



Multi-Parameter Intelligent Inversion of Embankment Soil Based on Monitoring Data

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INFORMATION

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ABSTRACT

Accurately obtaining the mechanical properties of embankment soil is the core component for achieving precise calculation and mastering the operational status of the embankment. To achieve precise identification of multiple key material parameters of the embankment soil, this paper proposes an inversion method that integrates monitoring displacement information with intelligent algorithms. This approach comprehensively utilizes monitoring data from multiple monitoring points and different times to collaboratively invert multiple key parameters of the embankment soil. The study establishes a finite element model of the embankment based on the Cvisc (Burgers-Mohr) viscoelastic-plastic constitutive theory, which describes the creep behavior of soil. Orthogonal experimental design is employed to generate multiple parameter combinations of the soil, and numerical simulations are conducted to obtain displacement increments at various monitoring points over time, thereby forming a training sample set. On this basis, using the displacement increment sequences from multiple monitoring points at different times as input, a Back Propagation (BP) neural network improved by the Whale Optimization Algorithm (WOA) is trained to establish a nonlinear mapping model from displacement sequences to material parameters. Subsequently, the material parameters of the soil are inverted based on the actual displacement sequences from multiple monitoring points at different times. This method is applied to the Tongma Embankment for parameter inversion. Verification shows that the displacements calculated using the inverted parameters are in good agreement with the monitoring values, with an average relative error of approximately 2.8%. The results indicate that this method can effectively invert multiple parameters of the soil, thereby providing a reliable basis for precisely understanding the mechanical properties of the soil and the state of the embankment.

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1 Introduction

Embankment structures constitute key components of flood control systems, whose safety is directly linked to the protection of human lives, assets, and regional economic progress. The precise identification of soil material parameters thus represents an imperative prerequisite and a critical

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undertaking in the safety assessment of these structures. Due to the inherent uncertainty of soil material parameters, traditional experience methods face challenges in directly obtaining parameters that accurately reflect actual engineering conditions. Inverse analysis, as a method for deriving material parameters from monitoring data, offers a significant technical solution to overcome this difficulty [1–3].

There are various inversion methods for soil parameters, such as the direct inverse method, optimization method, and spectral method. In recent years, alongside traditional optimization methods, intelligent algorithms have gained prominence as research hotspots due to technological advancements [4]. As a significant branch of intelligent algorithms, artificial neural networks demonstrate unique advantages in solving complex parameter inversion problems through their powerful nonlinear fitting capabilities [5,6]. The core idea of intelligent inversion through artificial neural networks lies in constructing a computational bridge that connects numerical models with monitoring data, thereby establishing a high-precision and high-efficiency nonlinear mapping relationship from monitoring displacements to soil material parameters using intelligent algorithms. Numerous scholars have applied the back-propagation (BP) neural networks in related research [7,8]. Training samples constructed through numerical simulation effectively capture the mapping relationship between parameters and responses. This method provides a crucial foundation for the engineering application of intelligent inversion technology. Building upon this, many scholars have optimized network structures and training algorithms to continuously enhance model performance. For instance, Dong et al. [9] employed a genetic algorithm-enhanced BP neural network to predict the optimal design parameters of reinforced soil embankments with wrapped faces; Qu et al. [10] employed particle swarm optimization (PSO) to optimize a BP neural network for cloud inversion analysis of the surrounding rock parameters surrounding the underground powerhouse at the Shuangjiangkou Hydropower Station. Zhou et al. [11] employed an optimized inversion method based on multi-population genetic algorithm-improved BP neural network and response surface method (MPGA-BPNN RSM) to determine optimal creep parameters for high Concrete-Faced Rockfill Dams (CFRDs). The Whale Optimization Algorithm (WOA) [12], proposed in recent years, demonstrates significant advantages in global optimization due to its unique spiral hunting mechanism and swarm intelligence characteristics. It has been successfully applied in various fields including hydrology [13] and mechanical energy [14]. This paper combines the WOA algorithm with the BP neural network for the inversion of embankment soil material parameters. By optimizing the initial weights and thresholds of the BP neural network, the model enhances its global search capability and convergence stability, thereby further improving the inversion accuracy for material parameters.

The actual displacement of embankment soil is typically governed by multiple constitutive parameters. Therefore, establishing a multi-parameter collaborative inversion method holds significant value for characterizing the overall mechanical properties of embankment soil and enhancing the accuracy of numerical simulations. In existing research, Xiong et al. [15] effectively enhanced the spatial representativeness and identification accuracy of embankment soil mechanical parameter inversion by incorporating multi-point displacement data. Further studies [16] confirmed that employing monitoring data at different times for collaborative inversion of material parameters strengthens the constraints in the inversion process and improves the stability of results. However, existing studies predominantly focus on the use of single-dimensional information, while studies that deeply integrate monitoring data from multiple monitoring points and different times, and further conduct collaborative inversion of multiple parameters, remain relatively limited. Building upon this research foundation, this paper integrates monitoring data from multiple points and over different times to perform collaborative intelligent inversion of multiple key parameters for embankment soil. This inversion method effectively

utilizes monitoring data to mitigate the effects of random errors and local disturbances. It significantly enhances the interference resistance and global representativeness of multi-parameter identification results, enabling them to more accurately reflect the comprehensive mechanical properties of the soil. Consequently, the method offers superior applicability and practicality in engineering practice.

This study constructs a finite element model of the embankment based on viscoelastic-plastic constitutive theory. Initially, the study selects representative soils and their parameters to be inverted, and then orthogonal experimental design is employed to generate parameter combinations representative of the soils. For each parameter combination, forward finite element numerical simulations are conducted to compute displacement increment sequences at various monitoring points across different times, thereby forming the training dataset. Subsequently, a BP neural network improved by the WOA is trained to establish a nonlinear mapping model that takes displacement increments as input and outputs material parameters. By inputting the field-monitoring displacement increment sequences into the well-trained mapping model, collaborative inversion of multiple soil parameters is achieved, thus establishing an intelligent inversion framework for multiple parameters of embankment soil that integrates monitoring data from multi-point and different times. To validate the effectiveness of the proposed method, this paper applies it to the Tongma Embankment project to inversely determine the soil material parameters. The inverted parameters are then substituted back into the finite element model for forward computation, and the calculated displacements are quantitatively compared with the monitoring data to verify the reliability of the inversion method.

2 Research Method

Soil in embankment engineering exhibits plastic deformation and creep deformation during long-term operation due to sustained loading and time accumulation. This complex mechanical behavior directly impacts the long-term stability of embankment structures. The Cvisc viscoelastic-plastic constitutive model establishes a framework capable of simultaneously accounting for both elastic-plastic deformation and viscous creep characteristics in soil by parallel coupling the Burgers creep model with the Mohr-Coulomb plasticity model [17,18]. Its component combination model is illustrated in Fig. 1.

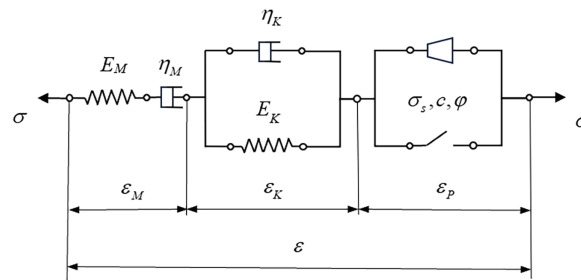


Figure 1: Schematic diagram of the Cvisc model

As shown in the figure, the total strain (ϵ) in the Cvisc creep model primarily consists of three components: the strain of the Maxwell body (ϵ_M), the strain of the Kelvin body (ϵ_K), and the strain of the Saint-Venant body (ϵ_P). Specifically, Maxwell characterizes the soil's transient elastic response and long-term viscous flow properties through the transient elastic modulus (E_M) and viscosity coefficient (η_M); the Kelvin body describes the soil's delayed creep behavior via the delayed elastic modulus

(E_K) and viscosity coefficient (η_K), reflecting the soil's viscoelastic adjustment process; The Saint-Venant body employs the Mohr-Coulomb yield criterion to define plastic strain (ε_p). When the stress (σ) exceeds the yield limit (σ_s), irreversible plastic flow occurs. This strain is independent of time and depends solely on the stress state, where cohesion (c) and internal friction angle (φ) are key parameters governing plastic strain development. This model couples elastic, viscous, and plastic mechanisms, enabling the Cvisc model to not only capture the elastic-plastic response of soil under short-term loading but also effectively simulate the cumulative creep deformation process under long-term loading [19].

The one-dimensional creep equations for the Cvisc creep model are as follows:

$$\text{When } \sigma < \sigma_s, \varepsilon = \sigma_0 \left[\frac{1}{E_M} + \frac{t}{\eta_M} + \frac{1}{E_K} \left(1 - e^{-\frac{E_K}{\eta_K} t} \right) \right] \quad (1)$$

$$\text{When } \sigma \geq \sigma_s, \varepsilon = \sigma_0 \left[\frac{1}{E_M} + \frac{t}{\eta_M} + \frac{1}{E_K} \left(1 - e^{-\frac{E_K}{\eta_K} t} \right) \right] + \varepsilon_p \quad (2)$$

In the equation: σ_0 represents the constant stress; ε denotes the strain. Under low stress conditions, the model sequentially exhibits three characteristic stages: transient elastic deformation, decaying creep, and steady-state creep. When stress exceeds the long-term strength, the model can simulate the nonlinear process of accelerated creep up to shear failure [20]. This constitutive relationship effectively simulates the deformation process of embankments, providing a reliable theoretical foundation for subsequent parameter inversion.

In the computational analysis of embankment engineering based on the Cvisc constitutive model, the finite element method has been widely adopted due to its exceptional capability in handling complex boundaries and nonlinear problems, enabling efficient and precise solutions [21,22]. Based on the Cvisc constitutive theory describing soil creep behavior, this study establishes a finite element model of the embankment. To generate parameter combinations that effectively cover the parameter space, after determining the reasonable value ranges of multiple soil material parameters and dividing them into different levels uniformly, the orthogonal experimental design method grounded in mathematical statistics and the principle of orthogonality is employed to systematically devise a multi-factor, multi-level parameter combination scheme. This method can use a small number of highly representative parameter combinations to reflect the characteristics of the full parameter space. Consequently, orthogonal experimental design allows for the selection of a small yet highly representative set of parameter combinations from all possible ones. For each parameter combination, the displacement increment sequences at multiple monitoring points over different times under that specific parameter combination are solved through finite element calculations. Using the displacement increments from multiple points and times as the input layer of the neural network, while the corresponding set of material parameters to be inverted as the output layer, a sample dataset for inversion analysis is constructed. This study introduces the WOA to globally optimize the initial weights and thresholds of the BP neural network. The optimized algorithm is then used to train the samples, establishing a nonlinear mapping model between displacement increments and material parameters.

The BP neural network is a feedforward neural network that employs backpropagation of errors, exhibiting strong nonlinear mapping capabilities. It consists of an input layer, hidden layers, and an output layer. Input parameters enter through the input layer, undergo processing in the hidden layers, and are output through the output layer. Based on the error between the output parameters and the target parameters, the network weights and thresholds are updated in reverse, thereby approximating the output parameters toward the target parameters [23,24]. Its learning effectiveness is primarily

determined by the initial weights and thresholds. Since weights and thresholds are gradually adjusted along locally optimal directions, the network is prone to getting stuck in local minima.

WOA optimization algorithm is a heuristic optimization method inspired by whale hunting behavior, characterized by strong local exploration capabilities and global search capabilities [25]. Its mathematical formulas are primarily as follows:

$$X(t+1) = X^*(t) - AD, p < 0.5 \quad (3)$$

$$X(t+1) = D'e^{bl} \cos(2\pi t) + X^*(t), p \geq 0.5 \quad (4)$$

In the formulas: $D' = X^*(t) - X(t)$, $D = CX^*(t) - X(t)$, $A = 2ar - a$, $C = 2r$; a is a constant linearly decreasing from 2 to 0 during iteration; p and r are random numbers between [0, 1]; $X(t)$ represents the current whale position and $X^*(t)$ represents the optimal solution at each iteration, where t denotes the iteration count; D' denotes the optimal hunting position for the i -th whale; b is a constant defining the spiral characteristics. A larger b increases the span per spiral turn, while a smaller b densifies the spiral turns. Typically, $b = 1$ is set; l is a random number between $[-1, 1]$, controlling the radius and angle of the spiral [26].

In the whale optimization algorithm, A represents the distance coefficient. When $A > 1$, the whale moves away from the current optimal solution, escaping the local optimum to achieve global optimization. When $A < 1$, the whale converges toward the current optimal solution. Parameter p is a probability threshold that controls the selection between prey search and spiral encirclement during algorithm iterations. When $p < 0.5$, the whale performs either random search or encirclement search based on the value of A . When $p \geq 0.5$, the whale exhibits bubble attack behavior, where it gradually approaches local optima through spiral position changes, achieving local exploration. Employing the WOA algorithm to optimize the search process for BP neural network weights and thresholds prevents the network from getting stuck in local optima during training. It also reduces sensitivity to initial parameters, thereby enhancing training speed, computational accuracy, and stability [27,28].

Based on the trained WOA-BP neural network model, the displacement increment sequences from multiple monitoring points at different times in an actual embankment section are inputted. Through forward computation, the nonlinear mapping model outputs the optimal estimated values of the corresponding soil material parameters, thereby establishing an intelligent multi-parameter inversion method for embankment soil that integrates monitoring information from multiple monitoring points at different times. Finally, the inverted parameters are substituted back into the initial finite element model for forward calculated. By comparing the degree of agreement between the calculated displacements and the monitoring displacements, the reliability of the inversion results and the effectiveness of the entire theoretical framework are objectively verified. The technical workflow is illustrated in Fig. 2.

3 Engineering Case Study

The Tongma Embankment is a secondary flood control embankment along the Yangtze River mainstem, located on the left bank within Anqing City in the middle and lower reaches of the river. The section analyzed in this paper is situated at the Juwang segment of the Tongma Embankment, which is a renowned soft-ground section with a history of multiple severe landslides and collapse incidents. This embankment section features low-lying terrain and a broad water surface. Due to multiple heightening and thickening operations, it has developed a complex structure where new and old embankment bodies are interlaced and superimposed, resulting in certain soil heterogeneity [29]. This section

employs the previously described method, focusing on multi-parameter intelligent inversion analysis of key soils within the embankment body to obtain accurate soil material parameters.

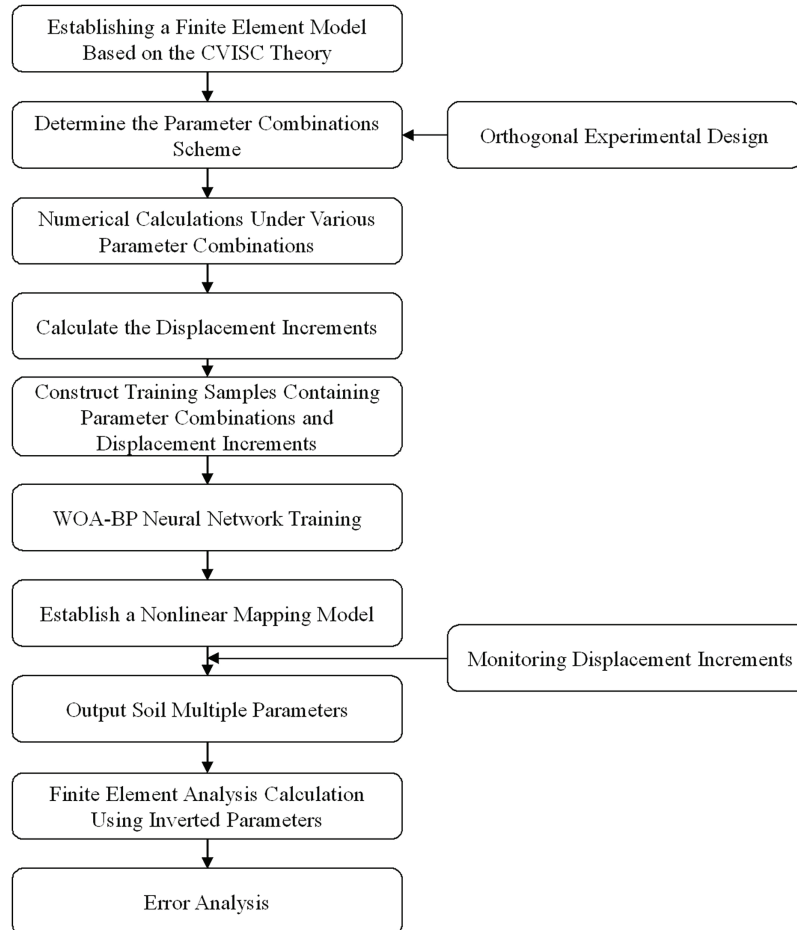


Figure 2: Technology roadmap

3.1 Monitored Information

Taking the monitoring period from July to August 2010 at the Tongma Embankment as an example, the embankment was subjected to sustained high water levels during this time. Based on the investigation of this embankment section [30], the cross-section is shown in Fig. 3. The embankment soil consists of: the slope soil layer (O_1) on the waterside, the fill soil layer (O_2) on the landside, the fill soil layer (O_3) on the old embankment body. The foundation soil comprises: the medium silty loam layer, the silty heavy loam layer, the heavy loam layer, and the silty fine sand layer. The displacement monitoring points CS-1 to CS-4 in the figure conducted displacement observations on 11 July, 20 July, 06 August, and 18 August, 2010 [31]. To effectively suppress random errors and fully utilize monitoring data, subsequent inversion analysis will integrate valid information reflecting soil parameters from multiple observation points and all monitored dates in five weeks.

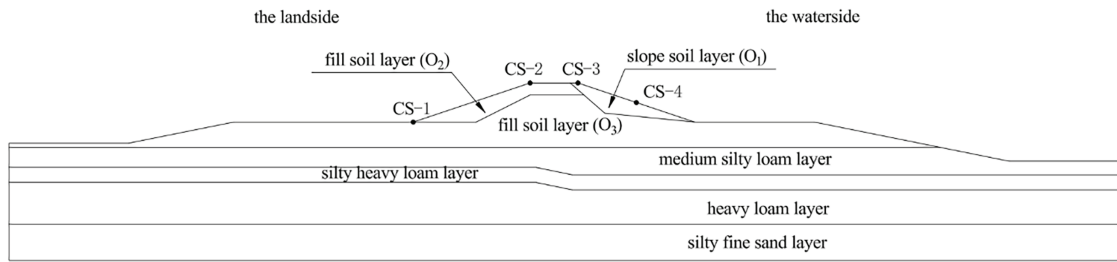


Figure 3: Calculated cross-section diagram

3.2 The Establishment of Finite Element Model

Based on Fig. 3, a finite element calculation model is established using the numerical simulation software ANSYS. The embankment height is 6.5 m, with a depth of 23 m below the toe. The model is uniformly discretized by means of a hexahedral (Hex) swept meshing technique. Based on the arrangement of four monitoring points along the embankment, their corresponding nodes in the computational model are determined. The model is subsequently imported into the advanced finite analysis software FLAC3D for numerical computation. Normal constraints are applied to both lateral sides of the model, while full constraint is imposed at the bottom, as shown in Fig. 4. The cross-section was subjected to water load and soil self-weight, and the calculation was performed using the Cvisc viscoelastic-plastic constitutive model.

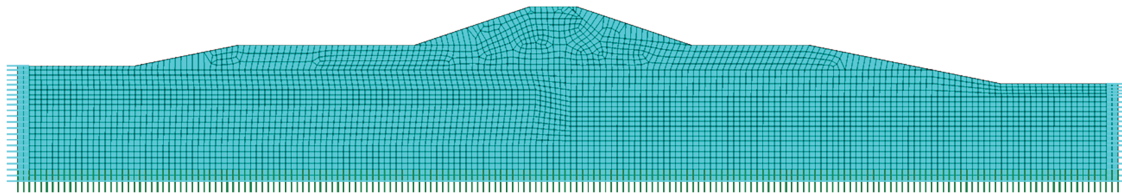


Figure 4: The finite element calculation model diagram

3.3 Intelligent Inversion of Parameters

3.3.1 Determination of Primary Inversion Parameters

Based on existing knowledge of the Tongma Embankment, it is understood that its foundation soil has a long formation history. For the old embankment section constructed in 1958, the main consolidation process of the embankment soil body can be considered essentially complete due to prolonged self-weight loading. However, the later-filled O_1 and O_2 soil layers may exhibit variations in compaction uniformity, resulting in relatively loose soil structures [29]. Based on the above engineering geological analysis, this study focuses on the O_1 and O_2 soil layers as the primary inversion targets.

When selecting inversion parameters, independent parameters with greater uncertainty or significant influence on the stress-strain behavior of the study subject are typically chosen. Based on the theoretical framework of the Cvisc constitutive model, the inversion parameters selected in this study are as follows: cohesion (c) and internal friction angle (φ), as core parameters of the Mohr-Coulomb strength criterion, directly determine the soil's shear strength and ultimate bearing capacity; The transient elastic modulus (E_M) governs the soil's transient elastic response; the delayed elastic modulus (E_K) characterizes delayed elastic deformation properties; the Maxwell viscosity coefficient

(η_M) reflects the material's long-term creep behavior; and the Kelvin viscosity coefficient (η_K) characterizes the stress relaxation behavior of viscoelastic materials. These six parameters comprehensively cover the deformation mechanisms of the Cvisc constitutive model, enabling a relatively complete characterization of the mechanical behavior of embankment soil.

3.3.2 Inversion Calculations

During inversion, reasonable parameter ranges are first established based on engineering geological survey data, laboratory geotechnical test results, and empirical values from similar projects. Based on *in-situ* test results of soil material parameters [30] and laboratory geotechnical tests on similar soils [32], this study defines reasonable ranges for cohesion and internal friction angle. For Burgers creep parameters, the ranges for the transient elastic modulus, Maxwell viscosity coefficient, delayed elastic modulus, and Kelvin viscosity coefficient are determined with reference to values provided in studies on creep test curve characteristics of similar soils engineering projects [33], as shown in Table 1.

Table 1: Range of values for inversion parameters

Inversion parameters		Value range
O ₁ soil layer	c/kPa	13~23
	$\phi/^\circ$	2~12
	E_M/MPa	12~18
	$\eta_M/\text{MPa}\cdot\text{s}$	$2 \times 10^8 \sim 6 \times 10^8$
	E_K/MPa	2~6
	$\eta_K/\text{MPa}\cdot\text{s}$	$8 \times 10^{12} \sim 3 \times 10^{13}$
O ₂ soil layer	c/kPa	2~10
	$\phi/^\circ$	21~31
	E_M/MPa	12~18
	$\eta_M/\text{MPa}\cdot\text{s}$	$2 \times 10^8 \sim 6 \times 10^8$
	E_K/MPa	2~6
	$\eta_K/\text{MPa}\cdot\text{s}$	$8 \times 10^{12} \sim 3 \times 10^{13}$

A three-level orthogonal experimental design method is employed to construct 54 combinations of material parameters. Numerical simulation analysis is conducted based on the established embankment finite element model. Taking 16 June, outside the inversion period, as the initial reference date. Finite element calculations are used to obtain the displacement increments relative to the initial date at monitoring points CS-1 to CS-4 for four monitoring dates: 11 July, 20 July, 06 August, and 18 August. Based on the aforementioned process, a dataset comprising 54 parameter combinations and calculated displacement increments is constructed. In this dataset, the displacement increments from each monitoring point and different times are used as input, and the corresponding parameter combinations serve as output. Subsequently, the WOA-BP neural network is trained to obtain a nonlinear mapping model that relates the displacement increments from multiple monitoring points and different times to the material parameters. Finally, by inputting the monitoring displacement increments from multiple monitoring points at different times into this trained nonlinear model, the collaborative intelligent inversion of multiple key parameters of the embankment soil can be achieved. The inversion results are presented in Table 2.

Table 2: Multi-parameter inversion results

Inversion parameters		Inversion results
O ₁ soil layer	c/kPa	17.6
	$\phi/^\circ$	6.7
	E_M/MPa	15.6
	$\eta_M/\text{MPa}\cdot\text{s}$	4.1×10^8
	E_K/MPa	3.8
	$\eta_K/\text{MPa}\cdot\text{s}$	1.0×10^{13}
O ₂ soil layer	c/kPa	4.3
	$\phi/^\circ$	24.8
	E_M/MPa	14.9
	$\eta_M/\text{MPa}\cdot\text{s}$	4.0×10^8
	E_K/MPa	3.6
	$\eta_K/\text{MPa}\cdot\text{s}$	9.9×10^{12}

3.3.3 Results Verification

Using the soil parameters obtained from the WOA-BP neural network inversion, forward calculations of the embankment displacements for each monitoring date are performed based on the established finite element model. The results are shown in Figs. 5–8. In these figures, displacement values are positive when upward and negative when downward.

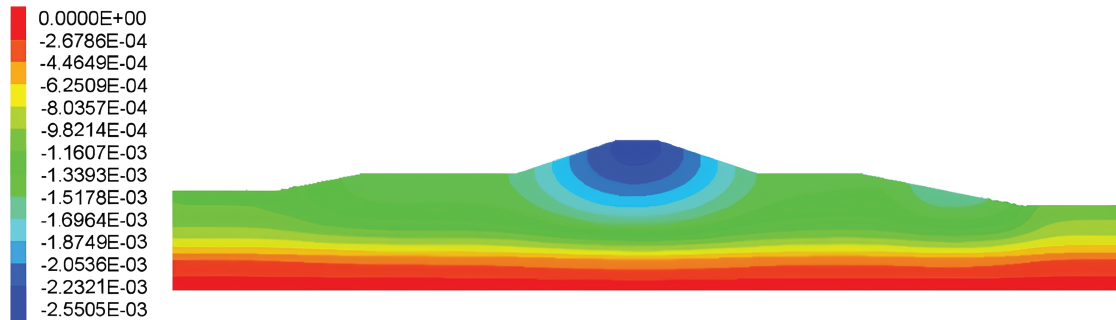


Figure 5: Displacement field of the embankment on 11 July (Unit: m)

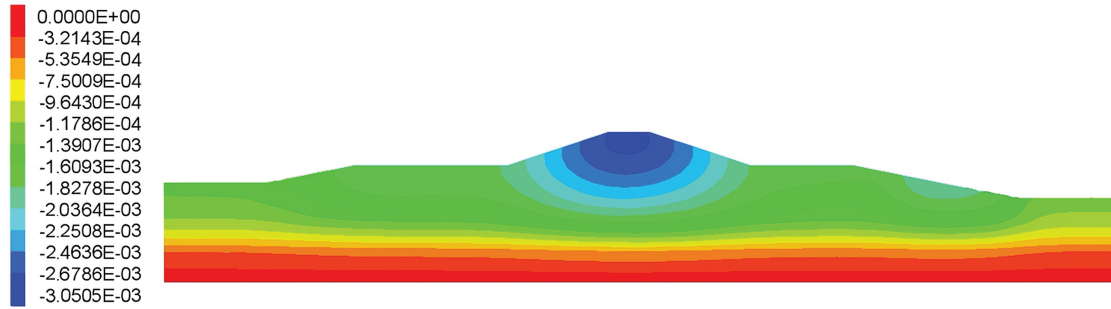


Figure 6: Displacement field of the embankment on 20 July (Unit: m)

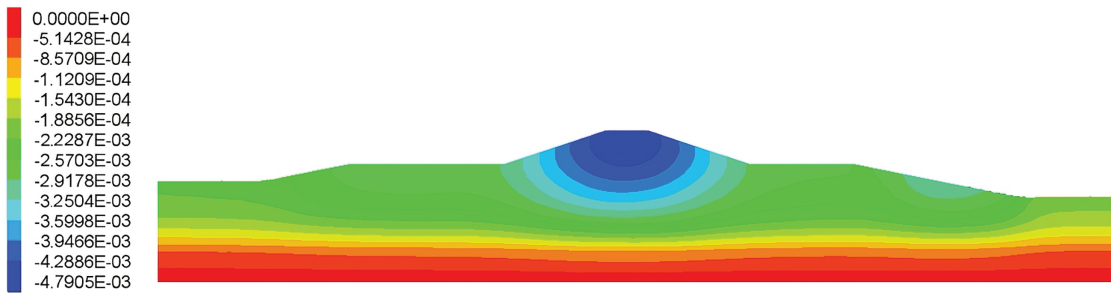


Figure 7: Displacement field of the embankment on 06 August (Unit: m)

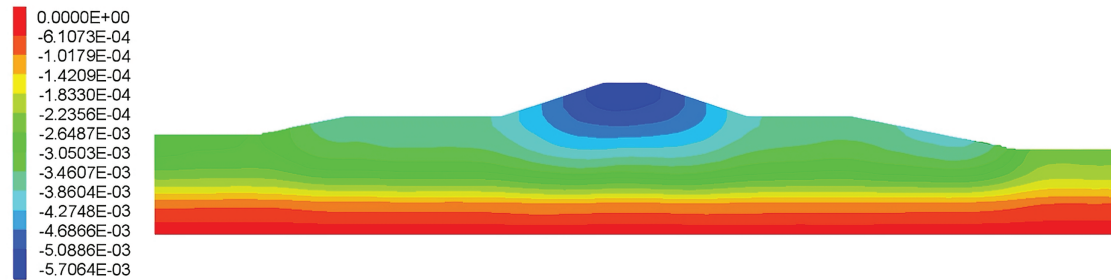


Figure 8: Displacement field of the embankment on 18 August (Unit: m)

Calculate the displacement increments at each monitoring point and compare them with the corresponding monitoring data, as shown in Figs. 9–12.

To quantitatively evaluate the inversion accuracy, an error analysis of above figures is performed using the following equation.

$$\delta = \frac{1}{n} \sum_{i=1}^n \left| \frac{S_i - Z_i}{Z_i} \right| \times 100\% \quad (5)$$

In the equation: δ denotes the average relative error; n represents the total number of data points; S_i is the calculated displacement increment for the i -th data point; Z_i is the monitoring displacement increment for the i -th data point. Substituting the data into the calculation reveals that the average relative error between the calculated displacement values of the embankment soil and the actual

displacement monitoring data is 2.8%. This demonstrates that the inversion method proposed in this paper achieves high accuracy in obtaining multiple parameters of embankment soil. The inverted parameters accurately reflect the actual mechanical properties of the soil, validating the reliability of this intelligent inversion method.

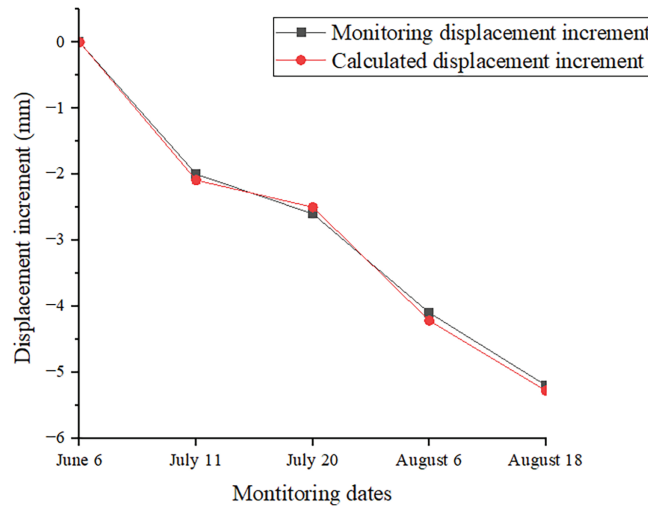


Figure 9: Comparison of displacement increments at CS-1

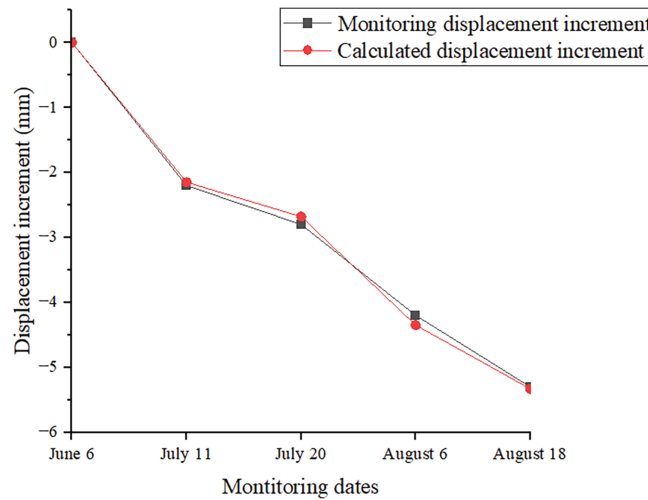


Figure 10: Comparison of displacement increments at CS-2

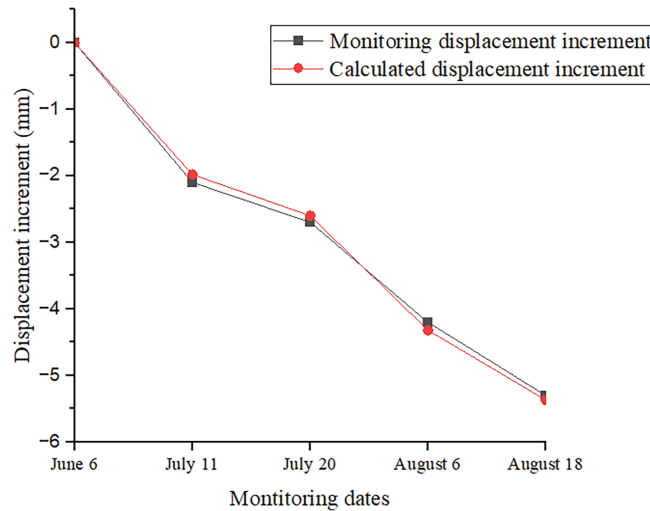


Figure 11: Comparison of displacement increments at CS-3

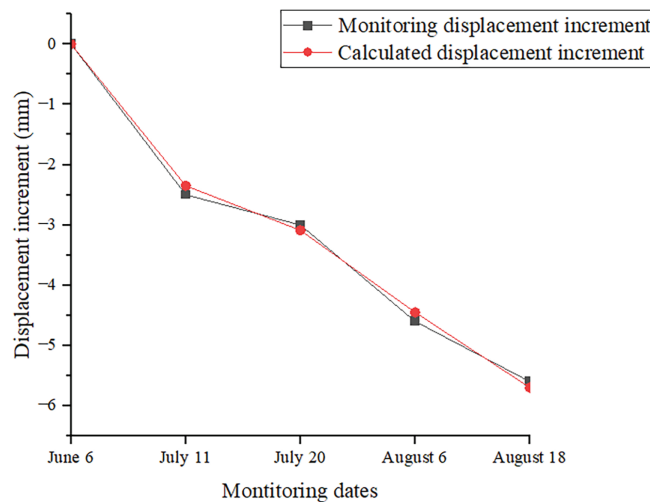


Figure 12: Comparison of displacement increments at CS-4

4 Conclusions

This study proposes a multi-parameter intelligent inversion method for embankment soil, integrating monitoring displacements data from different times and multiple points. The method first establishes a finite element model of the embankment based on the Cvisc constitutive theory. It then employs an orthogonal experimental design to generate the multi-parameter combinations of the soil. Displacement increments are calculated via finite element numerical simulation. Subsequently, the WOA-BP neural network is trained to establish a nonlinear mapping model between the displacement increments and the material parameters. Finally, intelligent inversion of the multiple soil parameters is achieved based on the displacement monitoring data. In an application to the Tongma Embankment, the method is employed to invert the embankment's soil parameters. The verification results demonstrate that the displacements calculated based on the inverted parameters show an excellent agreement with the monitoring data, with an average relative error of only 2.8%. Furthermore, the

method reasonably captures the displacement development pattern during the monitoring period, confirming its reliability. The proposed method effectively addresses the challenge of multi-parameter collaborative inversion in soil by integrating monitoring data from multiple monitoring points and different times. It accurately reflects the soil's mechanical properties, demonstrating outstanding engineering applicability and providing reliable support for precisely monitoring the operational status of the embankment.

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Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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