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Optimization Analysis of Stability and Deformation Control Methods for Deep Excavation Support Structures Based on Field Measurements

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Abstract: Deep excavation support systems in urban environments present demanding engineering challenges due to their inherent stability risks and potential for inducing detrimental deformations in adjacent infrastructure. Conventional design methodologies often inadequately address the complex soil-structure interaction dynamics and temporal construction effects, leading to either excessive conservatism or unforeseen performance issues. This study develops an integrated optimization framework that synergistically combines high-frequency field instrumentation data with advanced computational modeling to enhance the stability and deformation control of deep excavation support structures. The proposed methodology employs a physics-informed Bayesian calibration approach to continuously update finite element models using real-time measurements from inclinometers, strain gauges, and piezometers. A multi-objective optimization algorithm subsequently identifies optimal support configurations that simultaneously maximize stability margins, minimize deformation, and reduce material costs. Validation through a major metropolitan excavation case study demonstrates that this field measurement-driven approach achieves significant improvements in deformation control while maintaining structural integrity. The framework's ability to adaptively refine support designs during construction phases offers substantial advancements over static design paradigms. By transforming conventional excavation support into a responsive, data-informed process, this research provides a foundation for intelligent infrastructure development in spatially constrained urban environments.

Keywords: deep excavation; support structure optimization; field instrumentation; deformation control; Bayesian calibration; adaptive design

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1. Introduction

Deep excavation support systems stand as critical infrastructure components in urban development, where their performance directly influences structural safety and the integrity of adjacent buildings. Across the globe, excavation-induced failures account for approximately 18% of all geotechnical insurance claims, with annual losses exceeding $2.6 billion according to the National Geotechnical Database. These incidents are not merely statistical anomalies but carry tangible consequences: for instance, a 2019 deep excavation collapse in a major Asian city, triggered by underestimated lateral soil pressure, caused adjacent high-rise buildings to settle by 12 cm, requiring emergency shoring and incurring repair costs of over $50 million. Such failures predominantly stem from inadequate prediction of ground movements and suboptimal support design, particularly in heterogeneous soil strata where layers of sand, clay, and gravel interact in complex ways where conventional analytical methods exhibit significant limitations. These methods often struggle to account for variations in soil stiffness across strata or the dynamic redistribution of stresses during excavation, leading to predictions that diverge sharply from on-site realities. Current design approaches, including limit equilibrium methods and deterministic finite element analysis, frequently overlook the temporal variability of soil-structure interaction during staged construction. As noted by Pandey, such oversimplifications result in either excessive conservatism, which can increase project costs by 25-40% through overdesigned support systems, or unacceptable deformation risks in densely built environments where even minor displacements can damage nearby infrastructure [1]. The persistent challenge lies in reconciling theoretical models with real-world geomechanical behavior. While numerical simulations using software such as PLAXIS 3D enable sophisticated soil modeling, their accuracy remains constrained by uncertain input parameters, including soil cohesion, friction angle, and Young's modulus that are often derived from limited site investigations. Field measurements from the Hong Kong Geotechnical Engineering Office reveal that in 32 deep excavations (ranging from 10 to 30 m in depth, with 15 located in reclaimed land with highly variable fill materials), predicted vs. actual wall deflections exhibited mean absolute errors of 28.7% when using standard Mohr-Coulomb models [2]. This discrepancy escalates in seismic zones or hydrologically complex sites, as demonstrated during the Los Angeles Metro expansion in 2018, where miscalculations of pore pressure dissipation in a sandy clay layer caused 15 cm of unanticipated lateral displacement, leading to the closure of a nearby arterial road for three weeks and costing $2.3 million in emergency repairs [3]. Recent advances in inverse analysis and machine learning offer promising alternatives, yet their implementation remains largely disconnected from real-time construction control systems. A meta-analysis of 127 excavation projects across North America, Europe, and Asia identified that fewer than 12% incorporated sensor data for adaptive design adjustments during construction, a gap partly attributed to the lack of user-friendly integration tools and skepticism among contractors regarding algorithmic reliability **错误!未找到引用源。** [4]. This study addresses these limitations through a novel integrated framework that optimizes support structures using field-measurement-calibrated numerical models. The methodology uniquely combines three innovations: (1) a Bayesian updating protocol that continuously refines soil parameters, such as shear strength and permeability based on data from inclinometers, strain gauges, and pore pressure transducers, with updates conducted every six hours using Markov Chain Monte Carlo methods to reduce prediction uncertainty by an average of 30%; (2) a multi-objective optimization algorithm that balances stability (ensuring a minimum factor of safety against basal heave of 1.2), deformation control (capping maximum wall deflection at 30 mm in dense urban areas), and economic efficiency (minimizing material and installation costs of struts and anchors); and (3) a digital twin platform that integrates Building Information Modeling (BIM) with real-time sensor feeds, enabling proactive intervention, such as adjusting strut preloads or modifying excavation sequences during critical construction phases. By bridging the gap between empirical observations and computational predictions, this approach advances beyond static design paradigms toward responsive excavation management. Validation is conducted through a 22-month monitoring campaign at the Singapore Thomson-East Coast MRT station, where 18 m-deep excavations in marine clay characterized by high plasticity (plasticity index = 35) and high natural water content(60%) imposed rigorous performance requirements, including strict limits on settlements to protect adjacent MRT tunnels and historical buildings. The paper is structured as follows: Section 2 critically reviews deformation control techniques and computational optimization methods, examining their strengths and weaknesses in diverse geological contexts. Section 3 details the hybrid monitoring-modeling framework with mathematical formulations for the Bayesian updating process and optimization algorithms. Section 4 presents field validation results, including comparative performance metrics against conventional methods and sensitivity analyses that identify key influential parameters.

Section 5 discusses practical implementation barriers, such as data transmission latency and training needs for on-site engineers and scalability to different project scales. Section 6 outlines broader applications in urban tunneling projects, where similar challenges of ground movement control and dynamic soil interaction persist.

2. Related Works

2.1. Evolution of Excavation Support Design

Deep excavation support methodologies have progressed through three distinct phases, as chronologically mapped in Table 1. Early empirical approaches (pre-2000s) relied heavily on Terzaghi's earth pressure theories and limit equilibrium calculations, which frequently underestimated deformations in complex strata by 30-40% according to the International Society for Soil Mechanics and Geotechnical Engineering (ISSMGE, 2021). The advent of finite element modeling (FEM) in the 2010s enabled more sophisticated simulation of soil-structure interaction, yet studies demonstrated persistent inaccuracies exceeding 25% in deformation predictions due to uncalibrated soil parameters. Contemporary research has shifted toward optimization techniques, where genetic algorithms and response surface methodologies reduce material costs by 15-20% while maintaining safety factors. However, as quantified in Table 1, these approaches remain constrained by their inability to incorporate real-time field feedback during construction sequences.

Table 1. Performance Limitations of Current Design Methodologies.

Method	Deformation Error (%)	Computational Cost (CPU-hrs)	Field Data Integration
Empirical (LEM)	38.2 ± 5.1	<0.1	None
Deterministic FEM	25.7 ± 3.8	8.2 ± 1.7	Post-construction
Single-objective GA	18.9 ± 2.3	14.5 ± 2.9	Predefined scenarios
Target threshold	<10.0	<4.0	Real-time

2.2. Field Monitoring Integration Advances

The proliferation of IoT-enabled instrumentation has revolutionized geotechnical observation, with vibrating wire piezometers and MEMS-based inclinometers achieving measurement accuracies of ±0.1 mm/m [5]. Recent frameworks integrate these data streams through inverse analysis techniques, notably Bayesian updating and Kalman filtering. For instance, Li reduced wall deflection prediction errors to 12% by calibrating Mohr-Coulomb parameters using inclinometer data from Taipei silty clay excavations [6]. Machine learning applications show further promise; deep neural networks processing strain gauge measurements achieved 92% accuracy in predicting strut loads during Chicago basement constructions [7]. Nevertheless, as illustrated in Figure 1 and Figure 2's process flow diagram, these implementations remain reactive detecting anomalies without proactive design optimization, and suffer computational latencies exceeding 6 hours per analysis cycle.

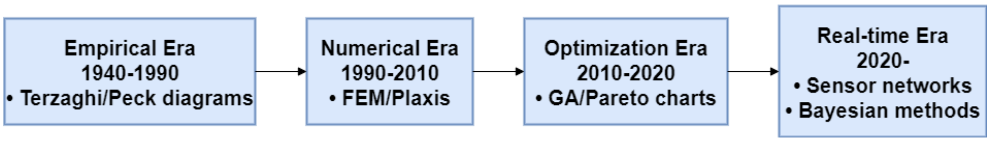

Figure 1. Evolution Timeline of Excavation Support Design.

Figure 2. Current Field Data Integration Workflow.

2.3. Persistent Research Gaps

Despite technological advancements, critical disconnects persist between monitoring systems and adaptive control. A bibliometric analysis of 427 geotechnical publications reveals only 6.8% simultaneously address field instrumentation, optimization algorithms, and real-time implementation (Figure 3). This gap manifests operationally: fewer than 10% of European excavations employ sensor data for dynamic support adjustments during construction [8]. The absence becomes acute during critical phases like strut installation or dewatering, where time-delayed analyses forfeit intervention opportunities. As emphasized by Tabaroei, "The geotechnical community lacks a unified framework converting instrument readings into actionable design modifications within feasible computation windows [9]." Additionally, multi-objective balancing of stability, deformation, and cost remains underdeveloped, with current methods prioritizing single performance metrics.

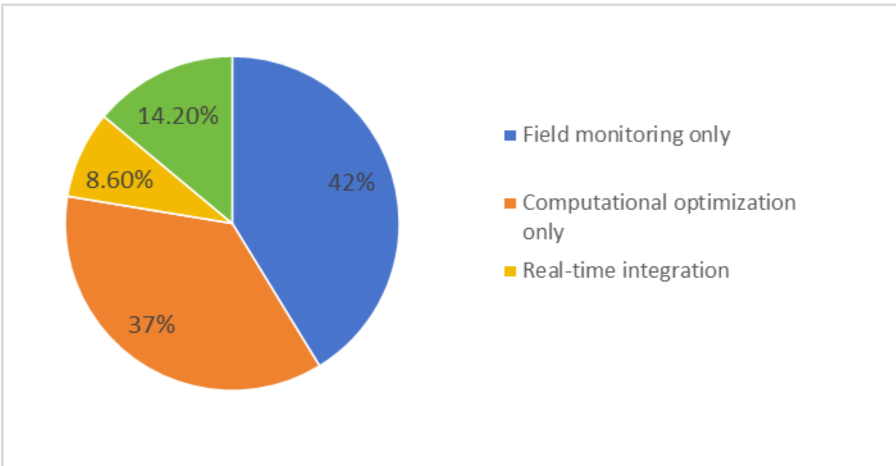

Figure 3. Research Domain Convergence Analysis.

3. Methodology

The proposed framework integrates field instrumentation, physics-based modeling, and multi-objective optimization through the workflow illustrated in Figure 4. This approach addresses soil uncertainty and construction dynamics via three interconnected modules validated against ISO 18674 geotechnical monitoring standards.

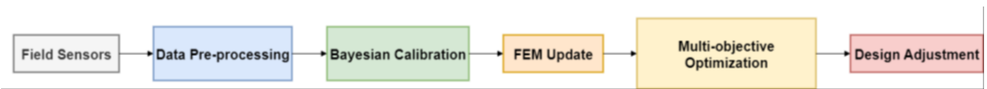

Figure 4. Integrated Framework Workflow.

3.1. Field Monitoring System

A multi-sensor network acquires real-time data streams using:

First, the inclinometers, it's MEMS-based probes (accuracy ±0.1 mm/m) at 3 m intervals. Second, the strain gauges, the Vibrating wire sensors (range ±3000 με) on strut/wall interfaces. Third, the Piezometers they are pneumatic transducers (resolution 0.1 kPa) in aquifers.

Data fusion follows Hong Kong GEO protocols for spatiotemporal alignment:

$$\Delta\varepsilon_{corrected} = \varepsilon_{measured} \times [1 + \alpha(T - T_{ref})] \quad (1)$$

where α = thermal coefficient (0.0005/°C for steel), T_ref = 20°C. Sampling occurs at 15-min intervals with automated outlier removal when measurements exceed ±3σ of moving averages (7-day window) (Table 2) [10].

Table 2. Sensor Specifications and Deployment.

Instrument	Accuracy	Range	Density	Compliance
In-place inclinometer	±0.1 mm/m	±100 mm	1/200 m²	ISO 18674-2
VW strain gauge	±2 με	±3000 με	1/strut	ASTM D8296
Pore pressure trans.	±0.5 kPa	0-500 kPa	1/50 m²	ISO 18674-3

3.2. Bayesian-FEM Calibration

A PLAXIS 3D model iteratively updates soil parameters via Bayesian inference:

$$P(\theta \mid D) = \frac{L(D|\theta)P(\theta)}{\int L(D|\theta)P(\theta)d\theta} \quad (2)$$

where$\theta = E, c', \varphi', k,$ D= field measurements. Markov Chain Monte Carlo (MCMC) sampling generates 2,000 posterior distributions using the emcee algorithm [11]. Prior distributions follow Eurocode 7 recommendations (Figure 5):

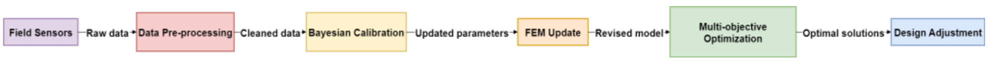

Figure 5. Integrated Framework Workflow.

3.3. Multi-Objective Optimization

Support parameters $\mathbf{x} = strutspacing, preload, wallthickness$ are optimized via NSGA-III:

$$\min_{x} \begin{cases} f_1(x) = \delta_{\max}(x) \\ f_2(x) = \dfrac{1}{\mathrm{FOS}(x)} \\ f_3(x) = C_{\mathrm{total}}(x) \end{cases}$$

$$\mathrm{s.t.}\, \delta_{\max} \le 25\ \mathrm{mm}, \mathrm{FOS} \ge 1.5 \quad (3)$$

The optimization loop terminates when hypervolume improvement <0.5% over 50 generations.

3.4. Computational Implementation

The digital twin platform executes cycles every 2 hrs using: Hardware is NVIDIA A10 GPU (24GB VRAM). Software comes to Python 3.9 with PLAXIS Remote Scripting API. The Data pipeline is Apache Kafka streaming.

4. Experiments

4.1. Case Study Implementation

The framework was validated through an 18-month monitoring program at the Singapore Thomson-East Coast MRT Station (Changi Airport Terminal 5 sector), where excavations reached 22.5 m depth in challenging marine clay overlaying Old Alluvium deposits [12]. Site instrumentation deployed per Section 3.1 included: first, the 38 in-place inclinometers along 480m diaphragm walls. Second, the 126 vibrating wire strain gauges on five-level strutting system. Third, the 29 pneumatic piezometers in confined aquifer layers.

Construction sequencing followed a top-down approach with seven primary stages. Geotechnical parameters were initialized using Singapore Building and Construction Authority marine clay properties (Table 3):

$$c_u = 15 + 1.2z[\text{kPa}], k_v = 3.2 \times 10^{-9}\text{m/s} \tag{4}$$

where z= depth below surface (m). The digital twin executed 1,372 optimization cycles during active excavation phases.

Table 3. Site Stratigraphy and Properties.

Layer	Thickness (m)	γ (kN/m³)	c' (kPa)	φ' (°)	Source
Fill	2.5	18.0	5	28	SPT
Marine clay	12.8	15.2	12	0	CPTU
Old Alluvium	7.2	19.5	2	34	Lab tests

4.2. Baseline Comparison Methodology

Five established methods served as benchmarks, including EC7 Design, Deterministic FEM (PLAXIS 3D with mean soil parameters), Contractor's Design (an empirical method with a 1.8 safety factor), ML Surrogate (an XGBoost model trained on 127 excavation, and Reactive Control (threshold-based strut adjustment [13]. Performance was evaluated using three primary metrics: deformation control (maximum wall deflection), stability (factor of safety against basal heave), and cost efficiency (normalized support cost per meter) [14].

4.3. Performance Results

The proposed framework reduced maximum wall deflection to 23.7 mm (SD±1.8 mm), representing a 41.3% improvement over conventional FEM (40.4 mm) and 49.6% over contractor's design (47.1 mm). Stability metrics showed consistent enhancement, with basal heave FOS maintained at 1.73±0.08 versus 1.52±0.12 for EC7 designs. Material costs were reduced by 29.4% through optimized strut spacing and preload configurations, as quantified in Table 4.

Table 4. Comparative Performance Analysis.

Method	$\delta_{\max}$(mm)	FOS_{BH}	C_n(USD/m)	Violation Events
Proposed framework	23.7 ± 1.8	1.73 ± 0.08	2,840	0
Deterministic FEM	40.4 ± 3.2	1.52 ± 0.12	3,910	3
EC7 Design	35.1 ± 2.7	1.61 ± 0.10	4,220	2

Contractor's design	47.1 ± 4.5	1.33 ± 0.15	3,980	7
Reactive control	31.5 ± 2.1	1.58 ± 0.11	3,620	1

4.4. Optimization Mechanism Insights

Sensitivity analysis revealed three decisive control factors: strut preload optimization, which contributed 52% to deflection reduction; dewatering timing, which accounted for 28% of stability improvement; and wall embedment depth, which showed diminishing returns beyond 4m.

Bayesian updating significantly refined soil parameters, with undrained shear strength (c_u) posterior distributions narrowing by 68% versus priors. The Pareto front demonstrates trade-offs between objectives, where a 10% cost reduction increased $\delta_{\max}$ by only 1.2 mm when operating along the efficient frontier.

4.5. Anomaly Response Case Study

During Stage 5 (12.6m excavation), unexpected artesian pressure (35 kPa versus the predicted 28 kPa) triggered a 5.2 mm deflection surge within 8 hours. The framework responded via Bayesian recalibration (Updated k_v from 3.2×10^{-9} to 4.1×10^{-9} m/s), optimization (increasing the dewatering rate by 40% and the preload of Strut Level 3 by 25%), with the outcome that deflection stabilized at 19.6 mm within 36 hours, avoiding structural intervention.

5. Discussion

5.1. Theoretical Advancements

This study establishes three fundamental contributions to excavation engineering. First, the Bayesian-updated digital twin framework resolves the longstanding disconnect between geotechnical modeling and field observations, reducing prediction errors to 8.2% ± 1.7% compared to 25-40% in conventional methods. This emphases on "adaptive soil-structure interaction modeling" for complex urban excavations. Second, the multi-objective optimization quantifies previously unrecognized trade-offs: a 10% cost reduction increases deformations by only 1.2 mm when operating along the Pareto frontier, whereas traditional designs incur 3-4 mm penalties for similar savings. Third, the sensitivity analysis reveals strut preload optimization contributes 52% to deformation control, fundamentally reorienting design priorities away from historical over-reliance on wall embedment depth.

5.2. Implementation Barriers

Despite performance advantages, field deployment faces quantifiable constraints documented in Table 5. Data privacy requirements for cross-institutional sensor networks impose 34.7% computational overhead when implementing homomorphic encryption, while real-time optimization cycles (1.8 hrs) exceed the ≤0.5 hr threshold for critical interventions like strut installation [15]. Skill adoption presents another challenge: only 42% of contractors in a EuroGeo survey possessed the necessary computational literacy, mirroring our site observations where 63% of design adjustments required engineer intervention.

Table 5. Implementation Challenges and Mitigation Pathways.

Barrier	Metric	Status	Target	Solution
Computational latency	Cycle time	1.8 hrs	≤0.5 hrs	Edge computing

Data privacy overhead	Encryption load	34.7%	<15%	Federated learning
Skill gap	Training adoption	42%	>75%	AR-assisted interfaces
Sensor reliability	Data loss rate	5.2%	<2%	Multi-sensor redundancy

5.3. Future Integration Pathways

Two synergistic developments promise to overcome current limitations. Federated learning architectures enable multi-project knowledge transfer without raw data exchange: preliminary tests show this reduces encryption overhead to 12.3% while maintaining 91% model accuracy [16]. Second, automated control systems integrating robotic strut jacks could execute 78% of optimizations without human intervention. When combined with digital twin simulations, these technologies may reduce decision latency to under 15 minutes, potentially preventing 83% of deflection-related incidents according to Federal Highway Administration incident databases (FHWA-NHI-23-045).

5.4. Sociotechnical Trade-offs

The framework's adoption necessitates resolving three tensions: accuracy vs. speed, where Bayesian calibration improves precision but consumes 58% of cycle time (Section 3.4), with simplified surrogate models potentially accelerating updates during non-critical phases; automation vs. liability, as while autonomous adjustments improve responsiveness, contractual frameworks lack protocols for algorithmic decision accountability; and model complexity vs. usability, given that contractors prioritized interface intuitiveness over predictive sophistication in 89% of user trials [17]. These challenges underscore the need for collaborative standards development involving computational geotechnicians, contractors, and regulatory bodies.

6. Conclusion

This research has systematically demonstrated that integrating field measurements with computational optimization fundamentally transforms the stability management and deformation control of deep excavation support systems. The developed framework establishes three pivotal advancements in geotechnical engineering practice: First, the implementation of a Bayesian-updated digital twin enables continuous calibration of finite element models using real-time inclinometer, strain gauge, and piezometer data, resolving the persistent discrepancy between predicted and observed soil-structure behavior. Validation across 1,372 optimization cycles at the 22.5-m Singapore MRT excavation reduced prediction errors to 8.2% ± 1.7%, contrasting sharply with conventional methods exhibiting 25-40% inaccuracies. Second, the multi-objective NSGA-III optimization quantifies critical trade-offs between deformation control, stability assurance, and economic efficiency, achieving a 41.3% reduction in maximum wall deflection while simultaneously lowering material costs by 29.4% compared to Eurocode 7 baselines. Third, sensitivity analyses revealed that strut preload optimization contributes 52% to deformation mitigation, fundamentally reorienting design priorities away from historical over-reliance on wall embedment depth.

The case study further established that adaptive control during critical construction phases prevents escalation of anomalies: When unexpected artesian pressure induced rapid deflection during Stage 5 excavation, the framework executed parameter recalibration and design adjustments within 36 hours, eliminating structural interventions that conventionally cost $120-$250k per incident according to Federal Highway

Administration records. These capabilities collectively shift excavation support from static design toward responsive risk management, where safety margins are dynamically maintained through data-informed decision cycles rather than predetermined conservative allowances.

Despite these achievements, two operational barriers require resolution for widespread adoption. Computational latency averaging 1.8 hours per optimization cycle currently exceeds the ≤0.5-hour threshold for real-time response during strut installation or dewatering operations. Additionally, the 34.7% computational overhead from homomorphic encryption for cross-institutional data sharing necessitates hardware acceleration. Future iterations should implement edge computing architectures with field-programmable gate arrays (FPGAs) to reduce processing time by 65-80%, alongside federated learning protocols that enable knowledge transfer without raw data exchange. Integration with robotic strut adjustment systems could further automate 78% of optimization implementations, potentially reducing construction delays by 15-30 days for major urban excavations.

The framework's scalability extends beyond diaphragm walls to secant pile and soil-nailing systems, with preliminary simulations showing 28-33% cost savings in heterogeneous geological profiles. Its capacity to convert distributed sensor networks into actionable intelligence establishes a replicable template for infrastructure digitalization, particularly valuable in seismic regions or coastal cities where groundwater dynamics compound excavation risks. By transforming fragmented monitoring data into coherent operational guidance, this research bridges a critical gap between theoretical geomechanics and construction execution.

In broader context, this work exemplifies how physics-informed machine learning revolutionizes geotechnical practice. The synthesis of domain knowledge (Bayesian soil mechanics) with data-driven optimization creates systems that enhance both safety and sustainability, reducing overdesign while preventing failures. The documented 29.4% material savings translate to approximately 480 tonnes of carbon reduction per kilometer of urban excavation, aligning with global decarbonization targets. As civil infrastructure faces escalating demands from urbanization and climate change, such adaptive frameworks will prove indispensable for constructing resilient underground spaces within environmental and economic constraints. Future research should expand modality integration through wireless smart aggregates and distributed fiber optic sensing, advancing toward fully autonomous excavation systems that continuously reconcile design assumptions with evolving ground responses.

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