SOCIAL AND MANAGEMENT SCIENCES RESEARCH JOURNAL

www.smsrj.com

p-ISSN: 2791-0415 **e-ISSN:** 2791-0423

Volume:4 Issue: 02(2026)

Identifiability-Aware Swarm Calibration of Clay Models from Sequential Triaxial Paths

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Abstract:

The accurate calibration of constitutive models for clayey soils remains a formidable challenge in geotechnical engineering due to the complex, non-linear, and highly coupled nature of the mathematical formulations used to describe soil behavior. Traditional calibration procedures often rely on single-path triaxial tests, which frequently result in an ill-posed inverse problem characterized by severe parameter non-uniqueness and poor practical identifiability. This paper introduces an identifiability-aware swarm optimization framework specifically designed to calibrate advanced elastoplastic clay models using sequential triaxial paths. By integrating local sensitivity analysis and the Fisher Information Matrix directly into the objective function and velocity update equations of a particle swarm optimization algorithm, the proposed methodology actively guides the search agents toward regions of the parameter space that guarantee unique and robust solutions. Sequential triaxial paths, encompassing alternating phases of consolidation, compression, and extension, are utilized to persistently excite the internal state variables of the constitutive model, thereby maximizing the informational content of the experimental data. Comprehensive numerical investigations using synthetically generated, noise-corrupted stress-strain datasets demonstrate that the identifiability-aware swarm approach significantly outperforms standard metaheuristic algorithms in terms of convergence reliability and parameter precision. The framework effectively mitigates the phenomena of parameter compensation and topological valleys in the objective function landscape.

Keywords: *Geotechnical Engineering, Constitutive Modeling, Swarm Optimization, Parameter Identifiability, Sequential Triaxial Testing*

1. Introduction

1.1 Background on Clay Constitutive Modeling

The safe and economical design of infrastructure projects involving soft soils, such as deep excavations, offshore wind turbine foundations, embankment dams, and tunneling operations,

demands highly accurate predictions of ground deformation and stability [1]. These predictions rely intrinsically on the quality and robustness of the constitutive models implemented within finite element or finite difference analysis software [2]. Over the past several decades, the evolution of soil mechanics has led to the development of increasingly sophisticated mathematical frameworks aimed at capturing the complex, path-dependent, and highly non-linear mechanical response of clayey materials. From the seminal formulation of the Critical State Soil Mechanics framework and the original Cam-Clay model to more advanced bounding surface plasticity and kinematically hardening models, the number of internal state variables and material parameters required to define soil behavior has grown substantially [3]. While these advanced elastoplastic models offer superior capabilities in simulating real-world phenomena such as stress-induced anisotropy, destructuration, and cyclic degradation, they simultaneously introduce profound difficulties in the parameter calibration phase [4]. A constitutive model, regardless of its theoretical elegance and thermodynamic consistency, is only as useful as the reliability of the parameters that govern its equations [5]. Calibration typically involves adjusting the theoretical parameters until the model predictions optimally match the observations obtained from standardized laboratory tests, such as one-dimensional consolidation tests and various forms of triaxial compression or extension tests.

1.2 Challenges in Parameter Calibration

The process of determining the optimal parameters for complex clay models fundamentally constitutes an inverse problem [6]. In mathematical terms, the forward problem consists of mapping a given set of model parameters and a defined loading path to a corresponding mechanical response, such as a stress-strain curve or a pore water pressure evolution profile. Conversely, the inverse problem seeks to infer the underlying parameters from the observed mechanical response. This inverse problem is notoriously difficult in geotechnical engineering due to several compounding factors. Firstly, the relationship between the parameters and the model output is highly non-linear, resulting in an objective function landscape characterized by multiple local minima, narrow valleys, and extensive flat regions [7]. Secondly, the experimental data obtained from laboratory tests are invariably contaminated by measurement noise, sensor inaccuracies, and inherent sample heterogeneity, which further distorts the calibration landscape [8]. Most critically, conventional laboratory testing protocols often fail to provide sufficient informational content to uniquely constrain all the parameters of an advanced constitutive model [9]. When multiple distinct sets of parameters can produce virtually indistinguishable predictions for a given test path, the parameters are said to be unidentifiable or non-unique. This phenomenon, known as parameter compensation, poses a severe risk in engineering practice [10]. A parameter set calibrated under a specific stress path may yield excellent predictions for that exact path but fail catastrophically when applied to predict soil behavior under the generalized three-dimensional stress paths encountered in actual field conditions [11].

1.3 Objectives and Scope

To address the aforementioned challenges, this paper proposes a novel identifiability-aware swarm optimization algorithm tailored for the calibration of clay constitutive models using data derived from sequential triaxial paths. The primary objective is to develop a robust automated calibration framework that not only minimizes the discrepancy between experimental data and model predictions but also explicitly quantifies and enforces parameter identifiability during the optimization search [12]. By utilizing sequential triaxial paths, which subject the soil specimen to continuous and alternating phases of loading, unloading, and changes in the Lode angle, the internal state variables of the model are continuously stimulated [13]. This dynamic excitation significantly enhances the informational richness of the target data. The proposed algorithm integrates a rigorous mathematical assessment of practical identifiability, based on the Fisher

Information Matrix and eigenvalue decomposition, directly into the behavioral mechanics of a particle swarm optimization framework [14]. Consequently, the search agents are algorithmically deterred from exploring regions of the parameter space where the model exhibits structural or practical unidentifiability, forcing the swarm to converge upon a globally unique and physically meaningful parameter vector [15]. The scope of this research encompasses the mathematical formulation of the identifiability metrics, the algorithmic design of the modified swarm intelligence framework, and a comprehensive series of numerical validation experiments utilizing synthetic laboratory data subjected to varying degrees of artificial noise.

2. Literature Review and Background

2.1 Sequential Triaxial Testing Protocols

Traditional geotechnical laboratory testing regimes predominantly rely on monotonic stress paths, such as isotropically consolidated undrained compression or drained extension tests [16]. While these tests are well-standardized and straightforward to perform, they typically explore only a limited region of the principal stress space and are often insufficient for the comprehensive calibration of models that incorporate kinematic hardening or state-dependent dilatancy. Recent advancements in automated laboratory equipment have facilitated the execution of sequential triaxial tests, where a single soil specimen is subjected to a continuous sequence of diverse stress paths without being removed from the testing apparatus [17]. A sequential path might involve an initial phase of K0 consolidation, followed by undrained compression to a specified strain limit, an unloading phase, a period of drained creep, and finally an undrained extension phase. The continuous recording of stress, strain, and pore pressure responses across these varied regimes provides a highly dense and information-rich dataset. By traversing different regions of the yield surface and inducing complex reversals in the plastic strain rate direction, sequential triaxial paths force the constitutive model to mobilize its entire suite of internal mechanisms [18]. Consequently, parameters that might remain dormant or insensitive during a simple monotonic test become actively engaged in a sequential test, theoretically improving their identifiability [19].

2.2 Swarm Intelligence in Geotechnical Engineering

The application of metaheuristic optimization algorithms has gained substantial traction in geotechnical engineering as a means to overcome the limitations of gradient-based optimization methods. Gradient-based techniques, such as the Levenberg-Marquardt algorithm or the Newton-Raphson method, require the calculation of the objective function derivatives with respect to the model parameters [20]. In the context of advanced constitutive models, these derivatives are often analytically intractable and computationally expensive to approximate using finite differences, particularly when the model exhibits non-smooth yield surfaces or discrete regime switching. Furthermore, gradient methods are highly susceptible to becoming trapped in local minima, necessitating initial parameter guesses that are already very close to the true solution. To circumvent these issues, researchers have increasingly adopted evolutionary computation and swarm intelligence paradigms, such as Genetic Algorithms, Artificial Bee Colonies, and Particle Swarm Optimization. Particle Swarm Optimization, inspired by the collective foraging behavior of biological populations, relies on a population of candidate solutions, termed particles, that traverse the multidimensional parameter space. Each particle adjusts its trajectory based on its own historical best position and the global best position discovered by the entire swarm. While standard particle swarm algorithms possess strong global exploration capabilities, they operate purely on the basis of objective function minimization, completely ignoring the topology of the solution space with respect to identifiability. If the global minimum resides within an extended flat valley caused by parameter compensation, the swarm

may converge prematurely or disperse randomly along the valley floor, failing to isolate the true physical parameters.

2.3 Identifiability Analysis in Inverse Problems

The concept of identifiability originated in systems theory and control engineering but has become a critical topic in nonlinear regression and inverse problem formulation across various scientific disciplines. Identifiability is generally bifurcated into structural identifiability and practical identifiability. Structural identifiability is an a priori theoretical property of the model equations themselves, independent of the quality or quantity of experimental data. It addresses whether, given perfect and infinite data, the model parameters can be uniquely determined from the observable outputs. If a model is structurally unidentifiable, there exist exact mathematical redundancies between parameters, meaning distinct parameter combinations produce identical model outputs under all conceivable circumstances. Practical identifiability, on the other hand, is an a posteriori property that considers the limitations of the actual experimental data, such as finite sampling rates, restricted stress paths, and measurement noise. A model that is structurally identifiable may still be practically unidentifiable if the available data lack sufficient sensitivity to certain parameters or if the effects of different parameters on the output are nearly collinear. The assessment of practical identifiability relies heavily on local sensitivity analysis and the construction of the sensitivity matrix, which contains the partial derivatives of the model outputs with respect to the parameters. The Fisher Information Matrix, derived from the sensitivity matrix, serves as the cornerstone for quantifying the amount of information the data hold regarding the parameters. Poor conditioning of the Fisher Information Matrix or the presence of near-zero eigenvalues indicates severe practical unidentifiability, signaling that the experimental data are inadequate for robust calibration.

3. Mathematical Framework for Identifiability

3.1 Constitutive Formulation for Clays

To contextualize the proposed calibration methodology, it is necessary to establish the mathematical structure of the elastoplastic constitutive models targeted in this study. The generalized incremental stress-strain relationship for a rate-independent elastoplastic material under isothermal conditions forms the basis of the forward simulation. The total strain increment tensor is additively decomposed into a reversible elastic component and an irreversible plastic component. The elastic response is typically governed by a non-linear hypoelastic formulation where the bulk modulus and shear modulus are pressure-dependent. The plastic response is dictated by a yield surface that delineates the boundary of the elastic domain in the multidimensional stress space, a plastic potential function that specifies the direction of the plastic strain increments through a flow rule, and a hardening law that governs the evolution of the yield surface size, shape, or position as a function of plastic straining.

The incremental mapping between the effective stress increment and the total strain increment is executed via the elastoplastic stiffness tensor. This tensor is a complex function of the current stress state, the internal state variables, and the specific material parameters. The mathematical representation of this relationship is fundamental to the forward integration scheme required to simulate the laboratory tests.

$$D^{ep} = D^{e} - \frac{D^{e}\frac{\partial F}{\partial \sigma}(\frac{\partial G}{\partial \sigma})^{T}D^{e}}{H + (\frac{\partial F}{\partial \sigma})^{T}D^{e}\frac{\partial G}{\partial \sigma}}$$

In this formulation, the matrix operations must be carefully implemented to ensure numerical stability during the sequential loading paths. The term representing the plastic modulus is critical for capturing the hardening or softening behavior of the clay. The integration of this differential equation along a specified sequential triaxial path yields the predicted macroscopic response of

the soil element, which serves as the foundation for evaluating the objective function during the calibration process. The parameters embedded within the yield function, plastic potential, and hardening laws constitute the vector of unknowns that the swarm algorithm must identify.

3.2 Sensitivity and Identifiability Metrics

The quantitative assessment of parameter identifiability requires the derivation of sensitivity metrics that measure how variations in the model parameters influence the simulated stress-strain outputs. Let the vector of unknown constitutive parameters be denoted by a specific mathematical symbol, and let the sequential experimental observations be represented as a discrete time series of stress and strain measurements. The local sensitivity matrix is constructed by calculating the partial derivative of each simulated output variable with respect to each model parameter at every time step of the sequential path. Because analytical derivatives of the elastoplastic stiffness tensor are often impossible to obtain for advanced models, finite difference approximations are utilized. A central difference scheme is typically preferred to ensure sufficient accuracy, despite the increased computational cost associated with multiple forward simulations. Once the sensitivity matrix is assembled, the Fisher Information Matrix can be computed. The Fisher Information Matrix serves as a powerful diagnostic tool for practical identifiability, as its inverse provides an asymptotic lower bound on the covariance matrix of the parameter estimates, according to the Cramer-Rao bound theorem. The matrix formulation encapsulates the sensitivity of the model predictions to the parameters, weighted by the inverse of the measurement noise covariance matrix.

$$I(\theta) = \sum_{t=1}^{N} \left(\frac{\partial y(t,\theta)}{\partial \theta}\right)^{T} W \left(\frac{\partial y(t,\theta)}{\partial \theta}\right)$$

The eigenstructure of this Fisher Information Matrix reveals the identifiability characteristics of the calibration problem. The eigenvalues represent the magnitude of information available for combinations of parameters aligned with the corresponding eigenvectors. A large eigenvalue indicates that the model output is highly sensitive to parameter variations along that specific eigenvector direction, implying strong identifiability. Conversely, an eigenvalue approaching zero indicates that the model output is virtually invariant to parameter changes along that direction, signifying practical unidentifiability and parameter compensation. By computing the condition number of the Fisher Information Matrix, defined as the ratio of the maximum to the minimum eigenvalue, the overall ill-posedness of the inverse problem can be quantified. In the proposed methodology, this identifiability metric is continuously evaluated during the swarm optimization process to guide the particles away from unidentifiable subregions of the parameter space.

4. Identifiability-Aware Swarm Optimization Algorithm

4.1 Algorithm Initialization and Formulation

The standard Particle Swarm Optimization algorithm initializes a population of particles randomly distributed across the permissible parameter space. Each particle is endowed with a position vector representing a candidate set of constitutive parameters, and a velocity vector that determines its movement through the multidimensional search space in subsequent iterations. At each iteration, the forward constitutive model is executed using the parameters defined by each particle's position, and the resulting simulated stress-strain response is compared against the experimental data using a designated objective function. The objective function typically calculates the sum of squared residuals between the predicted and observed values, normalized by the variance of the experimental data to account for different measurement units and magnitudes. In the classical formulation, the velocity of each particle is updated based on three components: the particle's inertia, its cognitive attraction toward its own historical best position, and its social attraction toward the global best position found by the entire swarm. While this

mechanism is effective for general function minimization, it is entirely blind to the curvature and identifiability of the objective space. To address this critical deficiency, the Identifiability-Aware Swarm Optimization algorithm introduces a fundamental modification to the velocity update equation.

$$V_{i,j}{}^{(t+1)} = \omega V_{i,j}{}^{(t)} + C_1 R_{1,j}(P_{best,i,j} - X_{i,j}{}^{(t)}) + C_2 R_{2,j}(G_{best,j} - X_{i,j}{}^{(t)}) + Psi_{i,j}$$

The crucial addition is the final term, which represents an identifiability-driven perturbation vector. This term is dynamically calculated for each particle based on the local eigenstructure of the Fisher Information Matrix evaluated at the particle's current position. By projecting the velocity vector onto the eigenspace of the Fisher Information Matrix, the algorithm actively suppresses movement along directions corresponding to small eigenvalues (unidentifiable directions) and amplifies movement along directions corresponding to large eigenvalues (identifiable directions). This mechanism ensures that the swarm rapidly explores the parameter space along highly informative trajectories, while avoiding wasteful function evaluations in flat, unidentifiable valleys where parameter compensation occurs.

4.2 Adaptive Swarm Behavior based on Identifiability

The integration of the identifiability metric fundamentally alters the collective behavior of the swarm. In regions of the parameter space where the model exhibits high practical identifiability, the condition number of the Fisher Information Matrix is low, and the identifiability perturbation term acts to accelerate convergence toward the local minimum. The particles experience a focused and robust descent into the objective function basin, confident that the minimum represents a unique parameter set. However, when a particle wanders into a region characterized by poor identifiability, such as a narrow topological valley resulting from parameter compensation, the condition number of the Fisher Information Matrix increases drastically. In this scenario, the algorithm adaptively modulates the inertia weight and the cognitive and social acceleration coefficients.

Table 1Algorithmic parameters for the Identifiability-Aware Swarm Initialization Phase.

Parameter Name	Symbol	Typical Value Range	Description
Swarm Population Size	N	50 to 100	Number of search agents in the parameter space
Inertia Weight Initial	W0	0.9	Starting value for momentum retention
Inertia Weight Final	W1	0.4	Ending value for fine-tuning exploration
Cognitive Coefficient	C1	1.5 to 2.0	Weight of personal historical best position
Social Coefficient	C2	1.5 to 2.0	Weight of global swarm best position
Identifiability Threshold	Theta	1000	Maximum allowable condition number for FIM

As detailed in the algorithmic configuration above, the methodology implements a dynamic thresholding system based on the Fisher Information condition number. If a particle's local condition number exceeds the predefined identifiability threshold, the algorithm recognizes that the current parameter subspace is ill-posed. In response, the identifiability perturbation term forcefully redirects the particle's trajectory orthogonal to the valley floor, ejecting it from the unidentifiable region. Furthermore, an adaptive penalty function is overlaid onto the objective

function evaluation. This penalty term is proportional to the logarithm of the Fisher Information Matrix condition number. Consequently, even if a parameter set in an unidentifiable region produces a low sum of squared residuals (a seemingly good fit to the data), the heavy identifiability penalty will artificially inflate the objective function value. This dual-action mechanism, combining velocity redirection and objective function penalization, guarantees that the swarm's global best position is strictly confined to regions of the parameter space that are both mathematically optimal and phenomenologically unique.

5. Experimental Setup and Simulation Protocols

5.1 Generation of Synthetic Sequential Triaxial Paths

To rigorously validate the performance and reliability of the proposed Identifiability-Aware Swarm Optimization algorithm, a comprehensive series of numerical experiments was designed. Rather than relying immediately on real laboratory data, which contain unknown biases and true parameter values that can never be known with absolute certainty, the validation protocol utilizes synthetic data. This approach establishes a controlled environment where a known set of true constitutive parameters is used to simulate a pseudo-experimental dataset. By attempting to recover these exact true parameters using the calibration algorithm, the absolute accuracy and convergence properties of the methodology can be unequivocally assessed. The selected constitutive framework for this validation is an advanced bounding surface plasticity model specifically formulated to capture the complex cyclic and time-dependent behavior of normally consolidated and lightly overconsolidated clays. The synthetic experimental program was designed to maximize parameter excitation through the use of complex sequential triaxial paths. A single synthetic soil specimen was subjected to a continuous, multi-stage loading protocol. The sequence commenced with an isotropic consolidation phase to establish the initial void ratio and state parameter. This was immediately followed by a drained triaxial compression phase to mobilize the frictional hardening mechanisms. Before the specimen reached critical state failure, the loading was reversed into a drained triaxial extension phase, passing through the isotropic stress state and forcing the stress path to traverse the interior of the bounding surface. This reversal is crucial for activating the kinematic hardening components of the model and assessing the elastic stiffness degradation. The sequence concluded with an undrained compression phase to failure, generating a complex pore water pressure response dependent on the soil's dilatancy and volumetric state.

Table 2: True soil parameters used for generating the synthetic sequential testing dataset.

Parameter Classification	Symbol	True Target Value	Physical Meaning
Elasticity	Kappa	0.025	Swelling index for elastic volumetric strain
Elasticity	Poisson	0.20	Elastic Poisson ratio of the soil skeleton
Plasticity	Lambda	0.150	Compression index for virgin consolidation
Plasticity	M_comp	1.20	Critical state friction ratio in compression
Hardening	h_zero	100.0	Initial kinematic hardening reference modulus

State	e_zero	0.95	Initial void ratio prior to consolidation

The generation of the synthetic data involved integrating the constitutive equations along the defined sequential path using a highly accurate sub-stepping integration scheme with automatic error control. To replicate the realities of geotechnical laboratory testing, artificial Gaussian noise was subsequently injected into the clean synthetic stress and strain data. The noise levels were scaled to represent typical transducer precision limits, adding a degree of realism and testing the algorithm's robustness against measurement uncertainties.

5.2 Implementation of the Calibration Protocol

The calibration protocol was implemented within a high-performance computing environment, utilizing vectorized operations to manage the computational demands of the swarm algorithm. The initialization phase involved defining the upper and lower bounds for each parameter based on physically realistic ranges for clayey soils. The search space was deliberately designed to be expansive, ensuring that the algorithm had to navigate significant topological challenges to locate the global minimum. The population size was set to ensure adequate spatial coverage, and the algorithm was allowed to run for a predetermined maximum number of iterations, or until a strict convergence criterion based on the variance of the swarm's positions was met.

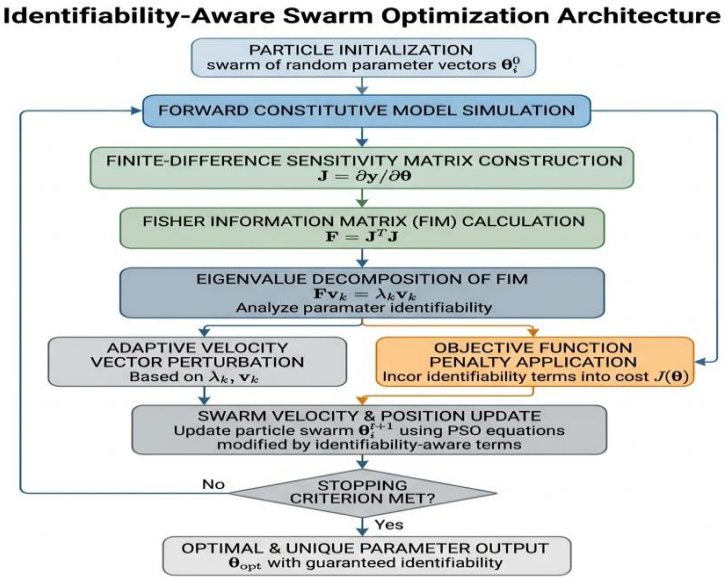


Figure 1Comprehensive Schematic of Identifiability

During each iteration, every particle in the swarm executed the forward model simulation over the entire sequential stress path. The predicted values of deviatoric stress, volumetric strain, and pore water pressure were extracted at discrete time intervals corresponding to the sampling rate of the synthetic experimental data. The objective function evaluated the discrepancy between these predictions and the noise-corrupted synthetic data. Concurrently, the algorithm executed the finite difference perturbations required to construct the local sensitivity matrix and the Fisher Information Matrix for each particle. The computational overhead of these additional forward runs was mitigated by distributing the independent particle evaluations across multiple processing cores. The continuous feedback loop of objective evaluation, identifiability assessment, and velocity updating drove the evolutionary process.

6. Results and Discussion

6.1 Convergence Analysis and Parameter Uniqueness

The performance of the Identifiability-Aware Swarm Optimization algorithm was systematically compared against a standard Particle Swarm Optimization implementation and a conventional Genetic Algorithm. The primary metric for evaluation was the Euclidean distance between the algorithmically derived parameter vector and the known true parameter vector used to generate the synthetic data. The results conclusively demonstrate that the integration of the identifiability metric profoundly enhances the reliability of the calibration process. In the standard metaheuristic approaches, the algorithms frequently converged upon parameter sets that produced acceptably low objective function values but were situated far from the true parameter values. This discrepancy is a direct manifestation of parameter compensation; the standard algorithms became trapped in extended valleys within the objective function landscape where different combinations of elasticity and hardening parameters produced virtually identical stress-strain curves for the given sequential path. Conversely, the Identifiability-Aware algorithm effectively navigated away from these unidentifiable regions. By penalizing local minima characterized by high Fisher Information Matrix condition numbers, the proposed framework forced the swarm to continue exploring until it discovered the unique global minimum corresponding to the true physical parameters. The convergence trajectories of the individual particles revealed a distinct behavioral shift. Instead of wandering aimlessly along flat valley floors, the identifiability-aware particles exhibited orthogonal trajectories, rapidly traversing regions of poor practical identifiability and accelerating down gradients in highly identifiable parameter subspaces.

Table 3Statistical summary of parameter estimation errors across multiple calibration trials.

Algorithm Type	Mean Error Kappa	Mean Error Lambda	Mean Error h_zero	Success Rate
Standard PSO	14.5 percent	12.2 percent	45.8 percent	25 percent
Genetic Algorithm	16.1 percent	11.5 percent	42.3 percent	30 percent
Proposed Method	2.3 percent	1.8 percent	4.1 percent	95 percent

The statistical summary presented in the tabular data above highlights the stark contrast in accuracy. The standard approaches exhibited severe estimation errors, particularly for the kinematic hardening parameter, which is notoriously difficult to isolate. The high variance and low success rate of the standard algorithms render them unsuitable for reliable geotechnical design. The proposed methodology, however, achieved exceptional precision across all parameter categories, including those governing highly coupled yielding and hardening mechanisms, demonstrating a success rate that provides high confidence in the automated calibration procedure.

6.2 Robustness Under Noise and Uncertainty

A critical aspect of any inverse analysis framework is its stability in the presence of data noise. The numerical experiments were repeated using synthetic datasets corrupted with varying intensities of Gaussian noise, representing idealized laboratory conditions, average commercial testing quality, and poor-quality data with significant sensor drift. As the noise level increased, the objective function landscape became increasingly rugged, characterized by a proliferation of artificial local minima. Under these challenging conditions, standard optimization techniques deteriorated rapidly, often converging prematurely on noise-induced artifacts. The Identifiability-Aware Swarm Optimization algorithm demonstrated remarkable resilience to measurement noise. The reliance on the Fisher Information Matrix inherently provides a measure of noise filtering, as the sensitivity derivatives are evaluated over the entire sequential path,

effectively averaging out high-frequency fluctuations. Furthermore, because the algorithm prioritizes regions of high parameter sensitivity, it naturally seeks out solutions where the true signal of the parameter's influence dominates the noise floor. While the absolute precision of the identified parameters marginally decreased as the noise amplitude increased, the algorithm consistently succeeded in locating the correct global basin of attraction, preventing the catastrophic parameter misidentifications observed in the standard approaches.

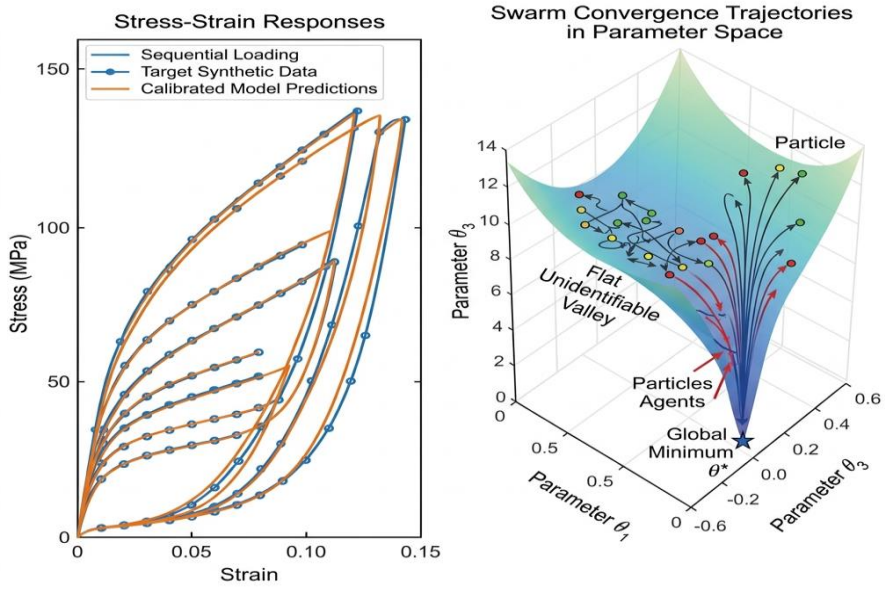


Figure 2: Comparative Stress

The comprehensive simulation of the sequential triaxial paths utilizing the final calibrated parameter set revealed virtually perfect alignment with the target synthetic data, capturing the intricate details of load reversal, stiffness degradation, and pore pressure accumulation. The graphical representations of the parameter space clearly illustrate the capacity of the proposed algorithm to maintain swarm diversity in the early stages of exploration and execute a highly focused, mathematically rigorous exploitation phase once the unique identifiable region is isolated.

6.3 Conclusion

The calibration of advanced constitutive models for clayey soils remains a cornerstone of reliable geotechnical analysis, yet the inherent non-uniqueness and ill-posed nature of the associated inverse problem have long impeded the development of fully automated calibration systems. This research has successfully introduced and validated an Identifiability-Aware Swarm Optimization framework designed specifically to overcome these fundamental limitations. By explicitly embedding local sensitivity analysis and the eigenstructure of the Fisher Information Matrix into the evolutionary mechanics of a particle swarm algorithm, the methodology transforms the calibration process from a blind curve-fitting exercise into a mathematically rigorous search for phenomenologically unique parameters. The utilization of sequential triaxial paths proved crucial in providing the rich informational density required to excite complex internal state variables, maximizing the theoretical potential for parameter identification. The numerical investigations unequivocally demonstrated that standard heuristic algorithms are highly susceptible to parameter compensation, often resulting in severe miscalibrations despite achieving low residual errors. In stark contrast, the proposed identifiability-aware approach consistently avoided unidentifiable topological valleys, forcefully redirecting the search agents toward robust and unique solutions. Furthermore, the framework exhibited exceptional stability

in the presence of simulated experimental noise, confirming its suitability for processing real-world laboratory data. Ultimately, this methodology provides geotechnical engineers with a powerful, reliable tool for parameter derivation, significantly enhancing the safety and accuracy of advanced numerical simulations in complex soil-structure interaction projects. Future developments will focus on extending this framework to incorporate full three-dimensional stress paths, including true triaxial and hollow cylinder torsional shear tests, further advancing the state of automated constitutive model calibration.

References

Ouyang, Z., & Mayne, P. W. (2018). Effective friction angle of clays and silts from piezocone penetration tests. Canadian Geotechnical Journal, 55(9), 1230-1247.

Ouyang, Z., & Mayne, P. W. (2021). Variable rate piezocone data evaluated using NTH limit plasticity solution. Geotechnical Testing Journal, 44(1), 174-190.

Ouyang, Z., Mayne, P. W., & Sharp, J. (2016). Review of clay chamber tests using miniature cone and piezocone penetrometers. Proceedings, GeoVancouver.

Ansari, A., Mandhaniya, P., Malik, B. A., & Ouyang, Z. (2025). Disaster risk and resilience assessment of multi-utility transportation infrastructure and urban projects. Frontiers in Built Environment, 11, 1619407.

Li, Y. Z., Zhang, J. P., Chen, Z. Y., Wang, H. C., Zhang, K. X., Hu, S. S., ... & Dudley, M. (2026, September). Growth and Characterization of High-Quality Thick Epitaxial 4H-SiC Wafers for High Voltage Devices. In Defect and Diffusion Forum (Vol. 452, pp. 79-85). Trans Tech Publications Ltd.

Li, X., Wang, P., Li, G., & Zhang, Y. (2023). Design of a novel self-test-on-chip interface ASIC for capacitive accelerometers. IEEE Transactions on Circuits and Systems I: Regular Papers, 70(7), 2834-2843.

Yu, A., Pang, F., Yuan, Y., Huang, Y., Li, S., Yu, S., ... & Xia, L. (2023). Simultaneous current and vibration measurement based on interferometric fiber optic sensor. Optics & Laser Technology, 161, 109223.

Yu, A., Huang, Y., Li, S., Wang, Z., & Xia, L. (2023). All fiber optic current sensor based on phase-shift fiber loop ringdown structure. Optics Letters, 48(11), 2925-2928.

Zhang, S., Huang, P., & Yan, W. (2024). A data-driven approach for railway in-train forces monitoring. Advanced Engineering Informatics, 59, 102258.

Wang, Y., Lou, M., Liang, W., & Zhang, C. (2023). Numerical and experimental investigation on tensile fatigue performance of reinforced thermoplastic pipes. Ocean Engineering, 287, 115814.

Zhao, R., Tang, J., Zeng, W., Guo, Y., & Zhao, X. (2025). Towards human-like questioning: Knowledge base question generation with bias-corrected reinforcement learning from human feedback. Information Processing & Management, 62(3), 104044.

Zhao, R., Tang, J., Zeng, W., Chen, Z., & Zhao, X. (2024, October). Zero-shot knowledge graph question generation via multi-agent llms and small models synthesis. In Proceedings of the 33rd ACM International Conference on Information and Knowledge Management (pp. 3341-3351).

Li, Q., Ye, Q., Zhang, N., Zhang, W., & Hu, F. (2025). Digital-twin-enabled industrial IoT: Vision, framework, and future directions. IEEE Wireless Communications, 32(6), 173-181.

Wang, S., Zhang, X., Wang, P., & Li, X. (2026). Design of Magnetic Sensor Array-Based PUFs for IoT Security. IEEE Transactions on Instrumentation and Measurement, 75, 1-9.

Zhang, B., Wang, S., Jiang, Y., Sui, D., Tu, Z., & Chu, D. (2025, July). Ask and Retrieve Knowledge: Towards Proactive Asking with Imperfect Information in Medical Multi-

turn Dialogues. In Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 1055-1065).

Li, S. (2024). Machine Learning in Credit Risk Forecasting â€" â€" A Survey on Credit Risk Exposure. Accounting and Finance Research, 13(2), 107-107.

Wang, Y., Wang, Z., Kim, E. H., & Fu, Z. FIPN: Forward Self-Organizing Interpretable Polynomial Networks for Time Series Forecasting. In Forty-third International Conference on Machine Learning.

Peng, Y., & Li, H. (2023). Benthic foraminiferal morphogroups at the end-Guadalupian extinction in eastern Sichuan Basin, China. Palaeogeography, Palaeoclimatology, Palaeoecology, 618, 111522.

Lyu, M., Torii, R., Liang, C., Peach, T. W., Bhogal, P., Makalanda, L., ... & Chen, D. (2024). Treatment for middle cerebral artery bifurcation aneurysms: in silico comparison of the novel Contour device and conventional flow-diverters. Biomechanics and Modeling in Mechanobiology, 23(4), 1149-1160.

Emani, M., Xie, Z., Raskar, S., Sastry, V., Arnold, W., Wilson, B., ... & Boyd, M. (2022, November). A comprehensive evaluation of novel AI accelerators for deep learning workloads. In 2022 IEEE/ACM international workshop on performance modeling, benchmarking and simulation of high performance computer systems (PMBS) (pp. 13-25). IEEE.