Research On Inversion Method of Soil Mechanical Parameters Based on Deep Neural Network

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Abstract. The accuracy of soil mechanical parameters has an important impact on the numerical simulation results of foundation pit engineering. Since the soil parameters often change during the construction process, the parameters need to be dynamically corrected in order to improve the accuracy of numerical simulation. In this paper, a soil parameter inversion method based on PSO-GA-BP neural network is proposed to simulate the construction deformation of the foundation pit support structure and invert key mechanical parameters such as soil elastic modulus (E) and cohesion (c) by combining the finite element simulation with the learning and optimization ability of deep neural network. The deep foundation pit project of a subway station in Wuhan is taken as an example, and the feasibility and accuracy of the method are verified by using on-site monitoring data. The results show that the PSO-GA-BP neural network integrates the global search capability of particle swarm optimization (PSO), the population diversity maintenance characteristic of genetic algorithm (GA), and the local refinement fitting advantage of back-propagation (BP) network, and the inverted soil parameters significantly improve the numerical simulation accuracy, and the maximal relative error is reduced to less than 5% from 14.15% before correction, which provides a reliable basis for engineering design and safety assessment. The maximum relative error is reduced from 14.15% before correction to less than 5%, which provides a reliable basis for engineering design and safety assessment.

Keywords: PSO-GA-BP; soil mechanics; parameter inversion

1 Introduction

Inversion of soil mechanical parameters is a key link in geotechnical engineering investigation and design, and its core objective is to deduce the soil intrinsic parameters inversely through the field monitoring data (e.g., displacement, pore water pressure, etc.) to provide a quantitative basis for engineering safety assessment. The traditional inversion method mainly relies on finite element numerical simulation and statistical regression modeling, and needs to repeatedly adjust the parameters for forward computation, which has bottlenecks such as low computational efficiency and difficulties in solving multi-parameter coupling [1]. Especially in complex stratigraphic conditions (e.g., soft soil, unsaturated soil) and multi-field coupling (seepage-stress-temperature),

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the traditional method is often assumed to simplify too much, resulting in the inversion results deviate from the actual. In recent years, with the popularization of Internet of Things (IoT) monitoring technology and the accumulation of engineering data, the parameter inversion method based on deep learning has gradually become a new path to break through the traditional limitations, which can effectively capture the complex correlation between the soil response and the mechanical parameters through the ability of end-to-end nonlinear mapping [2].

International academics have earlier explored the application of machine learning in geotechnical parameter identification. In 2018, a team from the University of California introduced a convolutional neural network into the inversion of soil parameters of shield tunnels, and synchronized the prediction of cohesion and internal friction angle by using the shield machine boring parameters and the surface settlement data, and the inversion error was controlled to be less than 12% [3]. In 2021, the National University of Singapore proposed a dynamic inversion framework by fusing the long and short-term memory network LSTM and Bayesian optimization dynamic inversion framework, successfully applied to the coastal soft foundation treatment in the compression modulus real-time update. Domestic research started a little late but developed rapidly, Tongji University developed a multi-objective inversion model of soil parameters based on adversarial generative network GAN in 2020, which can alleviate the problem of small data volume by generating virtual samples [4]; China University of Mining and Technology constructed a graph convolution network GCN model that takes into account the spatial variability of the strata in 2022, and realized 95% correlation coefficients in the inversion of surrounding rock parameters of the coal mine roadway. However, most of the existing studies focus on a single engineering scenario, and the systematic optimization of multi-parameter coupling, data noise interference, and model generalization ability is still insufficient [5].

Although the existing deep learning models (e.g., GAN, LSTM, GCN) have made progress in a single scenario, the existing methods have not effectively solved the challenge of coordinated inversion of multi-parameters (e.g., modulus of elasticity, cohesion, permeability coefficient); there are noise interference and small sample problems in the actual engineering monitoring data, and the generalization capability of the existing models is limited; deep learning as a “black box” is difficult to form a closed-loop verification with geotechnical theory, and the engineering credibility is insufficient [6]. Deep learning as a “black box” is difficult to form a closed-loop verification with geotechnical theory, and the engineering credibility is insufficient [7].

This paper proposes a PSO-GA-BP hybrid optimization model, which is innovative in combining the global search of PSO, the population diversity maintenance of GA and the local refinement fitting of BP network to break through the limitations of a single algorithm; generating the training data through finite element simulation to enhance the model's implicit learning ability of the geotechnical mechanics; and combining the validation of the Wuhan Metro deep foundation pit project with the actual data to promote the algorithm from the laboratory to the engineering site.

2 PSO-GA-BP Neural Network

As shown in Figure 1. Aiming at the shortcomings of traditional soil parameter inversion methods (e.g., finite element trial algorithm, statistical regression model), such as low computational efficiency and easy to fall into local optimization, this paper proposes a hybrid optimization model that integrates Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Back-Propagation (BP) neural network. Its core mechanism is:

Population Synergistic Search. The particle swarm optimization algorithm quickly approaches the global optimal region through group intelligence, avoiding the dispersion problem caused by the randomness of the initial value of the traditional trial algorithm. the PSO global fast convergence, through the particle swarm velocity-position iteration formula (Eq. 1), quickly approximates the optimal region in the solution space, avoiding the divergence problem caused by the random initial value.

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (g_{id}^{k} - x_{id}^{k}) \quad (1)$$

GA population diversity maintenance: introduction of crossover probability ($P_c = 0.8$) and variance probability ($P_m = 0.01$) to genetically recombine highly adapted individuals from PSO outputs to break the local optimum trap.

BP network refinement fitting. The GA-optimized weights and thresholds were used as the initial parameters of the BP network, and the Levenberg-Marquardt algorithm (Eq. 2) was used to fit the nonlinear relationship between the mechanical response of the soil body (e.g., settlement, pore water pressure) and the parameters (modulus of elasticity E and cohesion c) with high accuracy.

$$\Delta w = (J^T J + \mu I)^{-1} J^T e \quad (2)$$

The GA-optimized weight thresholds are used as the initial BP parameters, and the Levenberg-Marquardt algorithm (Eq. 2) is used to achieve high-precision nonlinear mapping. The input layer of the network is the field monitoring data (6 nodes: settlement, pore pressure, lateral displacement, etc.), the implicit layer is a hyperbolic tangent activation function, and the output layer is the parameters to be inverted (3 nodes: E, c, and permeability coefficient k).

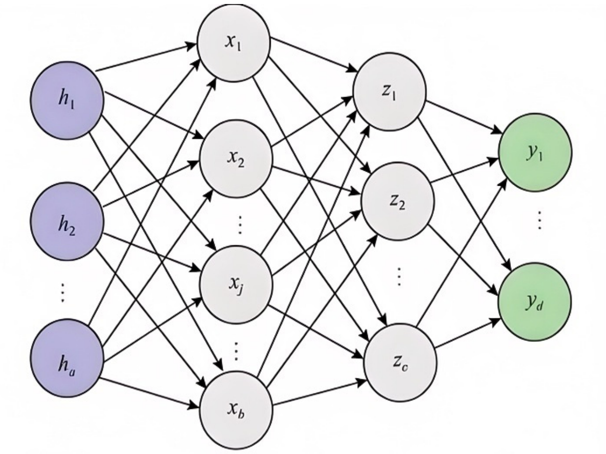

Fig. 1. PSO-GA-BP neural network

3 Engineering Examples

3.1 Overview of the Project

This paper takes the construction of a subway station in Wuhan as an example, this project is a three-story underground 14m island station, double-column transverse five-column six-span box structure, the main structure of the station adopts the cover excavation inverse method. The hydrogeological conditions of this project are complicated, and the soil layers from top to bottom are miscellaneous fill, plain fill, clay, silt, pebbles, strongly weathered siltstone, and moderately weathered siltstone. As shown in table 1.

Table 1. Distribution of soil layers and physical and mechanical properties

Name of soil layer	Thickness (m)	Modulus of elasticity E (MPa)	Cohesion c (kPa)	Permeability coefficient k (m/s)
Miscellaneous Fill	2.5	5.40	15.0	1.0×10^{-6}
Vegetative Fill	3.2	7.00	18.5	2.5×10^{-7}
Clay	5.8	12.00	25.0	5.0×10^{-8}
Powdery soil	4.5	27.00	12.0	1.0×10^{-7}
Pebble	6.0	115.00	8.0	1.0×10^{-4}

3.2 Numerical Modeling

In this paper, the standard section of the foundation pit was selected to establish the model. The model dimensions are 230 m in width, 50 m in length, and 80 m in depth to simulate the site soil layer. The standard section has a width of 49.5 m with an excavation depth of 28.8 m. According to the survey results, the site soil layer is divided into 7 layers. The soil model adopts solid unit, with full constraint at the bottom of the model and normal constraint around the model. The enclosing structure diaphragm wall adopts slab unit with a thickness of 1500mm; the thickness of the slab unit for the top slab of the foundation pit is set at 900mm; the thickness of the slab unit for the bottom slab of the foundation pit is set at 2750mm; the thickness of the slab unit for the structural floor slab is set at 400mm; the diameter of the beam unit of the concrete bored piles is set at 2300mm; and the diameter of the beam unit of the steel concrete columns is set at 900mm. station foundation pit The ABAQUS finite element model is shown in Figure 2.

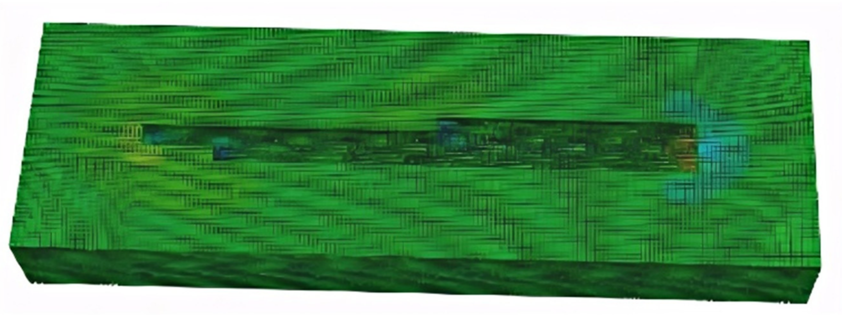

Fig. 2. Finite element model of standard section of station pit

3.3 Simulation Results

As can be seen from Figure 3, the inclination monitoring point No. CX39, from the measured data, the maximum deformation of deep horizontal displacement of the enclosure structure is 8.77mm, measured at the edge of the pit; the minimum deformation is 0.30mm, measured at the bottom end of the enclosure structure. from the simulation results, the maximum deformation of deep horizontal displacement of the enclosure structure is 9.44mm, located at the edge of the pit; the minimum deformation is 0.32mm The minimum deformation is 0.32mm.

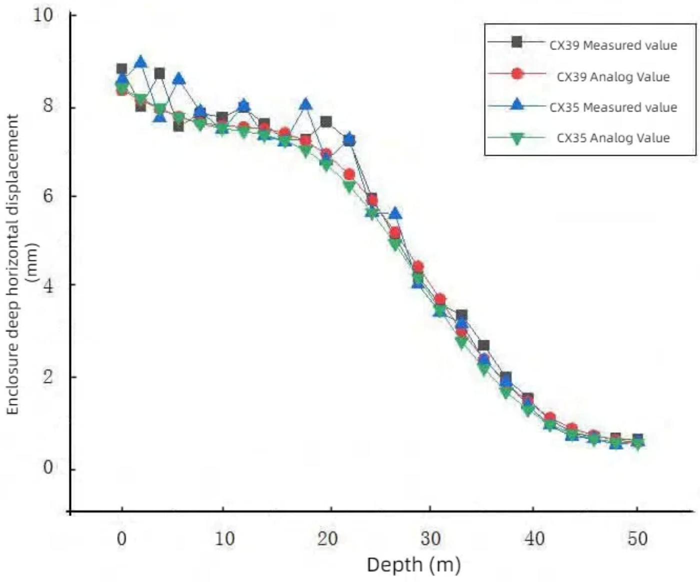

Fig. 3. Variation curve of deep horizontal displacement of the enclosure structure

The inclination monitoring point number CX35, from the measured data, the maximum deformation of deep horizontal displacement of the enclosure structure is 8.87mm measured near the edge of the pit; the minimum deformation is 0.30mm measured at the bottom end of the enclosure structure. From the simulation results, the maximum deformation of deep horizontal displacement of the enclosure structure is 9.53mm, located at the edge of the pit; the minimum deformation is 0.32mm, located at the The minimum deformation is 0.32mm, located at the bottom of the enclosure structure. Both measured and simulated results show that the deformation at the edge of the pit is the largest, gradually decreasing along the depth direction, and the overall deformation is forward tilting, and the simulation results show a larger maximum displacement and a slightly different minimum displacement value, with a maximum error of 14.15%.

4 Inversion Calculations

4.1 Selection of Inversion Model Parameters

Lubuo uranium analyzed the influence of the main parameters on the deformation of the foundation pit in the inverse method of construction, and without considering the correlation between the parameters, the modulus of elasticity is the most sensitive to the deformation of the enclosure structure of the deep foundation pit excavation in a single factor [8]. In this paper, the modulus of elasticity of the soil was chosen as the parameter to be inverted, and the choice of this parameter is crucial for the study of the performance of diaphragm walls in the enclosure structure, because it directly affects the deformation and stability of the soil. Also, since the diaphragm wall of the enclosing structure, which is the subject of this paper, is embedded in strongly weathered siltstone mudstone, it can be seen from Section 3.3 that the error between the measured and numerical simulation results at this location is small. This implies that the modeling of the description and prediction at this location are more accurate and well reflect the actual situation [9]. Therefore, the soil parameters for the inversion in this paper are the modulus of elasticity of five layers of soil above the strongly weathered siltstone mudstone. Where the range of parameter selection is taken within ±20% of the survey results [10].

4.2 Inversion Calculation Results

The PSO-GA-BP inversion model was built using MATLAB and the inversion model was trained by learning samples. The inversion results of the first five layers of soil parameters were obtained by inputting the measured data into the inversion model, and these results were organized in Table 2. From the tabular data, it can be observed that the inversion results were slightly adjusted relative to the initial values, with a maximum correction of 4.77% and a minimum correction of 0.37%.

Table 2. Inverse results of parameters

parameters	starting value	inversion value	degree of correction
E (1 MPa)	5.40	5.58	3.33%
E (2 MPa)	7.00	6.81	2.71%
E (3 MPa)	12.00	11.79	1.79%
E (4 MPa)	27.00	25.71	4.77%
E (5 MPa)	115.00	114.58	0.37%

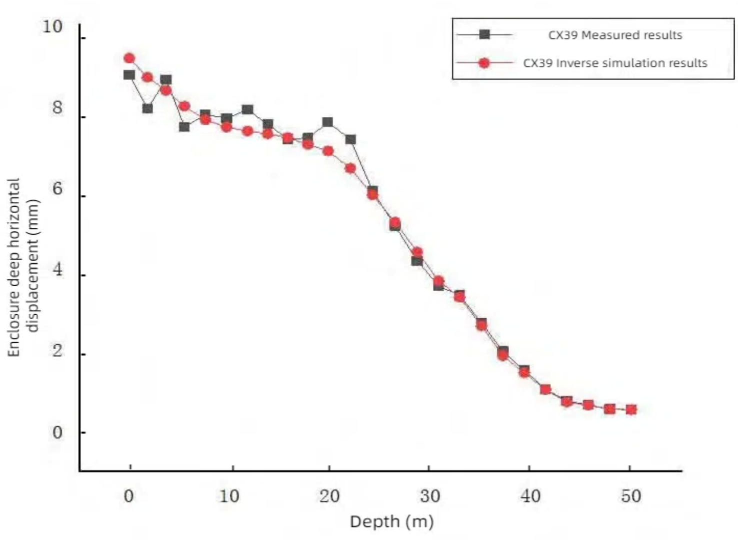

Fig. 4. CX39 Inversion simulation result graphs

In order to verify the reliability and applicability of the soil parameters obtained from the inversion, the average values of the inversion results of the soil parameters were used, and these average values were applied as inputs to the ABAQUS finite element model for the simulation of the enclosure structure from Figure 4. As can be seen, most of the horizontal displacement curves of the CX39 inversion simulation results are located above the measured results, and their absolute errors are within 1 mm, and the relative errors are basically within 5%. However, the maximum relative error is 9.91%, which may be caused by the abnormality of the measured values.

As can be seen , most of the horizontal displacement curves of the CX35 inversion simulation results are located above the measured results, and their absolute errors are within 1mm, and the relative errors are basically within 5%. However, the maximum relative error is 12.08%, which is caused by the abnormality of the measured value from Figure 5.

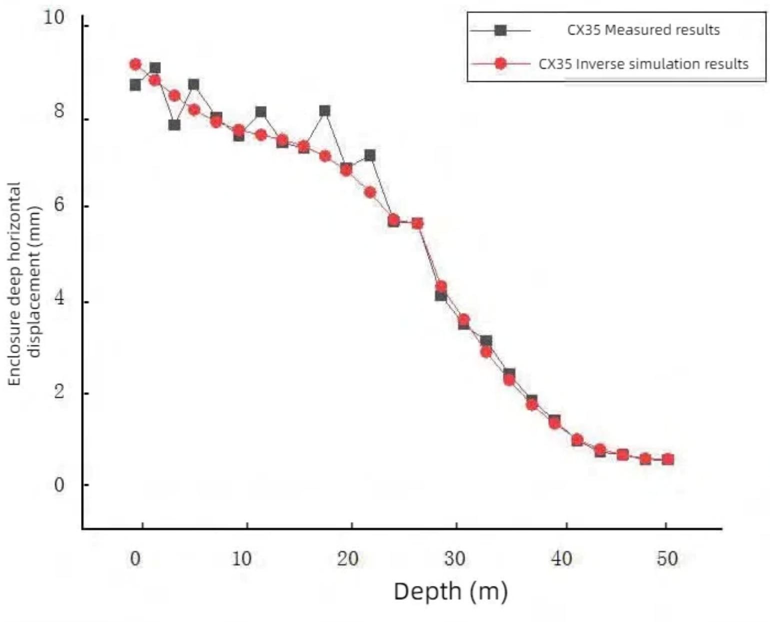

Fig. 5. Graph of CX35 inversion simulation results

It can be seen that the use of PSO-GA-BP neural network inversion of soil parameters in the simulation process has achieved significant results, closer to the actual values of soil parameters. Neglecting the measured anomalies, the inverse simulation results can reach the required accuracy of the project. Therefore, the PSO-GA-BP neural network inversion model can provide more accurate soil parameters for numerical simulation. This is of great to improve the accuracy and precision of the prediction resultssignificance, which provides powerful support and guidance for engineering design and analysis.

5 Conclusion

This paper takes the deep foundation pit construction of a subway station in Wuhan as an example, and adopts the PSOGA-BP neural network inversion method to obtain more accurate elastic modulus of miscellaneous fill, vegetative fill, clay, silt and pebble soil, and compares the simulation calculation results after the correction of inversion parameters with the measured results and the original simulation calculation results. In this paper, ABAQUS numerical simulation method was adopted to simulate the construction process of a subway station in Wuhan. The simulation results show that the overall deformation trend is consistent with the measured results, indicating that the simulation method has some degree of predictive ability. However, compared with the measured results, the numerical accuracy of the simulation results is insufficient, with a maximum error of 14.15%. This implies that the simulation results have large discrepancies in quantitative prediction and are not accurate enough. The inversion model constructed using PSO-GA-BP neural network successfully utilized the measured data to invert the soil parameters with minor corrections. Relative to the initial values, the maximum correction of the inversion results was 4.77% and the minimum correction was 0.37%. The parameter results obtained from the inversion were input into the ABAQUS model to correct the simulation calculations. The corrected numerical simulation calculations are closer to the measured values, and the deformation trend is consistent with the measured results. Although there is an error of about 10% in individual data due to the inaccuracy of the measured results, most of the data have an error of less than 5%, and the corrected simulation results are still able to meet the needs of deep foundation pit deformation prediction.

The current model still needs to rely on the simulation data generated by finite elements, and the generalization ability for extreme working conditions (e.g., sudden seepage) in the actual project needs to be verified; despite the improvement of model accuracy, the parameter inversion process still lacks the support of explicit mechanical theories; the current method needs to be trained offline, and it is difficult to satisfy the demand for real-time dynamic correction in the construction site. In the future, the intrinsic equations will be embedded into the network structure as constraints to enhance the interpretability of the model; multiple sources of information, such as BIM models and geo-radar data, will be integrated to improve the robustness in small-sample scenarios; and the lightweight model will be developed and integrated into the Internet of Things (IoT) monitoring terminals to realize real-time and automation of the parameter inversion.

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References

1. Pan, P. Z. , Tan, F. , Li, F. , Chi, F. , Liu, X. , & Wang, Z. . (2024). A three-dimensional numerical study on the stability of layered rock spillway tunnels in alpine canyon areas. deep Resources Engineering, 1(2).
2. Xiao, J. , Xudong, Z. , & Jiming, H. Y. . (2024). Research on the damaging mechanisms of expansive soil in subgrade. Mechanics of Advanced Materials and Structures, 31(9/12), 2362-2369.
3. Zhou, Z. , Huang, Y. , & Zhou, F. . (2024). Dynamic response of layered unsaturated soils under moving loads. Mechanics of Solids, 59(5), 2975-2991.
4. Ji, Y. , Shi, L. , Cui, Z. , Lu, X. , Di, S. J. , & Wang, D. . (2024). Analysis of seepage field characteristics of water diversion power generation system of pumped storage power station. iop Publishing Ltd.
5. Huh, H. , Goh, H. , & Kang, S. K. L. F. . (2023). Using the impulse-response pile data for soil characterization. Journal of Engineering Mechanics, 149(10), 13.
6. Ma, H. H. , Yuan, S. , Zhang, Z. Z. , Tian, Y. H. , & Dong, S. S. . (2023). Application of soil parameter inversion method based on bp neural network in foundation pit deformation prediction. applied Geophysics, 20(3), 11.
7. (2024). Research on the damaging mechanisms of expansive soil in subgrade. Mechanics of Advanced Materials and Structures, 31(11), 2362-2369.
8. Attri, S. , & Rani, S. . (2024). Axisymmetric consolidation of a poroelastic soil layer with impermeable surface. Mechanics of Solids, 59(3), 1376-1390.
9. Zhao, J. S. , Jiang, Q. , Pei, S. F. , Chen, B. R. , Xu, D. P. , & Song, L. B. . (2023). Microseismicity and focal mechanism of blasting-induced block falling of intersecting chamber of large underground cavern under high geostress. Journal of Central South University, 30(2), 542-554.
10. Zhang, G. , Shun-Chuan, W. U. , Zhang, S. H. , & Guo, P. . (2023). P-wave velocity tomography and acoustic emission characteristics of sandstone under uniaxial compression. Rock and Soil Mechanics, 44(2), 483-496.