

# Back analysis of a deep excavation - insights from manual and machine learning approaches

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**ABSTRACT:** The application of machine learning (ML) algorithms has significantly strengthened the capacity and efficiency of back analysis (BA). It also enables near ‘real-time’ back analysis (RTBA) to be undertaken in parallel with the fast-paced construction activity. Through a case study of back analyzing a deep excavation in over-consolidated London Clay, this paper presented both manual and ML back analysis results and discussed the factors which have impact on back analysis. The observation monitoring data plays a critical role in BA process, and the availability & reliability of data not only influence the convergence criteria but also dominate the outcome of BA. The choices of geotechnical analytical modelling, from Pseudo-finite element model (FEM) to two-dimensional (2D) FEM and three-dimensional (3D) FEM, coupled with different soil constitutive models were assessed in the case study as well. The performance of different back analysis cases was compared, despite different soil models, the multiple stages targeted back analysis gave better predications at all construction stages than the single stage targeted back analysis. In conclusion, it is subjected to the targeted observation data (e.g., displacement or force), the suitable FEM methods and soil constitutive models shall be selected to undertaken design and back analysis. Considering that more monitoring data will be available in future digitalized construction projects, it is rational to adopt the data-driven design approach (e.g., Observational Method). Thereby machine learning powered RTBA will become essential to support the data-driven design approach, in order to deliver sustainable and resilient construction projects.

**KEYWORDS:** Back Analysis, Machine Learning Back analysis, Monitoring, Case history

## 1 INTRODUCTION

With the growing volume of monitoring data available during construction, as well the rapid advancements in computational capabilities, back analysis (or inverse analysis) is becoming increasingly prevalent in geotechnical engineering projects. This process enhances the understanding of ground behavior, including soil-structure interaction, reduces uncertainties in ground response, and enables forensic analysis.

Back analysis is an inverse process used to confirm initial modelling assumptions and derive input parameters that yield model outputs consistent with field observations or measured phenomena (Gioda & Maie, 1980; Cividini, *et al.*, 1981). In practice, back analysis primarily employs numerical modeling, serving as a model calibration procedure that minimizes discrepancies between computational outputs and field monitoring data. The integration of big data analytics and machine learning algorithms has enabled mathematically rigorous optimization of back analysis, thereby achieving near real-time processing capabilities that align with geotechnical construction progress.

Through a case study of a deep excavation in London, this paper benchmarks the performance of manual versus machine learning back analysis methods. The key influencing factors in back analysis are examined and their impacts on parameter identification are discussed. Insights for back analysis practice are summarized i). consideration of FEM methods including soil constitutive models; ii). review and application of the observational data; iii). interpreting the outcomes.

## 2 BACK ANALYSIS TESTING

### 2.1 Case History

The case study focuses on a deep box excavation of the Western Ticket Hall at Crossrail Tottenham Court Road Station (TCR-WTH) in central London. This deep excavation comprised a near-rectangular geometry (about 41 m × 31 m in plan, see Figure 1) with a maximum depth of 29.5 m. The original design employed a bottom-up construction approach, utilizing a 1.0 m thick diaphragm wall supported by five levels

of temporary props. The excavation was situated within over-consolidated London Clay formation, presenting characteristic geotechnical challenges including stress relief and potential basal heave.

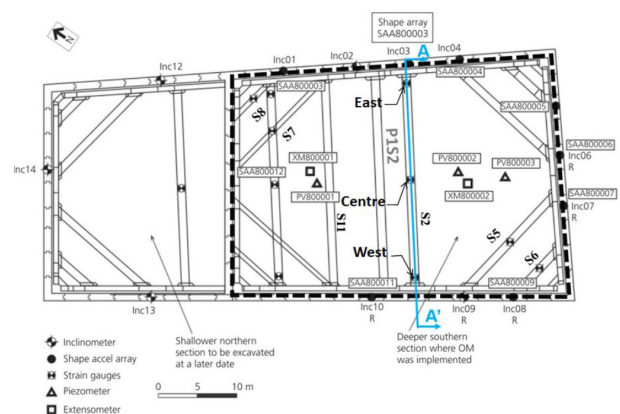


Figure 1 Layout of TCR-WTH with Instrumentation & Monitoring for deep box (Chen & Nicholson, 2022)

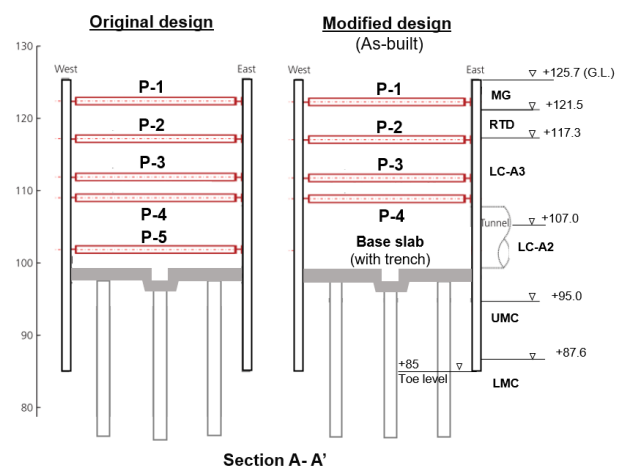


Figure 2 TCR-WTH deep box Section A-A' (Chen 2018)

During the construction, the manual back analysis was conducted using the available comprehensive monitoring data. This enabled project modification, ultimately permitting the omission of the lowest level of props (see Figure 2). The adaptation has achieved significant project savings, reducing both construction duration and associated costs without compensation of safety. (Yeow *et al.*, 2014).

This well-documented case history served as an ideal benchmark for systematically evaluating manual back analysis and investigating two distinct machine learning (ML) algorithms in back analysis: 1). a probabilistic statistical method incorporating Bayesian inference (Cañavate *et al.*, 2021), and 2). an optimization-based evolutionary genetic algorithm (Santos, 2015).

## 2.2 Considerations for Back Analysis

### 2.2.1 Numerical modelling

The original design of the TCR-WTH excavation was performed using Oasys FREW and Plaxis 2D models. The initial back analysis was manually performed using Pseudo-FE FREW model during construction. The restricted period of 2 weeks was the total time granted for the back analysis process and the modification of the design. Despite the limited time, due to the ability of the FREW model to simulate simplified 2D excavation sequences, around 200 analysis runs had been completed on one standard laptop computer within two weeks, up to 80 hours in total.

In order to conduct a thorough study, all three types of numerical modelling, from Pseudo finite element model (FEM) in 2D to proper 2D FEM and 3D FEM were assessed in the manual back analysis (Chen, 2018). When the simplified numerical Plaxis 2D FE model and the complex but sophisticated LS Dyna 3D FE model were adopted in simulating the same excavation sequences, the improvement in prediction of the actual three-dimensional soil-structure behavior was significant. However, the longer computational time was taken as expected. Summary of analysis time for the adopted FEM methods with variable soil constitutive models in manual back analysis is presented in Table 1.

Table 1 Manual Back-analysis Summary

	Model	Soil Model	Run/ Time*
1	<i>Pseudo-FE 2D (Oasys FREW)</i>	n/a	~ 200 / 80 hr. total
2	<i>Plaxis 2D FE</i>	Mohr-Coulomb HSS	<100 / ~ 4hr/ run < 25 / ~ 6hr/ run
3	<i>LS-Dyna 3D FE</i>	Mohr-Coulomb BRICK	< 10 / ~24 hr/run < 5 / ~30 hr/run

Note: 1. HSS = Hardening soil model with small strain stiffness. 2. The analytical time is indicative based on software version issued before 2018.

There does not seem to be a best FEM for manual back analysis, it depends on the objectives of the back analysis and allowable time to select the more suitable FEM conducting the back analysis. The decision must balance between the accurate prediction and complexity of numerical analysis, including types of FEM, numbers of analysis run, as well as the soil constitutive model choices which are available for 2D and 3D FE modelling.

### 2.2.2 Soil models

The manual back analysis during construction began with Oasys FREW model and then validated in Plaxis 2D model with the Mohr-Coulomb soil model. By this way, a like-to-like comparison within the limit time was able to be provided. Meanwhile, there were fewer numbers of soil model parameters to perform a more straightforward sensitivity or parametric study prior to back analysis. The sensitivity study

was proven essential that it significantly improve efficiency of back analysis. The soil stiffness was found as one of the most influential variable parameters in the TCR-WTH case study.

Soil stiffness is well-known to be non-linearly dependent on soil strain status. In particularly in the TCR-WTH case, up to 29.5m deep excavation undertaken within the over-consolidated London Clay formation, soil had experienced from small strain to medium / large strain. It becomes reasonable to employ non-linearly stiffened soil models to better simulate the actual soil behavior. For typical over-consolidated London Clay, BRICK model had a track record of modelling this type of soil, and it was applied in LS-Dyna 3D FEM manual back analysis. For comparison purposes, another available non-linear soil model in Plaxis 2D modelling - hardening soil model with small strain stiffness (HSS), was adopted and applied in manual Plaxis 2D back analysis as well.

Due to the increased numbers of model parameters in both BRICK and HSS soil models, and the correlations among different model parameters, the sensitivity study for these models were challenging in terms of volumes of results and interpretation. In contrast, ML back analysis can conduct sensitivity study for complex soil models within a relative reasonable period and provide indications of the more influential variable parameters for the subsequent efficient back analysis.

Considering the significant computational time to run a full-sequenced 3D FE model with non-linear soil model (e.g., over 24 hour per model run as shown in Table 1), manual back analysis must further reduce the numbers of model run if there are time limit for the back analysis to be completed. However, the more accurate predictions by 3D FEM shall not be neglected when the actual 3D construction problem is investigated.

### 2.2.3 Observation data

In back analysis, observation data is the selected monitoring data to be targeted in the process. It determines the convergency of back analysis and reflects the quality of back analysis. In the TCR-WTH manual back analysis, inclinometer data measuring the diaphragm wall displacements was regarded as primary observational data and applied in the back analysis. Other available monitoring data were used for reference check only, such as temporary prop forces monitored by vibrating strain gauges, ground heave measured by extensometers and groundwater pressure reflected by multiple levels of vibrating piezometers.

Given the importance of monitoring data in back analysis, the study of monitoring data in relation to back analysis revealed that reliability and availability of monitoring data are two key characters. Category of monitoring data has been based on these key characters (Chen & Nicholson, 2022).

The reliability of monitoring data is associated with accuracy of instruments and data errors (random and systematic errors). Despite how well the calibration has been conducted, installation of instruments has been executed and how carefully monitoring data has been taken, accuracy of instruments, data repeatability and random error of data are varied from project to project. Back analysis will have to accommodate the imperfect targeted data, but not simply accept the superficial value of the data. For instance, in manual back analysis, engineering judgement could be valuable in determining the convergency of analysis. In ML back analysis, certain measures can be implemented to tolerate the imperfect monitoring data, such as 'buffer zone' allowing multiple optimized predictions as good predictions, or 'control zone', focusing on more suitable monitoring datasets.

Another challenge to perform the near real-time back analysis (RTBA) is the availability of monitoring data. How quick the targeted monitoring data can be made available for back analysis? Can the back analysis time limit meet the project construction program? These are questions to be answered for RTBA. A pioneer trial of RTBA in a deep excavation project in London has proven the concept of RTBA (Chen, 2023). The trial RTBA has relied upon ML back analysis providing outcomes within 24 hours so that results review could fit with the fast-paced construction program.

### 2.3 Testing Scenarios

With the available TCR-WTH excavation case monitoring data, both manual and ML back analysis testing were conducted in this study. Testing cases are summarized as below, details of individual testing cases are discussed in the following sections:

- Case 1 - base case with the original characteristic design parameters applied in Plaxis 2D FE model using Mohr-Coulomb soil model.
- Case 2 - manual back analysis with Pseudo-FE FREW model during construction, also back analysis with Plaxis 2D model and LS-Dyna 3D model using Mohr-Coulomb, BRICK & HSS soil models at post construction study.
- Case 3 - probabilistic statistical Bayesian back analysis with Plaxis 2D model using Mohr-Coulomb soil model.
- Case 4 - genetic algorithm back analysis with Plaxis 2D model using Mohr-Coulomb and HSS soil models.

## 3 MANUAL BACK ANALYSIS

Manual back analyses for the TCR-WTH deep box excavation are summarized in Table 1. All manual back analyses have been targeted at single excavation stage, and inclinometer data as the targeted observational data. Table 1 shows clear difference in computational time, that the more complex the model is, a longer analytical time is required. The predicted wall deflection as back analysis result is compared against the targeted inclinometer data from Shape-Array-Accel (SAA) 803, at location of Section A-A' in Figure 1.

Manual back analysis results are presented in Figure 3. According to the uncorrected inclinometer data, which was the best possible evaluated data during construction, the predicted wall deflections by characteristic design parameters (Case 1) were significantly above the measurements. The manual back analysis with FREW model proposed London Clay stiffness can be improved to a higher  $E_u/c_u = 1000$  (Yeow *et al.*, 2014). This set of 'most probable' design parameters projected the wall deflections at subsequent excavation stages (Case 2 – FREW (1)), above the uncorrected inclinometer data with a considerable safety margin.

A thorough inclinometer data review at post-construction study revealed there was rotational error embedded in the inclinometer raw data. After correction, manual back analysis was retaken and targeted on the corrected inclinometer data. Three types of FEM (FREW, Plaxis 2D & LS-Dyna 3D) back analyses concluded that the further improved London Clay stiffness of  $E_u/c_u \geq 1600$  (Chen, 2018) could have been achieved. The predicted wall deflections from back analyses are compared against the corrected SAA8003 data at Section A-A' over individual excavation stages in Figure 3, shown as Case 2 – FREW (2), Case 2 – 2D FEM and Case 2 – 3D FEM.

The back analysis convergence was determined by matching the maximum deflection value and deflection curve profile. It was not the most robust process but depended on experiences in both modelling and construction. For instance, it is not preferable to have the under-estimated predicted wall

deflection from the back analysis. Also, the predicted wall deflection curve should match with the targeted monitoring data profile.

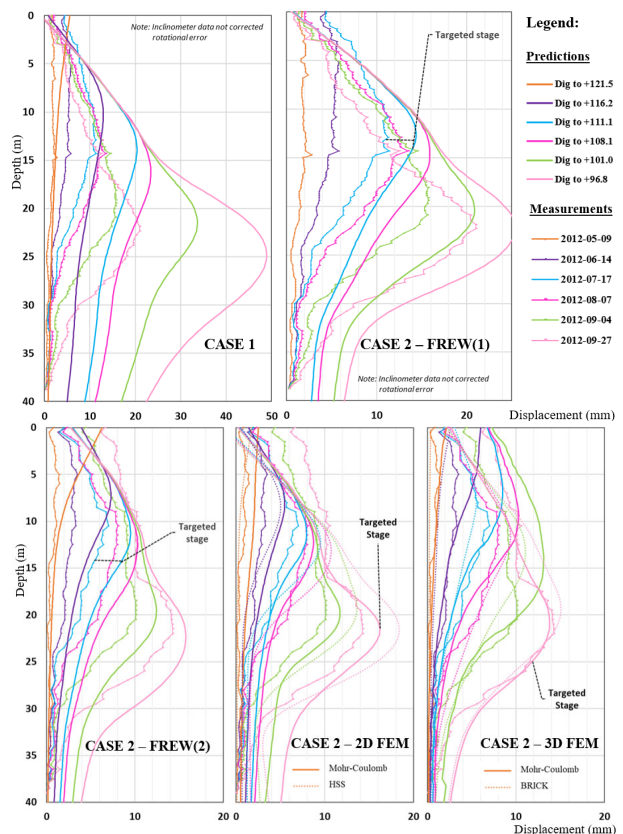


Figure 3 Manual back analysis predictions at Section A-A': wall deflections Vs observations.

### 3.1 Results

In the manual back analysis FREW (Case 2 -FREW (2)), an earlier stage of dig to +111.1mATD was targeted. The analysis was determined as converged when 'optimal' parameters predicted wall deflections matched well with the corrected SAA8003 data at each excavation stages. Although, more refined predictions could have been achieved if further analysis were conducted.

Given the soil behavior of non-linear stiffness in relation to shear strain, in the back analysis with 2D & 3D FEM, the final stage of dig to +96.8mATD was selected to be targeted. By the final dig stage, the London Clay formation had experienced the most significant shear strain due to the excavation activities, hence, the back analysis calibrated parameters would be more representative for the whole excavation construction. Despite fewer runs of 3D FEM back analysis, it was observed that the predicted wall deflections from both the Mohr-Coulomb and BRICK soil models (Case 2 – 3D FEM) matched well with the corrected SAA8003 data at each stage than those from the 2D FEM back analysis (Case 2 – 2D FEM). There could be other factors that affected the 2D FEM prediction, such as the simplified 2D modelling against the actual 3D construction.

Regarding the performance of non-linear soil models in manual back analysis, due to more model parameters and longer computational time per run, the calibration of model parameters using the associated ground investigation testing data is preferable. A set of model parameter to initiate the back analysis will be derived, and a good understanding of the correlations between parameters can be achieved.

In the predicted wall deflections, non-linear soil models indicated more precise predictions at earlier stages (e.g., HSS in Case 2 – 2D FEM and BRICK in Case 2 – 3D FEM), when the London Clay was lightly touched and remained at very small strain status. However, when shear strain increased, non-linear models seemed not to perform well. For example, an overestimation by the HSS model and an underestimation by the BRICK model were found in the predicted wall deflections at the later excavation stages. The further calibration of the correlated model parameters in future study might improve performance of these non-linear models.

#### 4 MACHINE LEARNING BACK ANALYSIS

The application of machine learning optimization algorithms significantly enhances the efficiency of back analysis in terms of shortening the computational time and the improvement in predictions. The back analysis testing Case 3 and Case 4 of the TCR-WTH deep box demonstrate the advantages of using machine learning optimization algorithms.

##### 4.1 Probabilistic Statistical Bayesian Method

Probabilistic statistical method is one of stochastic optimization approaches, this method has been successfully applied in back analyses to investigate ground engineering problems by Tarantola (2005). Based on the probabilistic method, Bayesian method has run the probabilistic calculations on a surrogated model to reduce the numerical burden (Cañavate *et al.*, 2015). Bayesian method was trialed in back-analyzing the TCR-WTH deep box excavation case, the detailing of the testing and results referring to the paper by Cañavate *et al.*, (2021). The predicted wall deflections from Bayesian back analysis ‘optimal’ parameters as testing Case 3 are presented and discussed in this paper.

Plaxis 2D FE model with the Mohr-Coulomb soil model was adopted in Bayesian back analysis. The single excavation stage back analysis was conducted by the minimum of three iterations updating variable parameters from the prior (initial) to posterior (updated) value ranges. The mean value of posterior value range was then treated as the ‘optimal’ parameter.

Firstly, the sensitivity study by Monte Carlo analysis was performed on all variable parameters, including modelling parameters and observational data. This in turn indicated the influence of parameter(s) at each node of the predicted wall deflection curve. Hence, the most influential parameters can be detected and selected as variables in the back analysis. This process filters out the least influential parameters and improve the back analysis efficiency. In the TCR-WTH back analysis, the targeted monitoring data is inclinometer data, the identified influential parameters include soil stiffness (e.g.,  $E_u$  &  $E'$ ) and observational data. The temporary prop stiffness (e.g., EA) values were also found to contribute to the predicted wall deflections near four propping levels. Moreover, the influence of prop stiffness value may vary significantly at different construction stages.

The systemically convergency control measures have been introduced to the Bayesian back analysis process, such as the controlled zone, it is a specific zone where the confidence level is high for both the targeted observational data and the predictions. Example of the controlled zone is illustrated in Figure 4. Bayesian method takes advantage of the statistical approach, allowing the change of confidence interval (CI, from 0 to 100%) for input variable and presenting the output of optimal value.

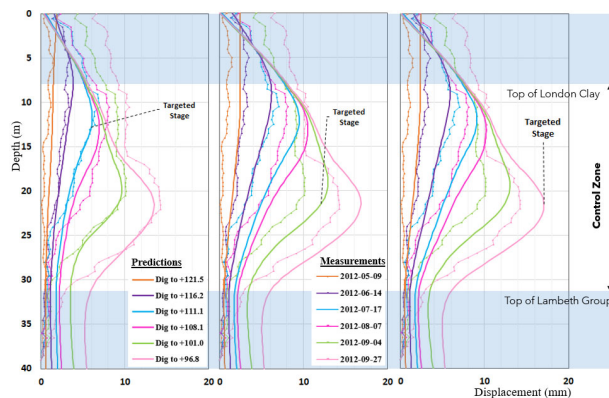


Figure 4 Bayesian back analyses (Case 3) predictions at Section A-A' wall deflections Vs observations.

##### 4.1.1 Single stage back analysis results

The predicted wall deflections against the corrected SAA8003 data at Section A-A' from the single stage Bayesian back analyses are presented in Figure 4.

The back analysis at stage of dig to +111.1mATD, the optimal parameters predicted the wall deflections that matched well with the targeted observations within the controlled zone. The predictions for earlier stages also matched well with the corresponding observations, but the forecasted deflections at later stages seemed slightly under-estimated, which could lead to potential less safe construction.

The single stage back analyses at later stages (e.g., dig to +101mATD and dig to +96.8mATD) did not manage to improve the predictions further. Moreover, both sets of optimal parameters calibrated from the later stages back analysis have over-predicted deflections for earlier stages.

##### 4.2 Genetic Algorithm

Evolutionary genetic algorithm is another stochastic optimization approach that had been applied in back analysis of excavation problems (Santos, 2015), a series of combinations of variable parameters could be treated as mathematical ‘optimal’ values of the specific analysis. Testing Case 4 was undertaken by genetic algorithm on the cloud-based platform ‘DAARWIN’ in which the sensitivity study function is built-in, and the cloud-based platform enables analyses of thousands of numerical models simultaneously.

As testing Case 3, Plaxis 2D FE model with the Mohr-Coulomb soil model was adopted in the genetic algorithm back analysis testing Case 4. Both single excavation stage and multiple excavation stages back analyses were conducted. As comparison, the non-linear HSS soil model was adopted in the Plaxis 2D FE model and applied in the genetic single stage and multiple stages’ back analysis. The default setting of the genetic algorithm would create 50 generations, up to 10,000 combinations of model runs for each back analysis.

The systemically convergency control measures, including the controlled zone, the least-square error function in curve fitting, and user defined conditions for the correlated variable parameters, have further improved the back analysis efficiency. For instance, some combinations have been ceased even before launching the analysis run due to unrealistic parameters’ correlation, and some combinations could not reach the final analytical stage so they would be eliminated from the pool of verified combinations.

The predicted wall deflections from genetic back analyses against the corrected SAA8003 data at Section A-A' are illustrated in Figure 5 (Mohr-Coulomb soil model) and Figure 6 (HSS soil model).

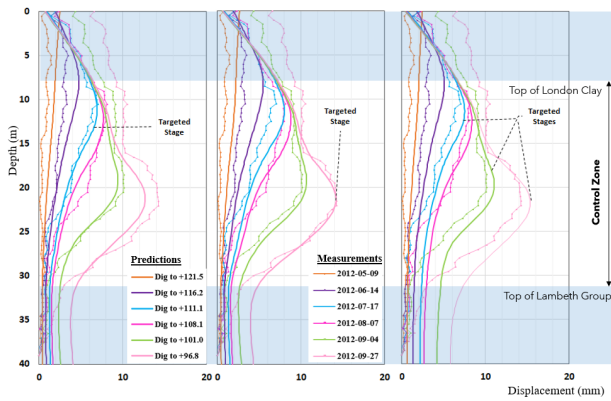


Figure 5 Genetic Algorithm back analyses (Case 4: Mohr-C) predictions at Section A-A': wall deflections Vs observations.

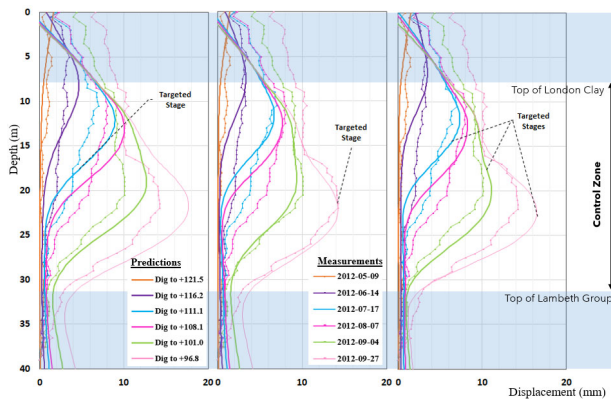


Figure 6 Genetic Algorithm back analyses (Case 4: HSS) predictions at Section A-A': wall deflections Vs observations.

#### 4.2.1 Single stage back analysis results

In single stage genetic back analysis with the Mohr-Coulomb soil model, the predicted wall deflections by the optimal parameters matched with the targeted observations within the control zone. Results from single stage back analysis (in Figure 5), either at the early stage of dig to +111.1mAOD or at the final stage of dig to +96.8mAOD, have illustrated the improved predictions. However, due to the limit of the Mohr-Coulomb soil model, the optimal parameters from the single stage back analysis can only represent the soil stiffness at the specific excavation stage. It was seen that the 'stiffer' optimal parameters obtained from early stage of dig to +111.1mAOD have forecasted the under-estimated deflections at later stages. Also, the 'softer' optimal parameters calibrated from later stage of dig to +96.8mAOD have back forecasted the over-estimated deflections at earlier stages.

It was hoped that the non-linear soil models could be the solution for non-linearly degraded ground stiffness with increasing shear strain. The HSS soil model representing the non-linear soil model was selected in single stage genetic back analysis. With an effort to increase the searching field (e.g., expand range of variable parameter values, generate more combinations), the obtained optimal HSS model parameters from the early excavation stage back analysis (dig to +111.1mAOD) did not show significant improvement in predictions, neither the improvement in overpredictions for later excavation stages.

In single stage back analysis at the final stage of dig to +96.8mAOD, the calibrated optimal HSS soil parameters showed the reasonable fitted predicted deflections with the targeted observations within the control zone. As well, the predicted deflections at the immediate previous excavation

stage (dig to +101.0mAOD) matched well with the corrected observational data, as illustrated in Figure 6. Though, this same set of optimal HSS soil parameters back forecasted the underestimated deflections for earlier excavation stages.

#### 4.2.2 Multiple stages back analysis results

Considering the powerful computation analysis capacity of cloud-based ML back analysis, it is possible to explore further by targeting the observational data from multiple stages. In this study, the multiple stages back analysis has been performed in genetic back analysis.

In multiple stages back analysis with the Mohr-Coulomb soil model, the corrected inclinometer data SAA8003 from three stages: dig to +111.1mAOD (early), dig to +101.0mAOD (middle), and dig to +96.8mAOD (final) were carefully selected to be targeted on. The calibrated optimal parameters were representative for the excavation, and the predicted deflections over individual excavation stages have shown good matching with the SAA8003 data from the corresponding stages, within the control zone, as shown in Figure 5.

In addition, the multiple stages back analysis with the HSS soil model was performed for comparison. The same observational data SAA8003 data from the selected early, middle, and final stages were targeted on the back analysis. The calibrated optimal HSS parameters showed improvement in the predicted wall deflections compared to the single stage back analysis. However, the substantial underpredictions between 15m and 25m below ground at early excavation stages were observed (see Figure 6). It is considered that the further calibration of the HSS parameters for LC-A2 sub-formation (corresponding to the identified levels) will be necessary.

## 5 DISCUSSION

### 5.1 Manual Vs. ML Back Analysis

A summary of computational analytical time of ML back analysis is presented in Table 2. It clearly illustrates that, from manual back analysis to ML back analysis, the improvement in computational time is fundamental. As well, the capacity of searching has been significantly expanded, such as the increased total numbers of runs conducted by ML back analysis. Consequently, the accuracy of prediction would have been strengthened, and the received optimal values from back analysis would be more representative for the studied problem.

Table 2 Machine learning Back-analysis (Plaxis 2D) Summary

Method	Soil Model	BA stage	Run/ Time
<i>Bayesian</i>	Mohr-C	single	~ 1,000 / ~ 24 hr
<i>Genetic algorithm</i>	Mohr-C	Single	~ 3,200 / < 4 hr
		Multiple <sup>1</sup>	~ 7,000 / ~ 24 hr
	HSS <sup>2</sup>	Single	~ 4,600 / < 8 hr
		Multiple <sup>1</sup>	~ 5,700 / ~ 24 hr

Note: 1. Example time is based on back analysis targeted on three dig stages, if less or more stages are selected to be targeted, the analytical time could vary slightly. 2. Only stiffness parameters of HSS model (e.g.,  $G_{0y}$ ,  $E_{ur}$ ,  $E_{50}$  and  $E_{ced}$ ) are treated as variables in the back analysis, if more model parameters are selected as variable parameters, the analytical time could increase.

### 5.2 Observational Monitoring Data

Back analysis convergency is highly depended on the targeted observations. The reliability and availability of monitoring data are two critical characters to determine whether the data is suitable to be applied in a back analysis, and how the back analysis convergency criteria could be updated. Especially in machine learning back analysis, the process is automatic, any

unsuitable targeted observation data would result in longer periods of analysis without the returned optimal values.

From multiple stages genetic back analysis examples, it indicates more 'reliable' observations to be targeted, the more representative optimal parameters can be calibrated from back analysis. In the TCR-WTH deep box excavation case, there were other monitoring data available, such as temporary prop force from as-built four levels of propping, ground heave from extensometers and groundwater pore pressure from piezometers. If these data could also be reviewed and applied in back analysis, it may help to further calibrated optimal parameters to represent the TCR-WTH excavation. However, this could be challenging to interpret the suitable monitoring datasets and establish the direct comparison in back analysis. For instance, the prop force monitoring data has been embedded noises from thermal effects and other construction activities, while the general numerical model can only simulate the static prop force induced from excavation.

### 5.3 Choice of FEM & Soil Models

Manual back analysis of the TCR-WTH deep box excavation case study demonstrated the significance of modelling. The choice of FE models, from Pseudo-FE, 2D to 3D, determined time of computational analysis. Additionally, soil constitutive models could add complexity in modelling, but provide more accurate predictions that require much longer analytical periods.

There shall be no such perfect FEM model. Depending on the purpose of analysis, the appropriate FEM and soil model shall be selected for the design analysis and back analysis. However, a good understanding of the selected FEM and the soil constitutive model is always useful to achieve an efficient back analysis and interpreting the outcomes.

### 5.4 Interpretation of Outcomes

From the above manual back analysis cases, it illustrated that engineering judgement was exercised in deciding convergency of back analysis, deriving the 'best estimated' parameters of back analysis, and the 'most probable' parameter for the modification design. Considering design is required to be conducted in accordance with design standards, the applied 'most probable' parameters are not necessarily same as the 'best estimated' ones.

In ML back analysis cases, there could be multiple combinations of parameters presenting good predictions matching the targeted observations. The 'optimal' parameters were the mathematical recommendation based on the defined convergency criteria. Engineer's judgement must be applied in interpreting the suitable 'most possible' design parameters from the calibrated 'optimal' parameters for design purpose.

The ideal circumstance is that the better forecasted the subsequent construction performance can be achieved with a set of 'magic parameters' calibrated from the back analysis of an early excavation stage. However, despite the efforts made in this back analysis study it seems unlikely to calibrate the 'magic parameters' by just one single excavation stage at early construction. It is a much-involved calibration process to identify the set of representative parameters for one project.

## 6 CONCLUSIONS

This paper presents the case study of back analysis of a deep box excavation in London Clay from the Crossrail project at Tottenham Court Road Station. Manual back analysis assessed three types of numerical modelling, from Pseudo-FEM to 2D and 3D FEM, coupled with different soil constitutive models. The back analysis results are highly dependent on the targeted

observational data applied in the back analysis. In general, the complex modelling, such as 3D-FEM, can provide more accurate predictions. However, the longer analytical time of the complex model should also be noted. ML methods significantly enhanced the capacity of back analysis, the more combinations from variables can be investigated within a shorter period, hence the reliability of outcomes from the back analysis will be strengthened. ML back analysis has enabled the possibility of conducting near real-time back analysis.

## 7 ACKNOWLEDGEMENTS

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