,and the output layer is the response of the network.The Gaussian function ϕ is widely interpreted in the statistical literature as the kernel,so the RBF network is a nuclear method (model) similar to nuclear regression [8].

If there is only one output layer unit, and w_n is the weight of the output layer,the mapping relationship is

$$f(x) = \sum_{n=1}^{N} w_n \phi(\|x - x^n\|). \quad (2)$$

RBF neural network consists of basis function center of hidden layer neurons C, center width D and hidden layer to output layer weight w_{kj} . If they are not selected properly, the processing capacity of RBF neural network will be greatly affected. The purpose of RBF neural network training is to determine these three parameters. The training of RBF neural network usually adopts the gradient descent method to adjust the parameters of center, width and weight to the optimal value by learning . The iterative formula is

$$w_{kj} = w_{kj}(t-1) - \eta \frac{\partial E}{\partial w_{kj}(t-1)} + \alpha[w_{kj}(t-1) - w_{kj}(t-2)], \quad (3)$$

$$c_{kj}(t) = c_{kj}(t-1) - \eta \frac{\partial E}{\partial c_{kj}(t-1)} + \alpha[c_{kj}(t-1) - c_{kj}(t-2)], \quad (4)$$

$$d_{kj}(t) = d_{kj}(t-1) - \eta \frac{\partial E}{\partial d_{kj}(t-1)} + \alpha[d_{kj}(t-1) - d_{kj}(t-2)], \quad (5)$$

here $w_{kj}(t)$ is the adjustment weight between the kth output neuron and the jth hidden layer neuron in the tth iteration calculation; $c_{ji}(t)$ is the center component of the jth hidden layer neuron for the ith input neuron in the tth iteration; $d_{ij}(t)$ is the width corresponding to the center $c_{ji}(t)$; η is the learning rate; E is the evaluation function of RBF neural network, and its expression is

$$E = \frac{1}{2}\sum_{k=1}^{N}\sum_{j=1}^{\eta}(y_{kj} - O_{kj})^2, \quad (6)$$

here O_{kj} is the target output value of the kth output unit when the first sample is input; y_{kj} is the real output value of the kth output unit when the first sample is input. Compared with BP neural network, RBF neural network is a local approximation network. It has good generalization ability, simple learning rules, strong memory ability and robustness. However, BP network is a global approximation network with a slow convergence rate in the learning process. Therefore, RBF network is selected to predict the bearing capacity of composite foundation of vibrating gravel pile.

The RBF neural network has a simple structure, simple training and fast learning convergence, and can approximate any nonlinear function. Therefore, the RBF network has a wide range of applications such as time series analysis, pattern recognition, nonlinear control and image processing. A typical RBF neural network model is shown in Fig. 1.

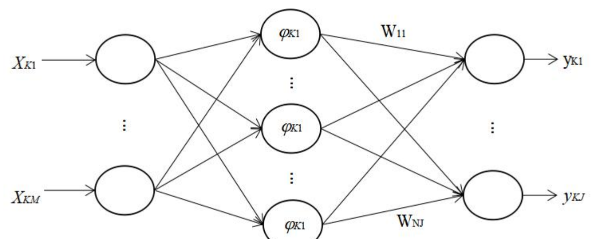

Fig. 1. Typical RBF neural network model

III. Construction Of RBF Neural Network Model

A. Network Structure

Applying the RBF network model to predict the bearing capacity of composite foundation of vibrating gravel pile requires a network training process. The essence of training is to converge the free parameters of the network to a desired level, that is, the specific implementation of the RBF network algorithm. In this paper, the neural network toolbox module function of Matlab software is used to realize this algorithm, and a prediction model of network training based on the main influencing factors of the bearing capacity of composite foundation of vibrating gravel pile and of the measured bearing capacity of foundation is established [9-11].

The main influencing factors are the same as those mentioned in the literature [5], namely the diameter of the pile, the effective length of the pile, the time of the vibration retention, the dense current, the filling factor, the moisture content, the natural density, the pore ratio, the replacement rate, and the thickness of the cushion [12]. In this paper, the 10 main influencing factors of the bearing capacity of composite foundation of vibrating gravel pile are taken as input, and the characteristic value of the measured bearing capacity of composite foundation is taken as the output to construct the RBF network model.Implicit layer of N basis functions

B. Learning Training Samples

In this paper, the data in [5] will be used, in which the first 20 sets of data are used as learning samples and the last 5 sets of data are used as promotional prediction samples. The data that is not normalized in learning training sample in the training model is shown in Table I.

IV. Learning and Analysis of RBF Network Model

A. Input Data

The neural network toolbox module of Matlab software writes the program according to the RBF network algorithm flow, and learns the data of the first 20 training samples in Table I. In order to eliminate a big difference in the value of input data of the training samples that will make convergence speed of the RBF neural network too slow and the generalization ability of the network reduced, the training sample data in Table 1 needs to be normalized. The standard normalization formula is

$$X' = \frac{X_i - X_{min}}{X_{max} - X_{min}}, \quad (7)$$

here X_i is the measured value of the input/output vector in the sample data; X_{max} is the maximum value of the input/output vector in the sample data; X_{min} is the minimum value of the input/output vector in the sample data.

The program we use to normalize P and T respectively according to the row is

[pn, minp, maxp, tn, mint, maxt] = prenmx(p, t).

TABLE I. TRAINING SAMPLE DATA (NORMALIZED)

(M:Measured characteristic value of bearing capacity of composite foundation /kPa)

Serial Number	Input value of training sample										M
	Diameter /m	Effective pile length /m	Retention time /s	dense current /A	filling factor	Moisture content /%	natural density /(g/cm3)	pore ratio	Replacement rate	cushion thickness /m	
1	0.50	9.1	20	79	1.35	32.1	1.93	0.827	0.156	0.51	268
2	0.49	9.0	15	77	1.36	30.8	2.02	0.735	0.150	0.48	294
3	0.49	9.0	16	78	1.34	28.7	2.11	0.635	0.162	0.50	276
4	0.51	8.9	15	75	1.32	29.5	1.98	0.753	0.157	0.49	285
5	0.48	8.9	14	76	1.38	33.2	1.99	0.801	0.152	0.50	291
6	0.19	8.8	16	79	1.69	30.4	2.07	0.688	0.154	0.49	270
7	0.52	8.9	17	80	1.34	27.8	2.14	0.600	0.148	0.52	304
8	0.49	9.1	18	73	1.37	35.3	2.05	0.769	0.156	0.51	295
9	0.51	9.1	18	77	1.31	32.6	2.07	0.717	0.153	0.49	289
10	0.53	9.1	19	76	1.30	27.8	2.12	0.616	0.155	0.52	292
11	0.52	9.0	20	72	1.38	29.2	1.97	0.758	0.161	0.55	287
12	0.51	8.9	17	71	1.38	28.6	2.01	0.734	0.147	0.52	278
13	0.50	8.9	16	74	1.36	31.4	2.17	0.623	0.156	0.53	275
14	0.48	8.9	18	76	1.38	27.8	2.12	0.616	0.153	0.52	288
15	0.49	8.9	17	77	1.38	30.7	2.06	0.700	0.168	0.51	311
16	0.50	9.0	15	76	1.37	27.6	2.12	0.613	0.166	0.49	305
17	0.50	9.0	18	76	1.36	25.5	2.07	0.625	0.153	0.49	316
18	0.52	9.2	17	78	1.36	29.4	1.99	0.749	0.158	0.52	286
19	0.52	9.1	16	79	1.37	31.3	1.95	0.805	0.162	0.51	283
20	0.51	9.1	14	74	1.39	26.5	1.92	0.766	0.157	0.53	277
21	0.49	9.1	19	73	1.33	29.8	1.98	0.770	0.163	0.48	296
22	0.50	9.0	18	75	1.38	30.6	1.97	0.777	0.169	0.50	285
23	0.51	8.9	17	76	1.37	29.5	2.08	0.762	0.175	0.49	279
24	0.49	9.1	16	77	1.35	28.7	2.14	0.751	0.172	0.51	288
25	0.49	9.0	17	79	1.39	31.5	1.96	0.789	0.166	0.51	290

B. Distribution Density (Spread) σ Selection.

We use Matlab R2016a to train the RBF network model. The first 20 samples were used as training samples for the RBF network to establish an RBF network model. The main code used in the program is

net=newrb(pN,tN,0,1.0,20,1).

That is to establish an RBF network with a target error of 0, a distribution density of 1.0, a maximum number of hidden layer neurons of 20, and each time adding 1 neuron.

Different distribution densities σ of the radial basis function will lead to different RBF network models. If the setting of σ is too large, a large number of neurons in the hidden layer are needed to satisfy the rapid change of the hidden layer function; but if the setting of σ is too small, it requires a lot of neurons in the hidden layer to satisfy the slow change of the hidden layer function. In this case, the performance of the network is very bad.,so we will set σ here to 0.4, 0.6, 0.8, 1.0 and 1.2 to see the difference in network accuracy. The relative errors between the predictive values and the true values of the last five sets of the RBF network model with different values of σ are shown in Table II.

TABLE II. RELATIVE ERROR AT DIFFERENT DISTRIBUTION DENSITIES

Serial number	spread=0.4	spread=0.6	spread=0.8	spread=1.0	spread=1.2
1	-0.0337	-0.0449	-0.0171	-0.0179	-0.0246
2	0.0036	-0.0073	0.0141	0.0050	0.0025
3	0.0252	0.0136	0.0455	0.0513	0.0554
4	-0.0069	-0.0184	0.0096	0.0054	-0.0106
5	-0.0137	-0.0252	0.0030	0.0004	-0.0100
Absolute value mean	0.0166	0.0219	0.0179	0.0149	0.0188

By comparing and analyzing Table II, it is found that we can obtain the minimum value of relative error when the distribution density σ is 1.0. Therefore, we establish an RBF network with a target error of 0, a distribution density σ of 1.0, a maximum number of neurons in hidden layer of 20, and each time adding 1 neuron.

C. Comparison with BP Network Results

The choice of hidden nodes has not been unified analytically so far when establishing a BP neural network. In order to reduce the learning time and system complexity and to determine the number of hidden units with the best result when the sample set and the convergence criteria are the same, the number of hidden nodes is often determined by experiments. The following are the common formulas of the predecessors: assume that there are n input neurons, m output neurons and n_1 neurons of the hidden layer. Then n_1 can be calculated by

$$n_1 = 2n+1, \tag{8}$$

$$n_1 = \log_2 n \tag{9}$$

or

$$n_1 = \sqrt{n+m}+a, \tag{10}$$

here a is a constant between 1 and 10.

By putting in enough hidden units first, and then gradually removing the hidden units that are not working by learning, until the non-shrinkable, we can also obtain n_1.

By using the above common formulas to determine the number of hidden units in the BP network, the number of hidden units can be selected as 11, 3, 4, 6, and 8 to observe their influences on network accuracy. The relative error between the predictive value and the true value of the last five sets of samples of the BP network model with different values of number of hidden units is shown in Table III.

TABLE III. RELATIVE ERROR OF DIFFERENT HIDDEN UNITS IN BP NETWORK

Serial number	3	4	6	8	11
1	-0.0206	-0.0310	-0.0275	-0.0306	0.0453
2	0.0172	0.0591	0.0356	0.0029	-0.0351
3	0.0391	0.0812	0.0578	0.0258	0.1260
4	0.0458	0.0291	0.0248	-0.0511	-0.0302
5	-0.0049	-0.0109	-0.0123	0.0024	-0.0341
Absolute value mean	0.0255	0.0981	0.0316	0.0226	0.0541

According to the analysis of Table III, the relative error obtains the minimum value with 8 hidden units. The BP neural network is thus established. The main procedure code is

net=newff(minmax(P),[8,1],{'tansig','purelin'},'trainl').

That is to establish a BP neural network with the 8 hidden units, the *tansig* transfer function of hidden layer, the *purelin* transfer function of output layer, and the *trainlm* weight learning function.

Therefore, we can compare the prediction results of the RBF neural network with those BP neural network. The prediction results are shown in Table IV.

TABLE IV. COMPARISON OF RBF AND BP NETWORK PREDICTION RESULTS

Serial numbers	Measured value/kPA	Predictive value/kPA	Relative error/%
1	296	290.7135	-0.0179
2	285	286.4282	0.0050
3	279	293.3110	0.0513
4	288	289.5465	0.0054
5	290	290.1134	0.0004

It can be seen from the analysis of Table IV that the relative error of prediction results using the RBF network is smaller than that of the BP network, and using RBF network takes less time to calculate. Therefore, the RBF neural network has a better predictive effect on the bearing capacity of composite foundation of vibrating gravel piles.

D. Analysis of RBF Neural Network Results

Using the established RBF neural network model, the last five sets of sample data in Table 1 are input to predict the bearing capacity of composite foundation of vibrating gravel pile. The comparison between the predictive values and the measured values is shown in Table V.

TABLE V. COMPARISON OF PREDICTIVE AND MEASURED VALUES OF RBF NETWORK SAMP

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Absolute value mean**	**time /s**
Relative error of BP network prediction /%	-0.0306	0.0029	0.0258	-0.0511	0.0024	0.0226	2.9130
Relative error of RBF network prediction /%	-0.0197	0.0050	0.0513	0.0054	0.0004	0.0149	1.6710

According to Table V, the maximum relative error between the predicted values obtained by the RBF neural network and the measured values is 0.0513%. The model has high precision and can meet the requirements of engineering design, indicating that using RBF neural network to predict bearing capacity of composite foundation of vibrating gravel pile is completely feasible.

V. CONCLUSION

In this paper, a prediction model of bearing capacity of composite foundation based on RBF neural network is established. The prediction results of the model show that this model has higher prediction accuracy than the model based on BP network and fully meets the engineering requirements. It is feasible and more suitable to use the RBF neural network to predict the bearing capacity of composite foundation of vibrating gravel pile. Using RBF network provides a new artificial intelligence solution for the rapid design of verification for the bearing capacity of composite foundation of vibrating gravel pile.

ACKNOWLEDGMENT

This work was financially supported by the Fundamental Research Funds for the Central Universities under grant 3132018226, 3132019319 and National Natural Science Foundation of China under grants 51509030 and 61803065.

REFERENCES

[1] Fang Yushu. Problems in the use of eigenvalue word, definitions and reasons for the bearing capacity of foundations[J]. Chongqing Architecture, 2016, 15(06): 31-33.

[2] Su Guoshao, Zhang Yan, Yan Liubin. Gaussian process model for predicting bearing capacity of CFG pile composite foundation[J]. Computer Engineering and Applications,2011,47(04):236-238.

[3] Li Wanqing, Yan Guanyong, Meng Wenqing, Shi Huawang. Prediction of bearing capacity of CFG pile composite foundation based on wavelet neural network[J]. Journal of Hebei University of Engineering(Natural Science Edition), 2011,28(04):1-5.

[4] Wang Zhongwan. Prediction of bearing capacity of CFG pile composite foundation based on HPSO-SVM [D]. Liaoning University of Engineering and Technology, 2018.

[5] Qu Jianwei, Cai Peng. Application of BP Neural Network in Prediction of Bearing Capacity of Composite Foundation of Vibrating Gravel Pile [J]. Subgrade Engineering, 2017(04): 200-203.

[6] Shao Guangcheng, Zhang Kun, Wang Zhiyu, Wang Xiaojun, Lu Jia. Prediction model of groundwater depth based on IABC-RBF neural network[J/OL]. Journal of Zhejiang University (Engineering Science), 2019(07): 1-8.

[7] Wang Yu, Zhou Jianyong. Research on Forecasting of Ningbo Metro Fans and on Advertising Operation Mode Based on RBF Neural Network[J]. Logistics Science and Technology, 2019, 42(05): 87-91.

[8] Li Ming.Potential Profile Modeling Method Based on Gaussian Radial Basis Function Network[J]. Modern Computer(Professional Edition), 2018(08):14-16.

[9] Deng Mingchun, Li Gang. Comparison and Analysis of Several Typical Neural Network Structures[J]. Information Technology and Informatization, 2008(6): 29-31

[10] Xue Xinhua, Wei Yongxing. Prediction of bearing capacity of CFG pile composite foundation based on ANFIS[J]. Journal of Railway Engineering, 2010, 27(6): 42-47.

[11] Cheng Xing, Liu Liliang, Tang Guoping, Sun Lijun. Evaluation of Soil Corrosion Rating of Buried Steel Pipeline Based on MATLAB Neural Network[J]. China Chemical Equipment,2018,20(04):41-48.

[12] Gu Haijiao. Application of Vibrating Gravel Piles in Soft Soil Foundation Reinforcement[J]. Subgrade Engineering, 2010, 28(2): 48-51.