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Introduction to Real-Time Back Analysis and recent developments related to the Observational Method

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ABSTRACT: Real-time Back Analysis (RTBA) has emerged as a promising approach in geotechnical engineering, driven by advancements in numerical analysis, cloud computing, instrumentation data availability, and interdisciplinary collaboration. RTBA enhances decision-making by integrating live or near-live observation data with improved predictions from numerical models, aligning closely with the principles of the Observational Method (OM). This paper provides a comprehensive definition of RTBA within the context of OM and explores its transformative potential in geotechnical practice. The study highlights the dual components of RTBA: observation and prediction, which combine real-time field measurements with computational models to accurately replicate geotechnical construction projects. These components enable engineers to modify designs, thereby reducing risks and/or improving project outcomes. RTBA improves the responsiveness of construction projects to unforeseen site conditions and facilitates proactive decision-making. However, its implementation faces notable challenges, including the availability of near real-time accurate and reliable instrumentation data, managing the complexity of model calibration, handling and storing large volumes of data, and navigating the coordination requirements between project parties, including contractors, designers, independent checkers, and clients. Addressing these issues is critical to fully realize the potential of RTBA. Essential practices, including establishing long-term baseline monitoring to account for environmental effects and instrument noise, as well as implementing redundancy through alternative measurement methods, are proposed. These measures ensure the quality and reliability of input data, which are pivotal for successful back analysis.

KEYWORDS: Observational Method, numerical modelling, probabilistic methods, data bases, model calibration, optimization.

1 INTRODUCTION

The Observational Method (OM), as summarized in Peck's Rankine Lecture (1969) and formally defined in the CIRIA Guide 185 (Nicholson *et al.* 1999), provides a structured approach for managing geotechnical uncertainty during construction while minimising over-conservatism in designs. OM is conceptually structured around a data block and a decision block (Figure 1, left). The data block collects field observations that guide decisions in the decision block, with the primary flow of information indicated by solid arrows in Figure 1. Crucially, OM allows feedback between data collection and decision-making (dashed arrows in Figure 1), enabling design adjustments as construction progresses. The implementation of back analysis or Real-Time Back Analysis (RTBA) introduces a model block into this framework (Figure 1, right). The model block receives inputs from the data block, processes these using (most of the time) numerical analysis, and provides outputs to inform decisions (decision block). This creates a dynamic feedback loop among data, model, and decision blocks, enabling proactive refinement as projects evolve.

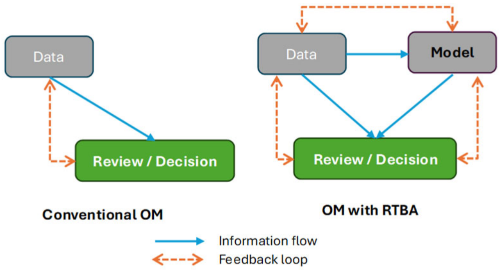

Figure 1. Conventional Design vs OM design with RTBA.

The outcome of RTBA within OM is an updated design model informed by live or near-live observational data. This serves three essential purposes:

- Model verification, where agreement between predictions and measurements confirms the validity of the original design model;
- Model adaptation, corrections of any discrepancies between original design model and measurements; RTBA of observations can give insights into ‘cause-effect’ relationships and facilitate significantly improved understanding of system behavior; and;
- Forward prediction, allowing the design team to anticipate system responses and proactively adapt designs and modify contingency plans.

2 RTBA & THE OBSERVATIONAL METHOD

Conventional OM typically uses predefined trigger values for monitoring data, assuming that remaining within these thresholds confirms model reliability and design assumptions. However, this approach may be inadequate when prior experience is limited or when site conditions deviate significantly from initial assumptions. While forward prediction can enhance decision-making, it requires a model capable of capturing key behaviors throughout construction, not solely the stage for which the design criteria is considered. Therefore, successful implementation of OM depends on the rapid availability of high-quality monitoring data and site observations of construction processes, which are compared with trigger values during site review meetings to inform design adaptations (Figure 2). This requires maintaining design flexibility throughout construction and close collaboration among stakeholders to ensure that the instrumentation and monitoring (I&M) system, ground model, and numerical models are continually updated to reflect actual site conditions.

2.1 *RTBA in the framework of OM*

Over the past 15 years, advances in electronic monitoring systems, database management, and computational resources have greatly improved the speed and amount of data collection, which facilitate the opportunity to conduct near-real-time updates of numerical models (here, “near” indicates that a certain level of processing is required, meaning the results are not “immediately” available) using field data. However, trigger values in conventional OM are often still based on limited site investigation data, requiring conservative assumptions that can restrict opportunities for optimization during construction. Recent advances in computational power, numerical modelling and the application of machine learning algorithms now enable RTBA by allowing rapid back-analysis of construction performance and continuous reassessment of design models during construction. Within the OM framework, the goal of RTBA is often to refine designs based on updated models, detect deviations in design assumptions and to define new, data-informed trigger values for routine site reviews. The frequency of these review meetings varies by project type (e.g. tunneling often requires daily reviews, basement excavations typically weekly reviews). Figure 2 demonstrates how the OM provides a recognized framework to integrate RTBA into the construction process. Although RTBA is often applied within the OM framework, it can also be used independently, for example in research applications or to inform the design of future projects.

Despite its great potential, RTBA also faces key challenges:

- Integrating computationally intensive numerical models into workflows to achieve truly “real-time” updates.
- Managing the time lag between data acquisition and predictive modelling.
- Ensuring that design changes undergo independent review (e.g., CAT3 checks) to maintain compliance and safety.

2.2 *RTBA & OM: Ab Initio vs Ipso Tempore*

Peck identified the “Ab Initio” approach to OM, which integrates OM planning from project inception. However, in practice, OM is often implemented reactively after construction has commenced, adopting conventional designs with observed site conditions.

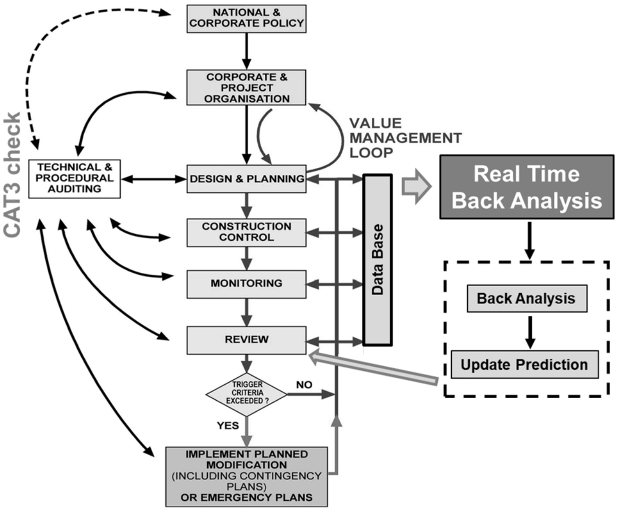

Figure 2. OM Process with RTBA (modified from CIRIA Guide 185).

CIRIA C760 (Gaba *et al*. 2017) introduced the term “Ipso Tempore” (Figure 3 summarize the different approaches) to describe this reactive use of OM (*Approach C*), which occurs when movements or forces are lower than initially predicted (allowing design refinement) or exceed predictions (necessitating additional support measures) (*Approach D*). Most OM applications currently fall within this Ipso Tempore approach, placing significant pressure on the back-analysis process during construction. This operational pressure has been a primary driver for the interest in developing automated RTBA systems, which promise to enhance geotechnical design practice through real-time data integration, predictive capability, and design adaptability.

3 FUNDAMENTALS OF RTBA

3.1 *Back Analysis vs Real-Time Back Analysis*

In broad terms, “back analysis” refers to the process of determining a set of input conditions, including input parameters that produce outputs consistent with observed phenomena (Cividini *et al*., 1981). This is typically performed using numerical models, with the primary aim of improving the reliability of the ground model and overall system performance (including ground-structure interactions and construction process interactions) and enhancing predictive capabilities for subsequent construction stages.

“Real-Time Back Analysis” extends conventional back analysis by requiring that analysis results are returned in near real-time, ensuring alignment with the construction program without introducing delays. While the concept of RTBA is gaining traction in geotechnical engineering, there remains a lack of consensus on its precise definition and scope. Within this context, the OM offers a recognized framework for the systematic integration of RTBA into the construction process, enhancing OM by coupling observed behavior with updated design models (see also section 2). This integration enables informative decision-making through the timely evaluation of model parameters, allowing engineers to adapt designs dynamically to reflect actual site conditions.

	Ab initio		**Ipso tempore**	
	A	**B**	**C**	**D**
Approach	*Optimistically proactive*	*Cautiously proactive*	*Proactive modifications*	*Reactive corrections*
When implemented	The OM is planned **from project inception**		**Starts with conventional design** with no explicit intention of applying the OM	
Back analysis requirements	Necessary before construction starts from available reliable and relevant case study data	Preferable, but not essential	Necessary – from assessment of initial construction stages	

Figure 3. Summary of OM Approaches (modified from CIRIA C760)

The practical implementation of RTBA faces demanding requirements, including the need to deliver analysis results within tight project timelines, the processing of large volumes of monitoring data, and managing the increasing complexity of modern construction. These challenges necessitate the use of advanced numerical models, often coupled with machine learning and/or optimization algorithms to enable RTBA to operate effectively. An application of RTBA was trialed during a deep shaft excavation project in London (Chen, 2023), where the success of the approach was facilitated by the timely availability of monitoring data and the deployment of cloud-based, machine-learning-driven back analysis. This method enabled comprehensive review and processing of observational data while advanced algorithms facilitated the rapid creation and evaluation of thousands of numerical models within a short timeframe, supporting prompt design updates in line with site observations.

It is important to note that RTBA introduces additional layers of complexity that can hinder its practical adoption if not managed effectively. RTBA is not simply about conducting back analysis “very quickly”; it requires that reliable analysis outputs are made available and shared with project stakeholders in a timeframe that allows them to influence ongoing design and construction decisions. The value and potential of RTBA lies in its capacity to maintain a reliable digital model which is continuously updated, enabling project teams to respond proactively to observed site behavior and optimize construction processes. The effectiveness of RTBA is therefore influenced by the complexity of the numerical model, sophistication of constitutive laws, management of monitoring and construction data quality, and strategies for addressing data interpretation challenges. These factors are discussed herein.

3.2 *Workflow of RTBA*

Figure 4 presents a workflow illustrating how RTBA can be integrated within the practical implementation of the OM. A critical initial step involves reviewing—and often modifying—existing I&M systems to ensure that reliable data can be collected within appropriate timescales to support real-time analysis. Here, ‘observations’ extend beyond standard I&M measurements to include detailed records of construction activities, enabling a clear understanding of cause-and-effect relationships that must be explicitly incorporated into the RTBA process.

‘Critical observations’ must be defined, which are those parameters used for establishing OM trigger levels (see also section 2), such as wall displacements in retaining wall construction or groundwater pressures during dewatering. These critical observations directly inform the development of the RTBA numerical model and influence key modelling decisions, including the selection of suitable constitutive models (see section 4). For effective practical application, it is essential to define specific construction stages where RTBA outputs will directly support OM decision-making. These stages, along with associated data requirements, should be identified and agreed upon in advance with all relevant stakeholders, including the main contractor, designer, specialist subcontractors (e.g., instrumentation providers), client advisers or independent checkers, and associated 3rd party (e.g., owners of nearby infrastructure). Once construction is underway and observational data from a key stage becomes available, RTBA can be executed, typically requiring several iterations to achieve an ‘acceptable’ match between the model outputs and the observed data. The criteria for what constitutes an ‘acceptable’ match should be defined on a project-specific basis and will require sound engineering judgment informed by prior experience with OM implementation. During early construction stages, particular attention should be paid to the potential impacts of non-linear system behaviors on subsequent construction phases. This includes considerations of soil-structure interaction, geometric changes, and material non-linearities, depending on the level of sophistication of the RTBA numerical model used. These factors are critical, as decisions made within the OM framework often carry significant safety, cost, and program implications.

By embedding RTBA within the OM workflow in this structured manner, it becomes possible to refine the ground model dynamically, improve predictive capabilities, and enhance decision-making throughout the construction process while maintaining alignment with project timelines.

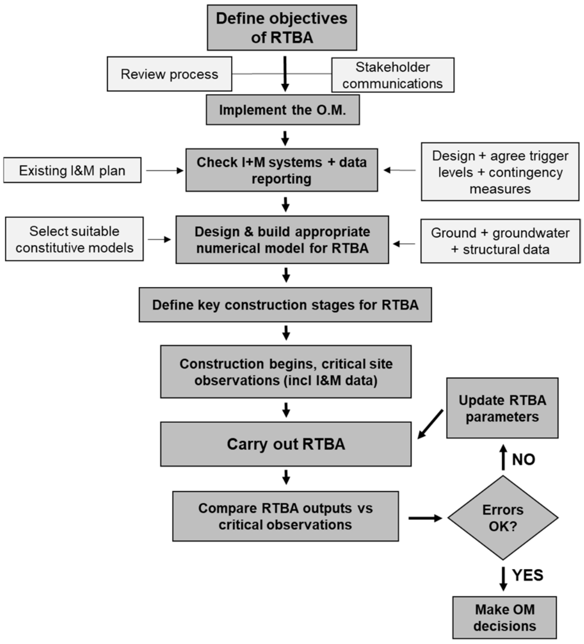

Figure 4. Conceptual workflow for RTBA

4 DUAL COMPONENTS OF RTBA: OBSERVATION AND PREDICTION

4.1 *Component I: Observation*

Good observations have been recognized as essential for understanding the ground and/or ground-structure interaction behavior; however, faulty monitoring data needs to be considered in the back analysis process.

As Peck (1969) pointed out, there were several reasons for imperfect data. Moreover, for back analysis, Peck suggested that the monitoring results *should be regarded as working documents, issued whenever the information needs to be brought up to date.* From this, it becomes clear that Peck’s lecture reflected the dynamic character of monitoring data, measurements change with time.

In the context of RTBA, it is essential that monitoring data corresponds accurately to the construction timeline and is reviewed within an acceptable range of measurement error. This ensures that the back analysis reflects actual site conditions and provides reliable outputs for informed decision-making. To achieve high-quality data review, Chen & Nicholson (2022) recommend focusing on the following key aspects:

- Installation: Data errors frequently arise from issues during the installation process or while taking measurements. Ensuring proper installation and consistent measurement procedures is essential for data reliability.
- Baseline Establishment: A sufficient period of pre-construction monitoring is necessary to establish a reliable baseline against which construction-related changes can be measured.
- Routine Data Review: Regularly reviewing monitoring data alongside detailed construction activity records is critical for validating the data and understanding its context within the project timeline.
- Well-Planned Instrumentation Strategy: Designing an instrumentation and monitoring system that is targeted to capture the essential parameters needed for Back Analysis improves the relevance and quality of the collected data.

By systematically addressing these aspects, the quality of observations used within RTBA can be significantly enhanced, supporting more accurate model calibration, effective decision-making, and risk reduction throughout the construction process.

4.1.1 *Instrumentation & monitoring data*

Effective instrumentation and data coordination are crucial for the success of RTBA. Timely acquisition, systematic review, and early detection of errors or departures from expected behavior are central to the practical implementation of OM.

In practice, monitoring data may not always align with the design model due to environmental variations, unrecorded site activities, or unforeseen events. Establishing an adequate instrumentation baseline before construction is essential for identifying deviations from expected behavior, yet this step is often overlooked due to time/program or resource constraints.

Even with a well-planned monitoring program, data collected for RTBA always requires interpretation before it can be reliably used. To structure this process, four data categories can be defined:

- Raw data: Unprocessed output directly from instruments, often containing noise, redundancy, and irrelevant signals requiring signal conditioning (e.g., amplification, filtering, and signal conversion for digital processing).
- Reduced data: Data processed or transformed into engineering units through filtering and calibration, allowing meaningful interpretation of the instrument signals.
- Reviewed data: Additional evaluation is essential due to the complexity of the ground and its sensitivity to environmental and anthropogenic factors. Instrumentation data should not be accepted at face value; a systematic review process is needed to confirm coherence, discard invalid data, and ensure data is transmitted promptly to a central, discoverable storage location. Visualization tools linked with APIs can aid in efficient sense checking and allow traceable, reversible corrections where necessary.
- Interpreted data: Curated, representative data for a specific construction stage, suitable for back analysis. Producing interpreted data may require addressing inconsistencies across instruments, removing outliers, estimating trends, and accounting for seasonal effects.

4.1.2 *Instrumentation & monitoring coordination*

Managing these data categories effectively requires the following clear role separation and coordination:

- Data gathering role: Responsible for handling raw and reduced data, including collection, verification, transmission, and interim storage. This role ensures correct signal conditioning, data reduction, and traceable application of necessary corrections. It is typically fulfilled by the instrumentation contractor, who has direct access to instrument suppliers and understands the instrumentation system.
- Instrumentation manager role: Responsible for delivering a reviewed dataset ready for use in RTBA. This role includes resolving technical issues during monitoring, liaising with the data gathering team, coordinating data transmission, maintaining organized, discoverable storage, and providing effective data visualization for inspection and review.
- Data usage role: Responsible for producing interpreted data for RTBA, focusing on identifying the most relevant and reliable data within large datasets. This role requires maintaining active communication with the other roles and relates to the data manager described in 4.1.3.

Effective communication and coordination among these roles are essential for successful RTBA implementation. This structured approach ensures that high-quality data is consistently acquired, reviewed, and interpreted in a timely manner, maximizing the value of monitoring data while reducing the risk of undetected errors. This enhances the reliability of the RTBA process and supports responsive design adjustments aligned with actual site conditions during construction.

4.1.3 *RTBA - Data management*

Data management is essential for OM with RTBA. As constitutive models become more complex and integrated with diverse field data, ensuring data quality, accessibility, and systematic handling is critical for reliable back analysis and adaptive decision-making. Geotechnical projects generate often very large volumes of data from instrumentation, field measurements, lab tests, and simulations. Managing these datasets in real time is challenging, so appointing a dedicated data manager (ICE, 2012) with tool (e.g., data platform) is recommended to oversee workflows, maintain consistency, enforce standards, and facilitate collaboration. Platforms should include visualization tools to help engineers interpret trends and assess behavior in real time. Automated data capture, cloud-connected monitoring, and advanced analytics have the potential to streamline this process. Common Data Environments (CDE) and standard formats (e.g., recommended by Association of Geotechnical Specialist, AGS) can enable seamless data sharing and integration. Data management goes beyond spreadsheets, starting with high-frequency automated capture of displacements, pore pressures, and stresses, followed by rigorous cleaning to remove noise, fill gaps, and validate data (e.g. Forrester *et al.*, 2008). Proper classification ensures correct interpretation of static baselines, dynamic responses, lab data, and back-analyzed parameters. However, uncertainty affects both data and models due to measurement errors, sensor drift, and incomplete soil characterization. Incorporating uncertainty quantification methods (e.g. Bayesian inference) into RTBA increases confidence and supports risk-informed decisions (e.g. Baecher & Christian, 2003), consistent with the adaptive OM philosophy.

As discussed in section 4.2.2, combining advanced data management with surrogate models and optimization (e.g., genetic algorithms) enables rapid evaluation of soil parameters' effects (Ferrero *et al.*, 2023), turning OM into an AI-enhanced framework (Powderham & O'Brien, 2020). Ultimately, data management serves not just as a logistical function, but also as an enabler of innovation. It is a key component in transitioning the OM from a largely interpretative tool into a digital, quantitative framework that leverages the full capabilities of modern sensing, computing, and predictive analytics. As geotechnical engineering continues to evolve in response to sustainability, safety, and performance challenges, the strategic implementation of data workflows will be indispensable in delivering resilient and adaptive infrastructure.

4.2 *Component II: Prediction*

The back analysis and RTBA of any geotechnical problem requires an appropriate model that idealizes the in-situ conditions and construction sequence. Successful implementation relies on the mathematical representation of the governing features of structural elements, construction details and last but not least of the hydro-mechanical behavior of the soil, typically formulated through a constitutive model that reflects key aspects such as non-linearity, anisotropy, and time-dependent effects. Therefore, to develop a reliable predictive model within RTBA, it is necessary to identify and update the key parameters that influence ground and structural behavior during construction. These RTBA parameters include:

- Soil and rock parameters: strength, stiffness, and permeability relevant to the construction stage and groundwater conditions.
- Stratigraphy and environmental conditions
- Structure properties: stiffness and interaction characteristics of retaining walls, tunnel linings, or foundations.
- Groundwater properties: pore pressure conditions, permeability distributions, and potential changes due to dewatering.
- Construction loadings: surcharges, excavation-induced stress changes, and external loads.
- Construction sequence: timing and staging of excavation, support installation, or loading phases.

By updating these aspects of system behavior through RTBA and incorporating them into the predictive model, engineers can anticipate ground and structural responses for upcoming construction stages with greater confidence. This predictive capability allows for timely refinement of design assumptions, adjustment of trigger levels, and proactive risk management within the OM framework. RTBA is therefore not solely about generating forecasts but about transforming observational data into actionable insights that actively guide decision-making, ensuring that the design model remains relevant and reliable throughout the construction process. Some details related to the constitutive model choice, model calibration, implementation aspects of automated RTBA and RTBA data management are discussed below.

4.2.1 *Constitutive model choice & calibration*

One important aspect of every back-analysis is the choice of the soil constitutive model. In principle, the soil model should be sufficiently sophisticated to capture the geomechanical behavior throughout the entire construction process. However, the complexity of soil behavior has given rise to the formulation of different classes of constitutive models (Wood, 2000). In the past decades researchers have developed constitutive models to incorporate features like stiffness nonlinearity, strain hardening, anisotropy, dilatancy, cementation, stress path dependency, rate and time dependency (e.g. Schanz *et al.*, 1999, Taiebat & Dafalias 2008, Doherty & Wood 2020). As these models advance in complexity, the number of model parameters increase, making the model calibration process laborious, costly and time-consuming. Methods for this challenge vary in complexity, ranging from simple approaches such as the squared error, to maximum likelihood methods, and to more sophisticated techniques such as Bayesian analysis, genetic algorithms, particle swarm optimization, and particle filters. Beyond the question of adopting either a deterministic (e.g. optimization approach) or probabilistic (e.g. Bayesian) approach for the calibration, it is equally important to recognize the role of observational error (deterministic) or observational uncertainty (probabilistic) during model calibration. Regardless of the level of model sophistication, all numerical simulations are only idealized imperfect representations of the real-world system. Therefore, in a live or near-live setting, it is important to recognize contributions of measurement error and noise. Both terms are often difficult to quantify due to uncertainties in the real-world environment and compatibility between numerical model and real-world system. Another important thing to recognize is that the calibration procedure typically aims to capture a single element response pertaining to specific stress paths, while the model is intended for implementation into boundary value problems. It is recognized that the different boundary value problems are more sensitive to a different set of material parameters, as this depends on the stress path that dominates the response and the permissible deformation range (Brinkgreve, 2005). Using a boundary value problem to perform the inverse analysis and calibrate material parameters is therefore preferable. Back analyses to establish soil parameters based on field observations have been performed in both deterministic and probabilistic approaches. However, when performing model calibration on the boundary value problem itself using real-world observations, it is important to recognize that computation costs are likely to be significantly greater, especially for 3D problems with complex boundary conditions and sophisticated constitutive equations. For live or near-live calibration to be viable, a computationally efficient method for numerical simulation must be available.

4.2.2 *Implementation aspects of RTBA*

RTBA aims to rapidly and efficiently update parameters, boundary conditions or other properties to ensure that numerical model predictions closely match site measurements. This iterative process involves minimizing the difference between observed and predicted data from the model, known as the objective function. This process can be performed by means of advanced global optimization algorithms. A central challenge in automated RTBA is integrating geotechnical numerical solvers (e.g., Plaxis2D, Flac2D) with optimization routines. This is achieved by developing software "wrappers" that provide a consistent interface to different solvers, enabling easy model setup, execution, and retrieval of results. These wrappers also ensure that predicted data correspond to specific observation points and construction stages, avoiding mismatches between simulation phases and actual site conditions—a common issue caused by limited communication between site technicians and design engineers (see also discussion above). Maintaining meaningful and physically realistic ranges of parameters/settings during optimization is critical. Therefore, soil parameters, for example, must be constrained within feasible limits to avoid non-physical or unstable solutions that could lead to solver failures. Employing soil parameter correlations and databases can reduce the number of parameters to be optimized and exclude unrealistic combinations, improving convergence and stability. Due to the computational expense of detailed hydro-mechanical numerical models (especially in 3D), repeated forward simulations required for optimization can be time-consuming. To address this, parallel computing clusters can be used to run multiple model evaluations simultaneously, significantly reducing real world total runtime. Alternatively, surrogate (meta) models trained via machine learning on precomputed simulation data offer a lightweight approximation of the full model, enabling rapid evaluation during optimization. However, surrogate models require careful training and validation with separate datasets to ensure accuracy, and this often introduces new complications and uncertainties in the calibration process, principally around the accuracy and reliability of the surrogate model itself. A detailed explanation of surrogate modelling in engineering design can be found in Forrester *et al.* (2008). On the other hand, once surrogates are established, they support sensitivity analysis, back analysis, and even design optimization by balancing cost and performance. State-of-the-art RTBA workflows integrate these components within automated frameworks that manage data collection, model training, solver interfacing, and optimization.

Based on the specific RTBA objectives discussed in section 3.2, as well as the availability and transfer frequency of project monitoring data (section 4.1), an efficient RTBA execution concept can be developed. When designing such an RTBA execution concept, care must be taken to ensure the timeliness and completeness of the incoming measurements required for back-analysis. RTBA results in turn should be delivered in time for discussion and decision making prior to the next construction stage.

5 CONCLUSIONS

The integration of Real-Time Back Analysis (RTBA) within geotechnical practice offers a robust (and fast) pathway to predictive, adaptive, and efficient design and construction, transforming the traditionally qualitative Observational Method into a quantitative, data-driven process. Crucial to success are high-quality monitoring data, robust automation protocols, and regular expert oversight to validate results and maintain engineering judgment in the loop. Leveraging digital technologies—including automated data acquisition systems, cloud-based data management, surrogate modelling using machine learning and optimization algorithms—enables geotechnical engineers to enhance predictive capabilities, optimize resource allocation, and improve the efficiency and safety of infrastructure projects. Advanced data management, including the implementation of Common Data Environments, systematic data cleaning, and uncertainty quantification, ensures traceability and trustworthiness of back-analysis results, supporting reliable forward predictions across multiple excavation stages. The integration of surrogate models trained on finite element simulations can significantly accelerate RTBA workflows while maintaining acceptable accuracy, particularly in hydro-mechanically coupled problems where computational costs are high. Automated optimization routines further enable design optimizations in near real time, allowing designers to adapt continuously to evolving site conditions.

However, the full potential of these innovations can only be realized if the engineering workforce is adequately equipped with the necessary skills. As the profession increasingly intersects with data science, software development, and automation, there is a growing need to upskill engineers in programming, statistical analysis, and data visualization, ensuring they can manage and interpret large, high-frequency monitoring datasets and leverage modern skillsets such as software development, database systems management, and cloud computing. As highlighted by Ground Engineering (2024), the skill shortage may represent one of the most significant barriers to the widespread adoption of RTBA and advanced digital workflows in geotechnical engineering. To support this transition, engineering education and professional development programs must adapt, fostering interdisciplinary training and promoting collaboration between geotechnical and data specialists. By embracing this evolution, the profession will be positioned to advance the Observational Method and RTBA from promising innovations to practical standards, enabling geotechnical projects to remain responsive and resilient while ensuring safety, efficiency, and predictive control throughout the construction lifecycle.

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