Prediction Method of Characteristic Value of Foundation Bearing Capacity Based on Machine Learning Algorithm

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Abstract

In this paper, a prediction method of characteristic value of foundation bearing capacity based on machine learning algorithm is proposed. Firstly, the influencing factors of foundation bearing capacity are analyzed, and then the prediction parameters of foundation pressure strength and foundation strength are calculated. The prediction error was obtained by comparing the difference between the predicted value and the actual intensity, which was used as the optimization value to improve the accuracy of the prediction results of the characteristic values of the subsequent bearing capacity. Then, by calculating the characteristic parameters of foundation mechanics and establishing the boundary conditions of foundation bearing capacity, the

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mathematical model of foundation bearing capacity is constructed, so as to complete the analysis of the mechanical characteristics of foundation bearing capacity. The analysis results and foundation strength prediction parameters are input into the RBF neural network model. On the basis of optimizing parameter weights by the improved Relief algorithm, the prediction results of characteristic values of foundation bearing capacity are obtained by using the hyperparameters of THE RBF neural network algorithm. Experimental results show that the prediction results of this method are always in a controllable range, and the prediction error rate is between 1.21% and 1.35%, and the prediction time is between 30.1 min and 32.5 min, indicating that this method has high prediction accuracy and timeliness.

Keywords: Machine learning, RBF neural network, improved relief algorithm, foundation bearing capacity, characteristic value, prediction.

1 Introduction

At a time when construction projects are booming, the research of foundation engineering has become a hot topic. Among them, the prediction of foundation bearing capacity is the most popular research topic in foundation engineering. Under the influence of different geological conditions, the strength of different strata and rock mass structure is different, and the load force reflected is different [1, 2].

There are many factors that can cause the bearing capacity of foundation to change, including the physical properties of soil, the specifications of superstructure, the depth of pile foundation and so on. Due to the exploration in the early stage of construction, the design parameters of related buildings could not be determined [3, 4]. Therefore, it is necessary to analyze the bearing capacity of foundation according to the soil structure and its mechanical properties.

With the increase of complexity and technical difficulty of construction engineering, the prediction of foundation bearing capacity is also put forward higher requirements. The characteristic value of foundation bearing capacity is the pressure value corresponding to the foundation soil pressure deformation curve within the deformation range, in other words, the maximum pressure that the foundation can bear [5]. A characteristic value estimation and prediction method of foundation bearing capacity is designed for deep foundation pit geotechnical engineering in reference [6]. The method firstly analyzes the load coefficient of deep foundation pit by determining the pressure value of groundwater on the foundation, then calculates the displacement of deep foundation pit in three-dimensional coordinates, and takes the calculation result as the final estimation value. A method for determining foundation bearing capacity based on artificial intelligence is designed in reference [7]. The method uses BP neural network to analyze the change of foundation bearing capacity, and constructs training set and test set, and obtains the calculation result of characteristic value of foundation bearing capacity quickly through iterative training.

However, it is found in practical application that the above traditional prediction methods have a certain increase in the prediction error rate and prediction time. Therefore, aiming at the shortcomings of traditional methods, this study designed a new prediction method of characteristic value of foundation bearing capacity based on machine learning algorithm.

2 Analysis of Influencing Factors of Foundation Bearing Capacity

This study analyzes the influencing factors of foundation bearing capacity from five aspects: pore ratio, liquid index, liquid limit, cohesion and compression modulus.

(a) Porosity ratio. Porosity ratio refers to the ratio of pore volume to solid particle volume in foundation soil [8, 9]. Suppose K represents the porosity ratio, which can be calculated from the volume of particles and the volume of soil particle gap:

$$K = \frac{V_v}{V_S} \tag{1}$$

Where, V_v represents the volume of particle itself, and V_s represents the volume of particle gap in foundation soil. There is a close relationship between void ratio and liquid index, which can directly change the bearing capacity of foundation.

(b) Liquid index. Liquid index is an important index to measure the hardness of soil, also known as consistency index [10]. It is represented by Y in this study, and its calculation process is as follows:

$$Y = \frac{S - S_P}{I_P} \tag{2}$$

Where, S represents water content in foundation soil, S_P represents plasticity index, and I_P represents plasticity parameter.

(c) Liquid limit. The liquid limit of foundation refers to the limit water content between plastic state and flowing state of foundation soil [11, 12]. In other words, the liquid limit describes the water content of a plastic soil that changes to a fluid form as the water content increases. When the soil moisture content exceeds the limit, the soil is in a flowing state and the joint force between soil particles decreases rapidly [13–15].

(d) Cohesion. In molecular state, the forces generated by physical and chemical reactions between soil particles are called cohesive forces. The ultimate shear stress of foundation soil under the condition of resisting external force is called shear strength [16].

Cohesion generally takes two forms, the first is true cohesion and the other is apparent cohesion. True cohesion refers to the shear strength generated by the change of foundation soil structure in cohesive soil, and its value is generally controlled at 5 kPa–10 kPa. The apparent cohesion is greatly affected by the moisture content in the soil. In dry soil, the value of cohesion is about 50 kPa–100 kPa. However, when it meets water, the cohesion rapidly decreases to a minimum of 5 kPa–20 kPa, so cohesion is closely related to the porosity ratio and liquid index in the soil.

(e) Compression modulus. In general, the slope of the initial position of the stress-strain curve is regarded as the modulus of compression. This factor can directly affect the compressibility of foundation soil and can also be used to judge the settlement of foundation [17, 18].

3 Calculation of Foundation Pressure Strength and Strength Prediction Parameters

The foundation pressure strength and strength parameters are calculated in this study as the auxiliary content of subsequent analysis.

According to the above analysis results of the factors affecting the bearing capacity of foundation, the pressure strength of foundation is calculated according to the Hoek-Brown strength criterion. Considering that the pressure intensity calculated by the original Hoek-Brown strength criterion is larger than the actual pressure intensity [19, 20], In order to avoid the influence of error values on the calculation results, generalized parameters are introduced into the calculation of Hoek-Brown strength criterion during the calculation process, and the following calculation formula is obtained:

$$\sigma_{\max} = \sigma_{\min} + \left(\frac{m\sigma_{\min}}{\sigma_c} \times s\right)^{\partial} \tag{3}$$

In the formula, m represents the structural empirical coefficient of ground base; s and ∂ represent the characteristic parameters of geological conditions; σ_c represents the uniaxial compressive strength of rock structure of ground base; $\sigma_{\max}$ and $\sigma_{\min}$ represent the maximum and minimum stress values of ground base respectively. The corresponding values of m, s and ∂ can be calculated by the following formula:

(a) Under the condition that the formation rock structure does not change, the bearing conditions of the foundation can be expressed as follows:

$$\begin{cases} m = m_i \exp\left(\dfrac{G-98}{16}\right)^{\partial} \\ s = \exp\left(\dfrac{G-98}{7}\right) \\ \partial = \dfrac{1}{2} + \dfrac{1}{6}\exp\left(-\dfrac{G}{15}\right) \end{cases} \tag{4}$$

(b) When the rock structure of the ground layer is disturbed by multiple factors, the bearing conditions of the base layer can be expressed as follows:

$$\begin{cases} m = m_i \exp\left(\dfrac{G-98}{16-12D}\right)^{\partial} \\ s = \exp\left(\dfrac{G-100}{7-2D}\right) \end{cases} \tag{5}$$

Where, G is the strength index of the ground base, D is the comprehensive disturbance factor, the value range is generally 0–1 [21], m_i represents the m value of the ground base corresponding to the completed rock structure, and ∂ value is consistent with the ground base structure under the condition that it is not affected by disturbance factors.

Through calculation, it is found that the stress intensity of ground base is different under different geological conditions, and the overall change of its numerical value accords with nonlinear characteristics [22, 23]. Therefore, given the known formation rock structural parameters m, s, ∂ and the uniaxial compressive strength σ_c of the rock structure in the base layer, a group of $\sigma_{\min}$ coefficients are randomly selected and the related number $\sigma_{\max}$ can be obtained through calculation. According to the Mohr-Coulomb strength criterion, the relational function formula can be obtained:

$$\sigma_{\max} = \frac{1+\sin_m}{1-\sin\phi_m}\sigma_{\min} + \frac{2c_m\cos\phi_m}{1-\sin\phi_m} \tag{6}$$

Where, c_m and φ_m respectively represent the cohesion of foundation structure and friction Angle of structural layer corresponding to the equivalent shear strength index of the base under the action of stress. The calculation process of the two is as follows:

$$\phi_m = \arcsin\left[\frac{6\partial m(s+m\psi)^{\partial-1}}{2(1+\partial)+6\partial m(s+m\psi)}\right] \tag{7}$$

$$c_m = \frac{\sigma_c\left[(1+2\partial)s+(1-\partial)m\psi\right](s+m\psi)}{(1+\partial)\sqrt{1+6\partial m(s+m\psi)^{a-1}}} \tag{8}$$

Where, ψ represents the ratio of the maximum coefficient value of the ground base under the confining stress to the uniaxial compressive strength. Thus, the foundation pressure intensity can be calculated as follows:

$$P = \frac{\phi_m}{\gamma H}\times\frac{\sigma_{\max}}{\sigma_c} \tag{9}$$

Where, γ represents the bulk density of foundation structure, and H represents the inclined Angle of foundation under stress.

According to the foundation pressure strength obtained above, the predicted parameters of foundation strength are calculated. The known parameters are converted into Mohr-Coulomb intensity parameters during calculation. Considering that the known parameters are based on nonlinear criteria, the converted strength parameters cannot be specified to a constant quantity, and the value of the strength parameters will change according to the stress under positive conditions [24]. Therefore, the coefficient values corresponding to the strength parameters are processed according to the instantaneous effect, and the coefficient τ, which usually points to a constant, is defined as the Mohr-Coulomb strength parameter, and its calculation formula is:

$$\begin{cases} \tau = f\times\theta\times\dfrac{\cot\theta_i-\cos\theta_i}{6} \\ \theta = \dfrac{1}{3}\left(\dfrac{\pi}{2}+\arctan\left(\dfrac{1}{\sqrt{h+1}}\right)\right) \end{cases} \tag{10}$$

Where, τ represents the instantaneous shear stress received by the foundation, σ' represents the positive stress coefficient of the foundation, $\theta_i = \arctan(\frac{1}{2h\cos^2\theta - 1})^{1/2}$ represents the internal friction Angle of the instantaneous stress of the foundation, $f = \tau - \sigma' \tan\theta_i$ represents the instantaneous structural cohesion of the foundation, and $h = 1 + \frac{14(m\sigma' + s\sigma_c)}{3m^2\sigma_c}$ represents the shear error between the predicted value and the actual value. The τ value obtained by formula (10) is the prediction parameter of foundation strength.

4 Analysis of Mechanical Characteristics of Foundation Bearing Capacity

4.1 Calculation of Mechanical Characteristic Parameters of Foundation

In the process of calculating foundation bearing capacity, it is usually necessary to consider the interaction of soil and the comprehensive condition of foundation, which is a very complicated problem [25]. Therefore, when analyzing the bearing capacity of foundation, the mechanical characteristic parameters of foundation soil are firstly calculated. When analyzing the properties of soil, coulomb criterion can be used to establish a concept diagram of stress relationship, as shown in Figure 1.

The three-dimensional stress changes can be converted into two-dimensional images to obtain the concept diagram as shown in Figure 1.

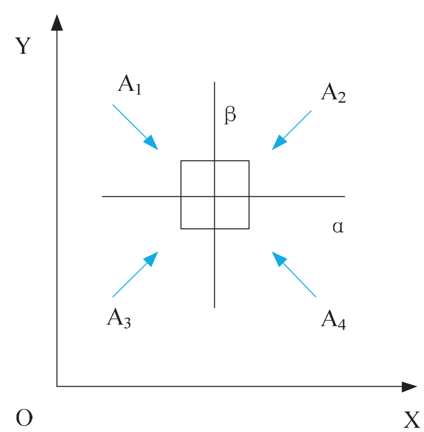


Figure 1 Conceptual diagram of stress relation of foundation soil.

In Figure 1, A_1, A_2, A_3 and A_4 represent the forces applied to the foundation soil; α and β represent the angles of the four forces and the particles of the foundation soil.

According to Figure 1, the radius function of average stress of foundation soil can be obtained as follows:

$$F = A_1 \times A_2 \cos\alpha + A_3 \times A_4 \cos\beta \tag{11}$$

In the formula, F represents the radius of the foundation soil to be calculated under the current state. By associating the four forces, the mechanical static differential equation of foundation can be obtained as follows:

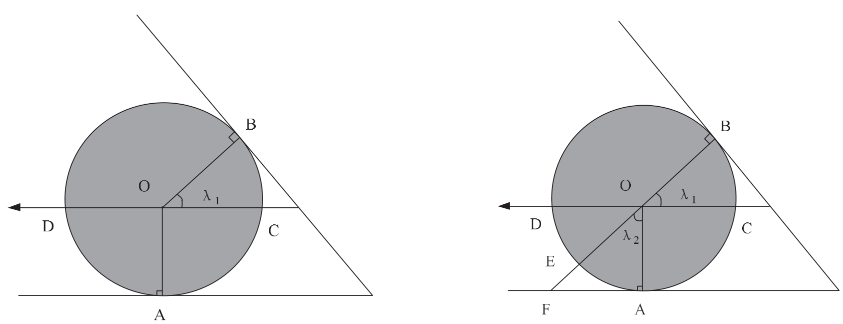
$$\begin{cases} \dfrac{\partial\theta_{A_1}}{\partial\alpha} + \dfrac{\partial\theta_{A_2}}{\partial\beta} = 0 \\ \dfrac{\partial\theta_{A_3}}{\partial\alpha} + \dfrac{\partial\theta_{A_4}}{\partial\beta} = 0 \end{cases} \tag{12}$$

4.2 Boundary Conditions of Foundation Bearing Capacity are Established

When establishing boundary conditions of foundation bearing capacity, it is necessary to solve basic stress conditions of foundation through boundary value domain, and soil parameters on both sides are shown in Figure 2.

In the mechanical properties of both sides of the foundation as shown in Figure 2, the soil contact equation of smooth surface can be established:

$$f_1 = c_1 + 2\cos\lambda_1 + \frac{r}{\sin\lambda_1} \tag{13}$$



(a) Smooth surface (b) Rough surfaces

Figure 2 Mechanical properties of soil on both sides of foundation.

Where, c_1 represents the circumference length of the standby ring in the smooth surface of foundation soil, r represents the radius length of the standby ring in the smooth surface of foundation soil, and λ_1 represents the Angle of $\angle BOC$ in the figure. In the rough surface, the equation is as follows:

$$f_2 = c_2 + 2\cos\lambda_1 + \frac{r}{\sin\lambda_2} \tag{14}$$

Where, c_2 represents the circumference of the spare ring in the rough surface of soil, and λ_2 represents the Angle of $\angle AOF$ in the figure. Through these two kinds of foundation bearing capacity characteristics, the difference solution can be directly worked out, and then the rigid condition foundation between different rock and soil stresses can be obtained. After multi-point crossing, the boundary conditions of foundation bearing capacity can be directly obtained as follows:

$$U = f_1 + f_2 \tag{15}$$

4.3 Construct the Mathematical Model of Foundation Bearing Capacity

In the process of constructing the mathematical model of foundation bearing capacity, the stress distribution in foundation soil is firstly obtained through the contact conditions of foundation, and the process is as follows:

$$\begin{cases} A_x = (x_1 + x_2)\sin\left(\dfrac{y_1 - y_2}{2} + \theta_1\right) \\ A_y = (x_3 + x_4)\cos\left(\dfrac{y_3 - y_4}{2} + \theta_2\right) \end{cases} \tag{16}$$

Where, A_x represents the coordinate value of foundation bearing capacity in the plane coordinate system x axis, A_y represents the coordinate value of foundation bearing capacity in the plane coordinate system y axis, x_1 and x_2 represent the x-axis slip variable characteristic coordinates composed of soil characteristics in the smooth surface, y_1 and y_2 represent the y-axis slip variable characteristic coordinates composed of soil characteristics in the smooth surface, x_3 and x_4 represent the x-axis slip variable characteristic coordinates composed of soil characteristics in the rough surface, while y_3 and y_4 represent the y-axis slip variable characteristic coordinates composed of soil characteristics in the smooth surface, θ_1 and θ_2 respectively represent the Angle between smooth surface and rough surface and foundation. On the premise that one point is known and the other point is solved, the mathematical model of foundation bearing capacity characteristics can be established as follows:

$$E_{\max} = 2\sum_{i=1}^{n} \frac{\delta_z + \delta_x}{2} \tag{17}$$

Where, $E_{\max}$ represents the maximum bearing capacity of foundation without considering the characteristics of foundation soil, δ_z represents the bearing capacity of the left end of foundation, and δ_x represents the bearing capacity of the right end of foundation. After collating formula (17), we can get:

$$e_{\max} = \frac{E_{\max}}{U} \tag{18}$$

Where, $e_{\max}$ represents the maximum foundation bearing capacity under the premise of considering the foundation soil, and U represents the boundary conditions of the bearing capacity under the rock-soil characteristics.

5 Characteristic Value of Foundation Bearing Capacity is Predicted by RBF Neural Network in Machine Learning Algorithm

As the core technology of artificial intelligence, machine learning has strong operational technology. Through the corresponding algorithm for computer data learning, deeply mining the existing information rules in the data, constantly adjust the rule storage mode, control the learning data in the system controllable range, to achieve the overall learning operation. The machine learning framework is shown in Figure 3.

Neural network is an important notice in the field of machine learning. It is a network model built by imitating the neural behavior characteristics of animals, which can be used to process distributed data by adjusting the association between internal nodes. Therefore, in order to accurately predict the characteristic value of foundation bearing capacity, RBF neural network is introduced in this study.

5.1 Construct RBF Neural Network Algorithm Model

RBF neural network is a single hidden layer feedforward neural network, which can be easily modeled in nonlinear systems. Because of its random nonlinear mapping characteristics and simple topology architecture, RBF

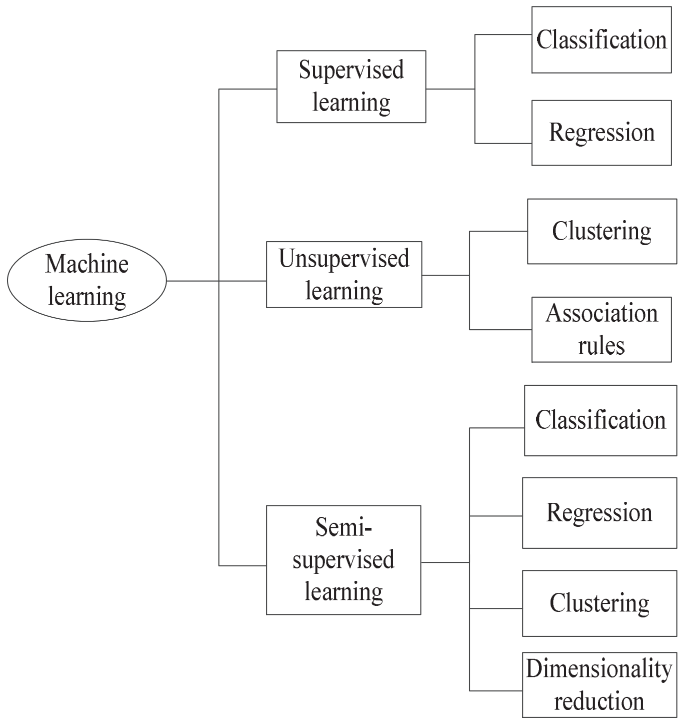


Figure 3 Machine learning framework diagram.

neural network is widely used in numerical prediction research. As the bearing capacity of foundation varies with the environment, it is difficult to explore its specific law according to the historical data. Therefore, the RBF neural network is used to construct a prediction model of characteristic value of foundation bearing capacity. The improved ReliefF algorithm is used to extract the mechanical characteristics of foundation bearing capacity and input them into the RBF neural network.

RBF neural network contains input layer, hidden layer and output layer, and each layer has different functions. The input layer is composed of some perception nodes, which connect the neural network algorithm structure with the external environment. The hidden layer covers a group of radial basis functions to complete the nonlinear transformation in the network. The output layer takes correlation processing of the output signal of the hidden layer and outputs the final signal value. The overall architecture of RBF neural network can be expressed in the form shown in Figure 4.

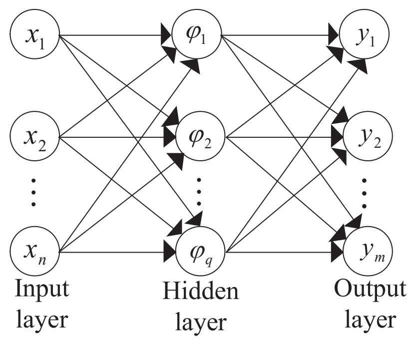


Figure 4 Schematic diagram of RBF neural network architecture.

There is no weight matrix from input layer to hidden layer in RBF neural network. Therefore, in order to predict the characteristic value of foundation bearing capacity, the improved ReliefF algorithm is used to select the characteristics of foundation bearing capacity.

Relief algorithm is a category of feature weight algorithm, which can distinguish data features according to the characteristics of data samples. However, the traditional Relief algorithm can only distinguish between two types of data samples and has great limitations. Therefore, in this paper, the traditional Relief algorithm optimized, in view of the foundation soil environment, the establishment of sample set, on the basis of random sample a R, then from belongs to a category with R find a neighbor sample is the sample set of R_A, again belongs to b category with R find a neighbor sample is the sample set of R_B, the process is as follows:

$$c_R = \frac{N(a+b)}{n(R+R_A+R_B)} \tag{19}$$

Where, n represents the number of features in the sample and N represents the total number of samples. On this basis, the prediction parameter τ of foundation pressure intensity and the mechanical characteristic parameter $e_{\max}$ of bearing capacity are introduced. After regional registration of spatial network, the fusion characteristic values are obtained as follows:

$$x = \frac{\tau + e_{\max}}{c_R} \tag{20}$$

The obtained fusion eigenvalues are input into the RBF neural network, and a set of random numbers are generated, which are taken as the initial weights of the network. The output information through the output layer is as follows:

$$z_C = \sum_{i=1}^{n} \omega_{iq} y_i^2(x) + \omega_q \tag{21}$$

Where, z_C represents the output value of the output layer, ω_{iq} represents the weight of the i-th neuron in the hidden layer and the q neuron in the output layer, and ω_q represents the weight value of the q neuron in the output layer. Since the parameter gradient of neural network should not be 0, the weight value range of neurons is (0,1).

5.2 Prediction of Characteristic Value of Foundation Bearing Capacity

On the basis of the above RBF neural network algorithm model, combined with the content of the previous chapters, the specific prediction process of characteristic value of foundation bearing capacity is designed. The steps are as follows:

Step 1: The influence factors of foundation bearing capacity are analyzed, and the foundation mechanical parameter group δ is constructed.

Step 2: Use SPSS software to carry out correlation calculation for the above obtained parameter groups of foundation mechanics, screen out the parameters whose correlation statistical tolerance is less than 0.05, and build the foundation mechanics database.

Step 3: Use the foundation mechanics data as input to establish a regression analysis model, and obtain the initial characteristic value f_{bc} of foundation bearing capacity, which is used as the foundation label.

Step 4: Calculate the parameters of foundation pressure strength and mechanical characteristics of bearing capacity, and obtain their weight values using the improved Relief algorithm. The process is as follows:

$$\begin{cases} \omega(\tau) = \dfrac{N}{n_\tau \times f_{bc}} \\ \omega(e_{\max}) = \dfrac{N}{n_{e_{\max}} \times f_{bc}} \end{cases} \tag{22}$$

In the formula, N represents the total number of samples, n_τ represents the characteristic number of foundation pressure strength parameters in the sample, and $n_{e_{\max}}$ represents the characteristic number of mechanical characteristic parameters of bearing capacity in the sample.

Step 5: Taking the two as constraint training RBF neural network, the characteristic value of foundation bearing capacity is:

$$f'_{bc} = \frac{(\omega(\tau) + \omega(e_{\max})) \times f_{bc}}{z_C \times \left(\min \sum_{\delta \in Y_1} (f_{bc} - y_1)^2 + \min \sum_{\delta \in Y_2} (f_{bc} - y_2)^2\right)} \tag{23}$$

Where, Y_1 and Y_2 represent two groups of mechanical parameter sets related to foundation bearing capacity, and y_1 and y_2 represent the output mean values of Y_1 and respectively.

Step 6: The hyperparameters of RBF neural network algorithm include the number of hidden layers and the number of hidden neurons. Therefore, the process of applying RBF neural network to predict the characteristic value of foundation bearing capacity is as follows:

$$F_{bc} = \left(\sum_{j=1}^{J} \omega_j y_j + \kappa_j\right) \times f'_{bc} \tag{24}$$

In the formula, J represents the number of layers of RBF neural network, ω_j represents the connection weight between different layers, y_j represents the output value of layer j, and κ_j represents the node threshold value of layer j.

6 Experimental Verification and Analysis

In order to verify the practical application effect of the prediction method of characteristic value of foundation bearing capacity based on machine learning algorithm proposed above, data simulation was carried out by simulation testing tool, and the feasibility of prediction results was concluded by analyzing the simulation data.

6.1 Experiment Design

In the experiment, ABAQUS finite element software simulation test tool was used to simulate the foundation sample creation, and the testing process was completed on the sample model. The parameters of sample model of simulated rock foundation are shown in Table 1.

Table 1 Parameters of simulated foundation sample model

γ/(kN·m^{-3})	σ_{cm}/MPa	m_i	G	D
21	1	13	8	0

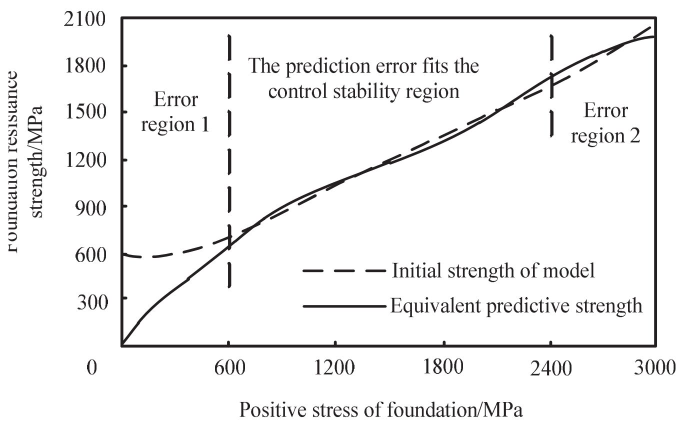


Figure 5 The equivalent envelope diagram of foundation for the transformation of predicted results.

6.2 Prediction Error Test

The bearing capacity prediction error is tested according to the test parameters set above, and the test results are converted into equivalent envelope diagram of foundation, as shown in Figure 5.

It can be seen from Figure 5 that although the convergence control effect of method of this paper is not obvious in the early stage of prediction, the prediction effect reaches the best when the positive stress value of foundation exceeds 600 MPa, and the predicted value is close to the initial value of the simulation model until the positive stress value of foundation exceeds 2400 MPa. Due to the double low disturbance of the friction Angle between the rock strata and the instantaneous shear stress of the foundation, the prediction error increases inversely, but the whole is still controllable. This shows that method of this paper is valid.

6.3 Contrast Test

In order to highlight the explicability of experimental results, method of reference [6] and method of reference [7] were compared to complete performance verification together with method of this paper from the perspective of prediction error rate and prediction time. The results are shown in Table 2.

Table 2 Statistical tables of predictive performance for different methods

Method	Number of Experiments/Times	Prediction Error Rate/%	Forecast Time/Min
Method of this paper	10	1.21	32.5
	20	1.35	30.9
	30	1.26	30.1
Method of reference [6]	10	3.54	58.4
	20	3.78	53.6
	30	3.32	55.8
Method of reference [7]	10	2.97	55.1
	20	3.06	63.9
	30	3.67	57.2

By analyzing the results shown in Table 2, it can be seen that with the increase of the number of experiments, the prediction error rate and prediction time of different methods also change. However, the method of this paper is always better than the two comparison methods in the numerical results of prediction error rate and prediction time. Among them, the prediction error rate of method of this paper is between 1.21% and 1.35%, and the prediction time is between 30.1 min and 32.5 min, indicating that method of this paper has high prediction accuracy and timeliness.

7 Conclusion

In order to improve the analysis effect of foundation bearing capacity and ensure the reliability of construction engineering, this study proposes a method for predicting the eigenvalue of foundation bearing capacity based on machine learning algorithm.

Based on the analysis of the factors affecting the bearing capacity of the foundation, the prediction parameters of the foundation pressure strength and the foundation strength are calculated. The mathematical model of the foundation bearing capacity is established by calculating the mechanical characteristic parameters of the foundation and establishing the boundary conditions of the foundation bearing capacity, so as to complete the analysis of the mechanical characteristics of the foundation bearing capacity. The analysis results and the prediction parameters of the foundation strength are input into the RBF neural network model, and the prediction results of the characteristic values of the foundation bearing capacity are obtained by using the super parameters of the RBF neural network algorithm.

According to the experimental results, it can be seen that the prediction results of this method are always in a controllable range, and the prediction error rate and prediction time are small, which shows that this method effectively realizes the design expectation.

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