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

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**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, which 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 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 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 error 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 model has a low accuracy of results. 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, and the neural network is used 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, which can meet the requirements of real-time detection of on-site construction quality and of engineering progress.

## II. PRINCIPLE 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, and the information outputted by neurons in the hidden layer is linearly weighted and output as the output result 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

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

or

$$\phi(\|x - t\|) = e^{-\frac{\|x - t\|^2}{2\sigma^2}} \quad (2)$$

If there is only one output layer unit, and  $w_n$  is the

weight of the output layer, the mapping relationship is

$$f(x) = \sum_{n=1}^N w_n \phi(\|x - x^n\|). \quad (3)$$

In RBF neural network, the weight from the input layer to the hidden layer is always 1, without learning, and the weight from the hidden layer to the output layer is adjustable. Usually, the supervised learning method is used for training. The training can use the least square method [8], or the error correction weight algorithm, that is,  $\delta$ —rule training. If  $\eta$  is a constant and  $d$  is the ideal output, the formula for modifying the weight is

$$W_i(n+1) = W_i(n) + \eta \sum_{k=1}^n (d_k - y_k) \cdot \phi(\|x - t\|). \quad (4)$$

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.

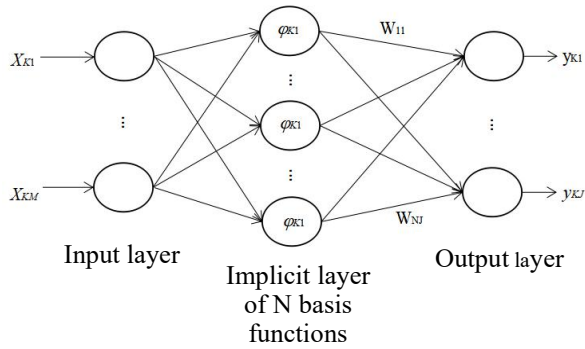


Fig. 1. Typical RBF neural network model

TABLE I. TRAINING SAMPLE DATA (UNNORMALIZED)

(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/cm <sup>3</sup> )	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

### 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.

#### 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 unnormalized data in learning training sample in the training model is shown in Table I.

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/cm <sup>3</sup> )	pore ratio	Replacement rate	cushion thickness /m	
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

#### 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 prevent big difference in the value of input data of the training samples, thus making 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

$$X' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (5)$$

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 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  $\sigma$  is 1.0. Therefore, we establish an RBF network with a target error of 0, a distribution density  $\sigma$  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 obtain 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

##### B. Distribution Density (Spread) $\sigma$ 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  $\sigma$  of the radial basis function will lead to different RBF network models. If the setting of  $\sigma$  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  $\sigma$  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  $\sigma$  here to 0.4, 0.6, 0.8, 1.0 and 1.2 to see how they affect the network accuracy. The relative errors between the predictive values and the true values of the last five sets of samples of the RBF network model with different values of  $\sigma$  are shown in Table II.

the experience of predecessors and own 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

$$n_1 = 2n + 1, \quad (6)$$

$$n_1 = \log_2 n \quad (7)$$

or

$$n_1 = \sqrt{n+m} + a, \quad (8)$$

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 is

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

That is to establish a BP neural network with the

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. This provides a new artificial intelligence solution for the rapid design of verification for the bearing capacity of composite foundation of vibrating gravel pile.

## ACKNOWLEDGMENT

number of hidden units of 8, the transfer functions of hidden layer and output layer of tansig and purein respectively, and the weight learning function of trainlm.

Therefore, we can compare the prediction results of the RBF neural network and the 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 it 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.

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