International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 1985-1996

https://doi.org/10.70517/ijhsa463157

Settlement monitoring method combined with iterative nearest point algorithm in geotechnical engineering soft ground treatment supported by intelligent sensing technology

Yan Zhang[1,*]
[1] Department of Water Resources and Civil Engineering, Hetao College, Bayannur, Inner Mongolia, 015000, China
Corresponding authors: (e-mail: yanzi0478_404@163.com).

Abstract Aiming at the uneven settlement which is easy to occur in the process of soft ground construction of geotechnical engineering, this paper introduces genetic algorithm into the neural network algorithm, which makes the population converge to the optimal solution by controlling the crossover probability and variance probability. The kd-tree is constructed using the foundation building point cloud to get the plane area of the foundation building point cloud. Alpha-shape algorithm is used to extract the contour lines of the foundation area, and the feature lines of the foundation plane area are obtained by fitting the results of contour line extraction. The feature line matching method is combined with the ICP algorithm to perform point cloud coarse alignment and point cloud fine alignment. The optimized neural network prediction model is used to predict and analyze the point cloud alignment results of the foundation based on the ICP algorithm. The stability of the GA-BP settlement prediction algorithm designed in this paper is verified by combining the error results of the GA-BP algorithm on soft ground settlement prediction in engineering examples. Comprehensive K161+050, K162+872, K175+600 section in the pile embankment settlement observation data and prediction data, GA-BP algorithm prediction of the maximum error, the minimum error of 9.53%, 0.66%, respectively, the model prediction data and the actual observation data similar to the prediction model has a good prediction accuracy.

Index Terms genetic algorithm, settlement monitoring, ICP algorithm, point cloud alignment, soft ground foundation

I. Introduction

With the accelerating process of urban modernization and construction, the number of geotechnical engineering projects is increasing day by day, which puts forward high requirements for soft ground treatment. The characteristics of these soft soils such as high water content, poor permeability, large pore ratio, easy compression, high sensitivity, etc. can easily cause the phenomenon of excessive settlement and uneven settlement of geotechnical engineering soft foundation, which seriously affects the safety and stability of geotechnical engineering [1]-[3]. In addition, due to the complexity of soft soil, there is a big difference between design and engineering reality, which can easily cause engineering accidents and increase the economic cost of the project [4]-[6].

Settlement of soft soil foundation is affected by various factors such as engineering geological conditions, hydrogeological conditions and external conditions [7]. Due to the complex composition of the soil itself, the nature of its formation process related to the complexity and variability, coupled with the process of obtaining soil parameters in the process of randomness and human influence, so the variability of the obtained soil performance indicators is very large [8]-[10]. Traditionally, the parameters involved in the project are treated as fixed values and appropriate calculation models are selected, and the factors that are not considered or are uncertain are considered in a general way with a safety factor, which is influenced by human factors and poorly standardized [11]-[13]. And in a large number of practice engineering, the relevant engineers and technicians according to the characteristics of geotechnical engineering, gradually apply the intelligent algorithm in the practice of settlement monitoring of soft ground, the various uncertainties or randomness in the project is reflected in the calculation model, effectively make up for and improve the shortcomings of the traditional design method [14]-[16]. Due to the complexity of the actual project, there is still a gap between the theoretical calculation results and the measured settlement, and in order to better guide the engineering practice, further research on the settlement calculation and prediction and reliability theory is needed [17], [18].

This paper analyzes the current problems in geotechnical engineering foundation construction, in which soft ground foundation needs to be optimized for treatment technology in foundation construction due to its own characteristics. Alpha-shape algorithm is used to extract the contour line of foundation area and get the feature line of foundation plane area. Then the feature line matching + ICP algorithm is used for the iterative alignment of two sets of point sets to improve the alignment accuracy of the point cloud, which is the basic support for the settlement monitoring of soft foundation. The BP neural network algorithm is optimized and the settlement prediction model of neural network is proposed. The optimized neural network settlement prediction model is predicted in the training set and test set. Analyze the application of GA-BP neural network model for soft ground settlement prediction in practical engineering.

II. Settlement monitoring methodology proposed in conjunction with the nearest-point iterative algorithm

II. A. Main problems of geotechnical foundation construction

II. A. 1) Level of treatment technology needs to be improved

At present, the overall level of geotechnical engineering foundation treatment technology is not high. The reason for this is that industrialization started late, and a large number of construction personnel have not been trained in professional and high-intensity engineering technology. Part of the geotechnical engineering construction system and equipment innovation is not mature, can not meet the needs of the era of construction, resulting in the use of geotechnical engineering in the use of low efficiency, can not play its real role. At present, the foundation treatment technology is still in a relatively weak stage, the lack of perfect industry standard system of foundation construction technology, it is urgent to further improve the standardization level of foundation treatment construction [19].

II. A. 2) Impact of natural factors

Geotechnical conditions and construction materials directly affect the construction quality of geotechnical engineering, and at the same time are important prerequisites for ensuring the quality of the project. There is often a lack of effective foundation protection measures in actual projects, which leads to the increasing influence of various uncontrollable natural factors on foundations. For example, before and after the pouring of concrete foundation base, it is necessary to try to speed up the construction speed and ensure the quality of the pouring, otherwise, once the heavy rain or snowstorm comes, it will seriously affect the progress and quality of the project. Or after the pouring is completed, when encountering hot weather, it is necessary to carry out appropriate covering and watering to cool down the temperature, otherwise the concrete solidification will produce a cavity, which will form cracks if it is light, or the foundation will collapse if it is heavy. It can be seen that natural factors have a great impact on geotechnical engineering foundation construction.

II. A. 3) Soft ground problems

(1) Soft ground has the following characteristics:

① Higher compressibility. By the soft soil pore ratio is greater than 1, the soil water content is large, there are many microorganisms in the soil, etc., soft ground compression is high, under the same conditions, the greater the plastic limit of soft soil compression is higher.

② Lower permeability. In the vertical level of soft soil is basically impermeable, which will not only bring great influence on drainage consolidation, but also will appear high pore water pressure at the beginning of loading, and will also reduce the overall strength of the foundation.

③ Stronger thixotropy. Since soft soil is flocculated structural sediment, it has a certain strength when the original soil is not damaged, but it may become dilute once damaged, which indicates that the soft foundation is prone to lateral sliding condition after being subjected to vibration loading.

④ Rheology is obvious. Rheology is a distinctive feature of soft ground, which will directly affect the shear strength of the soil layer, usually the shear strength of soft soil will not exceed 80%, and it is easy to cause settlement problems after completely eliminating the void pressure of soft soil.

(2) The problems easily caused by soft soil foundation are:

① Uneven settlement. Due to the soft soil layer in the particle distribution is relatively loose, and the soil layer itself has a large water content, at this time no treatment of its construction operations, it is very easy to cause uneven settlement phenomenon, and the construction safety and quality of the project has a great impact, in serious cases will also cause the project structure tilt or collapse.

② Insufficient loading force. Affected by the weak bonding between the soft soil particles, soft soil foundation bearing capacity is low, especially under the action of the external load, soft soil foundation is very easy to appear settlement and deformation, then carry out engineering structure construction on the soft soil foundation, is also prone to cause safety problems.

③ The foundation is not stable. Especially in the use of mechanical equipment for soft soil foundation vibration mixing, the flocculent structure in the soft soil layer will be destroyed, which will lead to foundation mobility enhancement problems, foundation infrastructure stability can not be guaranteed, and on the upper structure of the construction of solid safety constitutes a great threat.

II. B.Automatic Alignment Methods for Ground-Based Building Point Clouds

II. B. 1) Point cloud feature line extraction

Considering that the target to be segmented is a point on the plane, in order to get the planar region of the point cloud of the foundation building quickly, this paper firstly constructs a kd-tree by using the point cloud of the foundation building, and on the basis of which the normal information of the point cloud is estimated by the PCA transform analysis method. Then, starting from any seed point, the judgment of neighboring points with normal consistency is carried out to realize the planar region growth. The region growth condition can be expressed as:

$$\begin{cases} \left\| \overline{p_i p_j} \right\| < th_{d_{sw}} \\ \arccos(N_{p_i}^T \cdot N_{p_j}) < th_\theta \end{cases} \quad (1)$$

where p_i is the seed point and p_j is the neighborhood point. N_{p_i} and N_{p_j} are the normal vectors at the two points, respectively. $th_{d_{sw}}$] is the vertex distance threshold and th_θ is the normal angle threshold.

Due to a certain degree of randomness in the selection of seed points in the process of region growth, the same plane is usually split into multiple pieces in the above region growth results, therefore, region merging processing is required.

Feature line extraction and optimization: In order to extract the feature lines of point clusters in different foundation regions, this paper directly adopts the Alpha-shape algorithm for the extraction of the contour lines of the foundation regions, and on the basis of which, the feature lines of the foundation plane regions are obtained through the splitting process.

In order to facilitate the subsequent feature line matching, the contour line extraction results are segmented and fitted to obtain feature line segments in this paper. When splitting, the contour line is split into several sub-line segments by using the maximum deviation point of the straight line connected to the first and last endpoints on the contour line. Then, the least squares fitting method was used to further fit the contour points to obtain the feature line segments.

Considering the randomness of laser scanning and the influence of point cluster noise, redundant feature lines due to uneven distribution of point clouds or small planes usually exist in the above feature line extraction results, which need to be further optimized and processed.

(1) Short line elimination processing.

(2) Redundant line segments merging.

II. B. 2) Point cloud alignment

(1) Alignment primitives and similarity measures

In 3D space, at least two pairs of non-parallel lines are required to solve the effective transformation matrix of two sets of point clouds. In order to ensure the reliability of the matching, this paper further screens effective feature line pairs as alignment primitives for the results of the above optimization process. The alignment primitive is valid if the neighboring line segments satisfy the following conditions. i.e:

$$\begin{cases} d < 4d_{avg} \\ \pi/18 < \theta < 17\pi/18 \end{cases} \quad (2)$$

And the homonymous features are judged using the line pair angle and the length of the line segment as the similarity measure. For two sets of point clouds p and q, L_1 denotes the lengths of long line segments in the line pairs, L_2 denotes the lengths of short line segments in the line pairs, and d_p and d_q are the average point spacings of the two sets of point clouds, respectively. If the line pairs in the two sets of point clouds satisfy Eq. (3), they are considered as homonymous line pairs. i.e:

$$\begin{cases} \left| l_{1p} - l_{1q} \right| < 2(d_p + d_q) \\ \left| l_{2p} - l_{2q} \right| < 2(d_p + d_q) \\ \left| \theta_p - \theta_q \right| < \pi / 0 \end{cases} \quad (3)$$

(2) Point cloud coarse alignment

According to the similarity measure, find the homonymous line pairs in the two point sets to be aligned, and solve the final transformation model with the endpoints of the line pairs as homonymous points. In order to get the optimal transform relationship, this paper adopts the following method to iteratively traverse the line pairs in the two sets of point sets to get the best matching result:

STEP1: Based on the alignment primitives in the two sets of point sets, find the matching homonymous line pairs in the two sets of point sets using the similarity measure, and solve the initial transformation matrix using the quaternion method with the coordinates of the endpoints of the line pairs.

STEP2: Use the initial transformation matrix to process the line features in the point set to be aligned, and transform the point set to be aligned to the target point set.

STEP3: Count the number of line segments with the same name in the transformed set of points to be aligned and the target point set.

STEP4: Repeat steps STEP1~ STEP3 to traverse the alignment primitives in the point set one by one to get the number of pairs of lines with the same name in the transformed set of points to be aligned and the target point set, and take the transformation matrix with the highest number of pairs of lines with the same name as the optimal matching result.

STEP5: In order to make the rigid transformation matrix solving result more accurate, the endpoint coordinates of all the homonymous line segments are used to solve the transformation matrix, and this is used as the point cloud coarse alignment result.

(3) Point cloud fine alignment

Considering that the extraction of feature lines based on the point cloud will have certain errors, this paper further adopts the nearest point iteration (ICP) algorithm for the iterative alignment of the two sets of point sets based on the feature line matching, in order to improve the accuracy of the alignment results [20], [21]. The steps are as follows:

STEP1: For the coarse alignment point sets P and Q, find the points corresponding to Q in the point set P to generate the corresponding point pairs.

STEP2: Calculate the 6 parameters of the rotational translation and the transformation matrix R by the quaternion method.

STEP3: Rotate and translate the point set P using the above transformation matrix R to obtain a new point set P'.

The continuation of the iteration is determined based on the average distance between the corresponding points in the point set P' and Q. Thus, the problem of solving the optimal transformation matrix can be transformed into computing the rotation matrix R and translation matrix T that minimizes the value of $f(R,T)$:

$$f(R,T)=\frac{1}{n}\sum_{i=1}^{n}\left\|R_{P_i}+T-q_i\right\|^2 \tag{4}$$

STEP4: If the iteration continues, update the position of the point cloud to be aligned and continue with STEP1. Otherwise, end the iteration and get the final alignment result.

II. C.Neural network training and sedimentation prediction

II. C. 1) BP Neural Networks

A BP neural network is a multilayer forward network trained by back propagation of errors, which generally consists of an input layer, an output layer, and a number of intermediate (hidden) layers.BP neural networks have a number of advantages and features, the most important of which is the learning function. If you wish to utilize a BP neural network model to achieve a certain function, you must first train it to learn. That is to say, the algorithm is designed first, so that it can continuously adjust its weights during the calculation process. So that the learning process of neural network is also a continuous optimization process. When the learning is completed, the adjustment of the weights has also reached the optimum, and finally the neurons in each layer of the neural network store this learning result. The basic idea is to utilize the gradient search technique to make the error mean square deviation between the desired output value and the actual output value in a small and reasonable range.

(1) Error correction learning is to continuously adjust the connection weights according to the external feedback (desired output) from the output nodes to realize the learning process of the network and make the actual output of the output layer neurons consistent with the desired output. The training signal in error correction learning is:

$$e=(d_j-y_j)y_j'=\left[d_j-f(W_j^T X)\right]f'(W_j^T X) \tag{5}$$

where $f'(W_j^T X)$ is the derivative of the transfer function.

In order to adjust the connection weights w_{ij} from neuron i to neuron j, the squared error between the actual output of neuron j and the desired output can be defined as:

$$E = \frac{1}{2}(d_j - y_j)^2 = \frac{1}{2}\left[d_j - f(W_j^T X)\right]^2 \tag{6}$$

The error gradient is:

$$\nabla E = -(d_j - y_j) f(W_j^T X) X \tag{7}$$

During the adjustment of the connection weights W_{ij}, in order to ensure that the value of the error E is minimized, so the negative gradient of the error E should be proportional to the increment of the connection weight vector W_j, i.e:

$$\nabla W_j = -\eta \nabla E = -\eta (d_j - y_j) f^{'}(W_j^{\tau} X) X \tag{8}$$

That is, the connection weights w_{ij} from neuron i to neuron j can be adjusted as follows:

$$\Delta W_{ij}(n) = w_{ij}(n+1) - w_{ij}(n) = \eta x_i(n)(d_j - y_j) f^{'}(W_j^T X) \tag{9}$$

where η is the learning rate parameter and $\eta > 0$.

(2) Hep step learning

According to the method rule of Herb step, the connection weights w_{ij} of neuron i to neuron j can be adjusted as follows. If neuron i to neuron j are in the state of excitation, the connection between the two should be strengthened, and the mathematical relationship is described as shown in equation (10):

$$\Delta w_{ij}(n) = w_{ij}(n+1) - w_{ij}(n) = \eta x_i(n) y_j(n) \tag{10}$$

where $w_i(n)$ denotes the connection weight from neuron i to neuron j after the n th adjustment. $w_{ij}(n+1)$ denotes the connection weights from neuron i to neuron j after the $n+1$ th adjustment. η is the learning rate parameter, $\eta > 0$. y_j is the output value of node j. x_i is the output value of node i.

(3) Competitive Learning

Competitive learning rules can be applied when the BP neural network model uses unguided learning. Neural networks applying competitive learning rules usually have one competitive layer. For a particular input pattern X, each neuron in the competitive layer of the neural network will obtain the corresponding input weighted sum, if neuron j has the maximum weighted sum, then neuron j can win. The competitive learning rule can be described as:

$$\Delta w_{kj}(n) = \begin{cases} \eta(x_j - w_{ji}) & \text{If neuron j wins the competition} \\ 0 & \text{If neuron j competes for the failure value} \end{cases} \tag{11}$$

The BP algorithm is introduced with the example of BP neural network with a three-layer network structure, which is composed of an input layer, a hidden layer and an output layer, which are interconnected by correctable weights. The specific process and steps of the algorithm are as follows:

STEP1: Activation function. Assign random values to the connection weights V and W and the threshold values γ and θ in the interval [-1, 1].

STEP2: A learning sample (X^k, Y^k) is randomly selected for the network.

STEP3: The input layer receives input signals as received and computes, the output.

STEP4: Calculate the net input and output of each neural unit in the middle layer (hidden layer) according to Eq. (12) and Eq. (13) respectively. I.e.:

$$s_j^k = \sum_{i=1}^{n} w_{ij} x_i^k - \theta_j \quad j = 1, 2, \ldots, p \tag{12}$$

$$b_j^k = f(s_j^k) \quad j = 1, 2, \ldots, p \tag{13}$$

STEP5: Calculate the net inputs and outputs of each neural unit in the chemical output layer according to Eq. (14) and Eq. (15) respectively. I.e:

$$l_t^k = \sum_{j=1}^{p} v_{jt} b_j^k - \gamma_t \quad t = 1,2,\ldots,q \tag{14}$$

$$c_t^k = f(l_t^k) \quad t = 1,2,\ldots,q \tag{15}$$

STEP6: Based on the set desired output, calculate the correction error d_t^k for each neural unit in the output layer according to equation (16):

$$d_t^k = (y_t^k - c_t^k) f^{'}(l_t^k) \quad t = 1,2,\ldots,q \tag{16}$$

STEP7: Calculate the correction error e_j^k for each neural unit in the middle layer (hidden layer) separately according to equation (17):

$$e_j^k = \left[\sum_{t=1}^{q} v_{jt} d_t^k\right] f^{'}(s_j^k) \quad j = 1,2,\ldots,p \tag{17}$$

STEP8: Correct the connection weight V between the middle layer (hidden layer) and the output layer and the threshold value γ of each neuron in the output layer according to Eq. (18) and Eq. (19), respectively, where α is the learning rate parameter, and $0 < \alpha < 1$. That is:

$$\Delta v_{jt} = \alpha d_t^k b_j^k \quad j = 1,2,\ldots,p, t = 1,2,\ldots,q \tag{18}$$

$$\Delta \gamma_t = \alpha d_t^k \quad t = 1,2,\ldots,q \tag{19}$$

STEP9: Correct the connection weights W between the input layer and the intermediate layer (hidden layer) and the threshold value θ of each neuron in the intermediate layer (hidden layer) according to Eqs. (20) and (21), respectively, where β is the learning rate parameter, and $0 < \beta < 1$. That is:

$$\Delta w_{ij} = \beta e_j^k x_i^k \quad i = 1,2,\ldots,n, j = 1,2,\ldots,p \tag{20}$$

$$\Delta \theta_j = \beta e_j^k \quad j = 1,2,\ldots,p \tag{21}$$

STEP10: Randomly select the next learning sample for the network and return to step STEP3 until all the learning samples are trained.

STEP11: Determine whether the accuracy of the global error E meets the requirements, if $E \le \varepsilon$, then it meets the requirements, go to step STEP13, otherwise continue.

STEP12: Update the number of learning training times of the neural network, if the number of learning times does not meet the specified requirements, then return to step STEP2.

STEP13: End of training.

BP algorithm has a good mathematical idea and its nonlinear mapping ability is also very strong, but the BP neural network still has imperfections, there are some problems as follows:

(1) It is easy to appear local minima.

(2) Lack of theoretical guidance for the selection of the number of hidden layers and the number of neural units.

II. C. 2) Introduction of genetic algorithms

(1) Algorithm initialization. The relevant parameters of the genetic algorithm are set, the population size is 100, and the number of evolutionary generations is 200.

(2) Design of fitness function. The fitness function is used to assess the degree of superiority or inferiority of individuals in the model, and this paper uses the mean square error as the fitness function. Each individual in the algorithm represents a set of weights and biases. The fitness function $\text{fitness}(x)$ is:

$$\text{fitness}(x) = \frac{1}{N}\sum_{i=1}^{N}(T_i - \hat{T}_i)^2 \tag{22}$$

where N is the number of samples, T_i is the actual value, and $\hat{T}_i$ is the predicted value.

(3) Genetic algorithm iteration. The iterative process consists of three basic operations, selection, crossover and mutation, evolving generation by generation until it produces an individual that serves as a near-optimal solution to the problem [22], [23].

The purpose of selection is to choose the best individuals from the population that can move on to the next generation. Using a selection function based on a geometric distribution, the probability of selecting the best individual q is first selected, then a ranked list is constructed based on the fitness value of the individual in the population, and then the selection probability is calculated using the parameter of the normalized distribution s, which is cumulatively summed for easy use in the later selection of individuals. Among them:

$$s = \frac{q}{1-(1-q)^n} \tag{23}$$

$$fit(x(:,2)) = s(1-q)^{x(:,1)-1} \tag{24}$$

where n is the population size. $fit(x)$ is the selection probability.

The crossover operation enriches the diversity of individuals and improves the chance of discovering the global optimal solution. The process first randomly selects 2 individuals P_1, P_2 as the parents, and then generates a random mixing quantity α with a value range of 01. Linear interpolation of P_1, P_2 is carried out by utilizing α to generate 2 new child individuals C_1, C_2, thus:

$$C_1 = P_1\alpha + P_2(1-\alpha) \tag{25}$$

$$C_2 = P_1(1-\alpha) + P_2\alpha \tag{26}$$

The mutation operation is an auxiliary method for generating new individuals, and is an indispensable part of the local search for genetic algorithms to avoid prematurely falling into local optimal solutions during model computation. First determine the current number of generations c_t and the maximum number of generations m_t, then carry out mutation and choose the direction of mutation, and calculate the amount of change according to the mutation, and finally update the mutated individuals. Among them:

$$r = \frac{c_t}{m_t} \tag{27}$$

$$c_h = \Delta y(rand(1-r))^{\beta} \tag{28}$$

where r is the ratio. c_t is the current number of generations, m_t is the maximum number of generations, and c_h is the amount of variation. Δy is the maximum variation and β is the shape parameter.

III. Application of sedimentation monitoring methods to soft foundations

III. A. Point cloud alignment results

(1) Accuracy Evaluation Methods

Use feature line matching and ICP algorithm to complete point cloud alignment. Calculate the distance residual between the manually selected and algorithmically extracted feature points to complete the alignment.

Randomly select 300 points from the target point cloud (TLS) p and calculate the alignment distance residual by the following formula:

$$d_i = \left\| T\left(p_i;\theta^m\right) - \left(p_i;\theta^e\right) \right\| \tag{29}$$

where θ^m denotes the transformation parameters obtained by manually selecting the feature points, and θ^e denotes the transformation parameters obtained by algorithmically extracting the feature points.

(2) Alignment results

In this experiment, the airborne lidar (ALS) point cloud is the reference point cloud, and the ground-based lidar (TLS) point cloud is the point cloud to be aligned. The feature line matching method is utilized to complete the coarse alignment based on the canopy feature points. Based on the completion of the coarse alignment, the ICP algorithm is used for optimization.

The alignment distance residuals of the alignment method based on the foundation feature points are shown in Table 1. The alignment distance residuals of feature line matching method and feature line matching method + ICP are as follows, the average values of the two kinds of alignment distance residuals are 464.27 cm and 2.268 cm, respectively.The TLS point clouds of the five points are converted to ALS coordinate system, and the two kinds of point clouds are closely aligned, which indicates that the ICP fine alignment is able to optimize the results of the coarse alignment, and complete the point cloud alignment very well.

Table 1: Based on the method of the foundation feature point

Site	The matching method of the characteristic line is matched by the distance residue (cm)			The feature line matching method and the ICP match distance residual difference (cm)		
	Min	Max	Ave	Min	Max	Ave
1	692.63	756.09	714.52	0.59	3.25	1.56
2	104.55	137.12	126.01	0.91	3.42	1.67
3	443.21	489.95	471.33	0.93	3.67	1.59
4	351.21	445.24	426.04	0.50	8.04	4.93
5	552.04	604.75	583.45	0.72	3.67	1.59
Mean	/	/	464.27	/	/	2.268

III. B. Engineering Applications of Optimized BP Neural Network Prediction Models

III. B. 1) Overview of the project and geological conditions

The project is located in the northeastern part of Hunan Province and the southern edge of Dongting Lake. Geomorphology along the route mainly consists of lakeshore plains, micro-hills and river terraces.K137~K177+100 is lakeshore plains geomorphology, with flat terrain, mainly composed of river alluvial deposits and sediments of Dongting Lake. The general elevation is 24~28m, the rivers and canals are crisscrossed, and the lakes and marshes and ponds and weirs are scattered.

K177+100~K178+436 is a micro-hill landform, with a general elevation of 35~47m, with hillocks and gullies appearing one after another, the hillocks are mostly in the form of strips, and the gullies are more narrow and long, and the natural slope of hillock slopes is mainly 15~20°. The river terrace geomorphology area is mainly distributed on both sides of Xiangjiang River and Zijiang River tributaries, with low terrain, flat topography, and the ground elevation is between 26~28m, with the relative difference in elevation generally 1~2m.

Ground lithology: the first layer is artificial fill, the second layer is plow soil, the third layer is pulverized clay (low tenacity), the fourth layer is pulverized clay (medium dry strength and tenacity), the fifth layer is fine sand, and the sixth layer is pebbles.

The engineering characteristics of the geotechnical layers are evaluated as follows:

Tillage soil: plastic high compressibility soil, plant roots and corrosive matter content of about 5%, physical and mechanical properties of large differences, poor structural properties, can not be used as the road foundation bearing layer, should be dug out.

Powdery clay: according to the results of geotechnical test and field standard penetration test results for the hard plastic compressive soil, physical and mechanical properties are better, more shallow buried, strength is more uniform, can be selected for the road natural foundation holding layer.

Powdery clay: according to the results of geotechnical test and on-site standard penetration test results for soft-plastic high compression soil, its soil quality is poor, low strength, can be used as a composite foundation pile foundation bearing layer.

Fine sand: saturated with water, slightly dense according to standard penetration test, with general physical and mechanical properties, but it is buried deeper, with smaller thickness, and can not be selected as bearing layer of foundation pile.

Pebbles: water saturated, dense state, good physical and mechanical properties, less deformation, more stable distribution, but deeper buried, can be selected as the proposed roadbed pile foundation bearing layer.

III. B. 2) Monitoring content

The main study of Hunan Wuyi Expressway soft soil roadbed settlement and deformation monitoring values, monitoring values including foundation settlement and groundwater level, monitoring of the main line mileage number range of K161 + 050 ~ 162 + 872, K167 + 110 ~ K175 + 600. 62 monitoring sections, in each section of the left width, the center pile, the right width of each set a settlement plate, used to observe the cumulative settlement value of the soft ground foundation. The total number of monitoring data is 184.

III. B. 3) Optimized neural network modeling

The main factors affecting the settlement of soft soil roadbed are groundwater level, soft soil roadbed disposal method, etc. According to the monitoring data, four factors, namely, observation time, groundwater level, soft soil roadbed disposal method, and monitoring location, are taken as the input values of the BP neural network, so the input variables of the neural network are changed into a 4-dimensional vector, as listed below:

① Observation time: measured data.

② Groundwater level: measured data.

③ Disposal method of soft soil roadbed: cement mixing pile, dredging and replacement, biochemical enzyme curing, high pressure rotary spraying pile.

④ Monitoring location: general roadbed, access road, access road transition section, round pipe culvert, bridgehead transition section, bridgehead encryption section, bridgehead disposal section.

The model predicts the soft foundation settlement value, so the output vector is a 1-dimensional vector. And the data is normalized using Eq.

III. B. 4) Analysis of the results of the optimized neural network prediction model

The network learning rate in BP neural network is 0.001, the maximum number of iterations for training is 1000, and the minimum error of the training objective is 0.0003. The number of neuron nodes in the input layer is 4, the number of neuron nodes in the hidden layer is 10, and the number of neuron nodes in the output layer is 10, and the input layer and the output layer functions use tanh activation function. The first 150 sets of data from the monitoring data were used as training samples, and the last 60 sets of data were used as test samples.

The evaluation index results of BP neural network, PSO-BP neural network, fireworks algorithm optimized BP neural network (FWA-BP) neural network, RBF neural network, and genetic algorithm optimized BP neural network (GA-BP) on the training set are shown in Figure 1.

The RMSE values of the algorithms are 2.35, 1.68, 1.99, 2.64, and 1.82 in that order, and the GA-BP algorithm has a lower RMSE than the comparison algorithms. The bar length in the figure shows that the GA-BP algorithm is less than the comparison algorithm in RMSE, MAE, MAPE (%), MSE, and Mean Relative Error (%) evaluation metrics. Compared to the FWA-BP algorithm, the average relative error of the FWA-BP algorithm is 7.63%, which is 2.2% higher than the GA-BP algorithm.

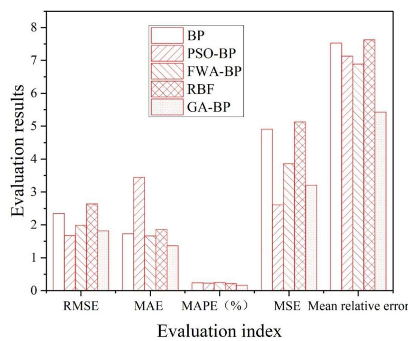

Figure 1: The different algorithms are evaluated in the training set

After the convergence of neural network training, the trained neural network is used to predict the test set data, and the prediction results of different algorithms on the test set are shown in Figure 2. The different algorithms were carried out for 30 times of sample prediction respectively, and it can be seen from the curve trend in the figure that the prediction curve trend of each algorithm is relatively similar. The GA-BP algorithm curve is closer to the actual measurement curve.

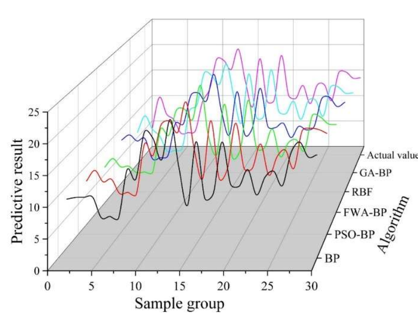

Figure 2: Different algorithms predict results on the test set

In order to further analyze the prediction accuracy of each algorithm, the distribution histogram of the actual values of 30 samples and the predicted values of each algorithm is plotted. The distribution histogram of the prediction results of each algorithm is shown in Figure 3. It can be seen that the prediction results of GA-BP algorithm are closer to the actual values. The distribution of the prediction results of FWA-BP algorithm and PSO-BP algorithm are more the same. The prediction result of RBF algorithm is higher.

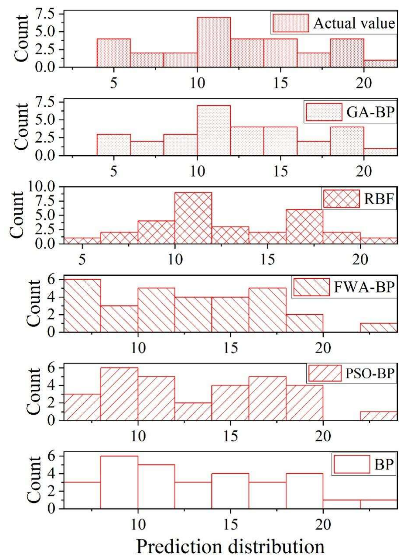

Figure 3: The prediction results of the algorithms are distributed

The statistics of the evaluation indexes of each algorithm on the test set are shown in Fig. 4, and the average relative error of GA-BP neural network test set is 6.28%, and the RMSE, MAE, MAPE and MSE are 1.25, 1.21, 0.17% and 2.36 respectively.Among the five kinds of neural network prediction models, the root mean square error RMSE, mean square error MSE, and the average absolute error of the soft ground settlement prediction model of the GA-BP neural network proposed in this paper are the smallest, indicating that the accuracy of the GA-BP neural network prediction model is better than that of the single BP neural network prediction model. error (RMSE), mean square error (MSE), and mean absolute error (MAE) are all the smallest, indicating that the accuracy of the GA-BP neural network soft ground settlement prediction model proposed in this paper is better than that of the single BP neural network model, PSO-BP neural network model, FWA-BP neural network model, and RBF model.

The root mean square error (RMSE) and mean absolute error (MAE) of the BP neural network prediction model for soft ground settlement prediction are larger compared to the other three models, which proves that the BP neural network is prone to fall into local minima during model training, and it needs to be optimized using the global optimization algorithm.

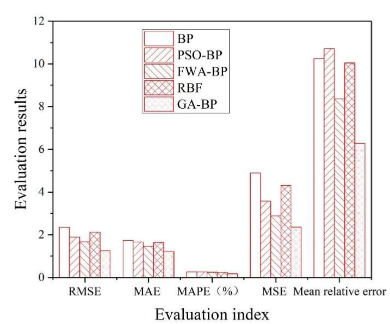

Figure 4: The results of the evaluation of the algorithms in the test set are calculated

III. C. Neural network model for soft ground embankment settlement prediction

The analysis example still adopts the observation data of settlement of mid-pile embankment in the cross section of K161+050~162+872 and K167+110~K175+600 in the soft foundation test project in the northeast of Hunan Province.

The trained GA-BP network is used to test the observation data of three sections after December 7, 2024, and the results of settlement prediction can better reflect the performance of the network, and each prediction is now compared with the actual value.

Comparison of the calculated settlement values of the center pile of K161+050 with the measured values is shown in Table 2, the maximum error occurring between the predicted and measured values of the GA-BP network in this monitoring range is 5.75%. On the 536th day of monitoring, the error between the predicted and measured values of GA-BP network is only 0.87%.

Table 2: K161+ 050 settlement values and measured values

Date	2024.12.14	2024.12.21	2024.12.28	2025.01.04	2025.01.11	2025.14.18
Day	522	529	536	543	550	557
Measured value (mm)	40.53	41.21	44.97	43.51	44.87	46.21
Predictive value (mm)	41.25	43.26	44.58	46.01	46.57	48.72
Error (%)	1.78	4.97	-0.87	5.75	3.79	5.43
Forecast final sedimentation (mm)				57.92		

Comparison of calculated settlement values and measured values of K162+872 center pile is shown in Table 3. On the 550th day, the settlement prediction error of GA-BP algorithm in K162+872 center pile out is 9.53%, at this time, the prediction error is larger, and more samples are needed for algorithm training.

Table 3: The sedimentation and the measured value of the pile in k162+ 872

Date	2024.12.14	2024.12.21	2024.12.28	2025.01.04	2025.01.11	2025.14.18
Day	522	529	536	543	550	557
Measured value (mm)	53.44	52.31	53.64	54.56	56.89	59.12
Predictive value (mm)	52.36	54.63	56.04	59.45	62.31	64.51
Error (%)	-2.02	4.44	4.47	8.96	9.53	9.12
Forecast final sedimentation (mm)				71.37		

The comparison between the calculated settlement values and measured values of the center pile of K175+600 is shown in Table 4.

The GA-BP algorithm produces less error in the settlement prediction data of K175+600 center pile, which is better than the prediction data of K161+050 center pile and K162+872 center pile.

Combining the observation data and prediction data of embankment settlement of K161+050, K162+872 and K175+600 section center piles, the prediction trend of GA-BP algorithm is close to the measured results, and the maximum error is 9.53%, so it can be predicted that the prediction of its long term trend can achieve more reliable results when the sample data are sufficiently large and sufficiently reliable.

Table 4: The sedimentation and the measured value of the pile in the k175+ 600

Date	2024.12.14	2024.12.21	2024.12.28	2025.01.04	2025.01.11	2025.14.18
Day	522	529	536	543	550	557
Measured value (mm)	325.63	334.26	356.25	361.25	370.81	379.25
Predictive value (mm)	334.15	340.12	350.19	365.28	373.26	382.92
Error (%)	2.62	1.75	-1.70	1.12	0.66	0.97
Forecast final sedimentation (mm)				367.43		

IV. Conclusion

In this paper, the feature line matching method and ICP algorithm are used for point cloud coarse alignment and point cloud fine alignment respectively, and the genetic algorithm is introduced to optimize the prediction model. The actual prediction error of the BP neural network prediction model optimized by genetic algorithm is analyzed through the application of engineering examples. The alignment distance residual of the feature line matching method + ICP is reduced by 462.002cm than that of the single feature line matching method. The accurate point cloud alignment results can assist the settlement monitoring and prediction of geotechnical engineering soft ground, which facilitates the acquisition of high-precision soft ground parameters, and the RMSE, MSE, and average absolute error of the GA-BP neural network soft ground settlement prediction model are all at the minimum value, which indicates the stability of the GA-BP neural network soft ground settlement prediction model proposed in this paper. Comparing different engineering monitoring points, the GA-BP neural network soft ground settlement prediction model appeared to have the largest prediction error of 9.53%, which is in the acceptable range, but more samples are needed to optimize the prediction error.

Funding

The scientific research project of Hetao College focuses on the bearing characteristics and application research of carrier piles in western Inner Mongolia (HYZY202109), Study on Bearing Characteristics and Application of Bearing Base Pile in Western Inner Mongolia.

References

[1] Zhang, W., Fan, C., Lei, M., & Li, Z. (2024). Design of treatment scheme and identification method of treatment effect for soft soil subgrade. Vibroengineering Procedia, 55, 8-13.
[2] Jiang, X., Lu, Q., Chen, S., Dai, R., Gao, J., & Li, P. (2020, February). Research progress of soft soil foundation treatment technology. In IOP Conference Series: Earth and Environmental Science (Vol. 455, No. 1, p. 012081). IOP Publishing.
[3] Sabrah, M. A. F., & Zainorabidin, A. (2023). Investigation of Soil Settlement Due to Different Shape of Load Applied on Soft Soil. Recent Trends in Civil Engineering and Built Environment, 4(1), 119-131.
[4] Chen, Q., Yang, Z., Xue, B., Wang, Z., & Xie, D. (2022). Monitoring and Prediction Analysis of Settlement for the Substation on Soft Clay Foundation. Advances in Civil Engineering, 2022(1), 1350443.
[5] Peduto, D., Nicodemo, G., Maccabiani, J., Ferlisi, S., D'Angelo, R., & Marchese, A. (2016). Investigating the behaviour of buildings with different foundation types on soft soils: two case studies in The Netherlands. Procedia Engineering, 158, 529-534.
[6] Zhou, S., Wang, B., & Shan, Y. (2020). Review of research on high-speed railway subgrade settlement in soft soil area. Railway Engineering Science, 28, 129-145.
[7] Jiang, X., Chen, X., Fu, Y., Gu, H., Hu, J., Qiu, X., & Qiu, Y. (2021). Analysis of settlement behaviour of soft ground under wide embankment. The Baltic Journal of Road and Bridge Engineering, 16(4), 153-175.
[8] Wang, Q., Zou, L., Niu, Y., Ma, F., Lu, S., & Fu, Z. (2023). Study on the Surface Settlement of an Overlying Soft Soil Layer under the Action of an Earthquake at a Subway Tunnel Engineering Site. Sustainability, 15(12), 9484.
[9] Cao, F., Ye, C., Wu, Z., Zhao, Z., & Sun, H. (2024). Settlement Calculation of Semi-Rigid Pile Composite Foundation on Ultra-Soft Soil under Embankment Load. Buildings, 14(7), 1954.
[10] Liu, Z., Gao, Y., Liao, J., & Zhou, C. (2022). Stochastic medium model for the settlement calculation of prefabricated vertical drains of soft soil foundations in the coastal area of south China. Journal of Marine Science and Engineering, 10(7), 867.
[11] Ding, Z., Jin, J., & Han, T. C. (2018). Analysis of the zoning excavation monitoring data of a narrow and deep foundation pit in a soft soil area. Journal of Geophysics and Engineering, 15(4), 1231-1241.
[12] Peng, B., Feng, R., Wu, L., Wei, K., & Wang, P. (2023). Settlement calculation method for peat soil foundations. International Journal of Geomechanics, 23(7), 04023094.
[13] Zhang, J., Huang, L., Gao, J., Wu, D., Cheng, G., Ren, Z., ... & Xue, H. (2025). Settlement Calculation Method of Lakeside Soft Soil Foundations Based on the Statistical Analysis of Physical and Mechanical Indexes. Transportation Research Record, 03611981241308869.
[14] Zhai, J. (2022). Machine‐Learning‐Based Road Soft Soil Foundation Treatment and Settlement Prediction Method. Scientific Programming, 2022(1), 3463413.
[15] Li, G., Han, C., Mei, H., & Chen, S. (2021). Application of the WNN‐Based SCG Optimization Algorithm for Predicting Soft Soil Foundation Engineering Settlement. Scientific Programming, 2021(1), 9936285.
[16] Luo, J., Wu, C., Liu, X., Mi, D., Zeng, F., & Zeng, Y. (2018, January). Prediction of soft soil foundation settlement in Guangxi granite area based on fuzzy neural network model. In IOP Conference Series: Earth and Environmental Science (Vol. 108, p. 032034). IOP Publishing.
[17] Ray, R., Kumar, D., Samui, P., Roy, L. B., Goh, A. T. C., & Zhang, W. (2021). Application of soft computing techniques for shallow foundation reliability in geotechnical engineering. Geoscience Frontiers, 12(1), 375-383.
[18] Ma, B., Li, Z., Cai, K., Hu, Z., Zhao, M., He, C., ... & Huang, X. (2021). An improved nonlinear settlement calculation method for soft clay considering structural characteristics. Geofluids, 2021(1), 8837889.
[19] Chen Mao. (2023). Study on soft soil foundation treatment technology in industrial building construction. Journal of Civil Engineering and Urban Planning,5(4).
[20] Runqi Liu,Bimeng Jie,Yanhang Tong,Junchen Wang & Yang He. (2025). Automatic virtual reduction of unilateral zygomatic fractures based on ICP algorithm: A preliminary study.. Journal of stomatology, oral and maxillofacial surgery,102220.
[21] Wei Huang,Hui Wang & Xinghong Ling. (2024). Optimised ICP algorithm based on simulated-annealing strategy. International Journal of Computational Science and Engineering,27(5),621-626.
[22] SAmirGhahremanian,AbbasAhmadi,HamidToranjzar,JavadVarvani & NourollahAbdi. (2025). Ecological and Statistical Evaluation of Genetic Algorithm (GARP), Maximum Entropy Method, and Logistic Regression in Predicting Spatial Distribution of Astragalus sp.. Scientifica,2025(1),4003408-4003408.
[23] Mustafa Sevindik,Celal Bal,Tetiana Krupodorova,Ayşenur Gürgen & Emre Cem Eraslan. (2025). Extract optimization and biological activities of Otidea onotica using Artificial Neural Network-Genetic Algorithm and response surface methodology techniques. BMC Biotechnology,25(1),25-25.