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Automatic back-analysis for embedded beam wall in stiff clay

Zoe Chan
Arup, Hong Kong, zoe.chan@arupcom

Troung Le, Jamie Standing, Ningxin Yang
Imperial College London, UK

David Foo, Paul Bailie
Arup, London, UK

ABSTRACT: The Observational Method is of growing importance for many deep excavations projects internationally. However, only limited real-time back-analyses are performed as they are time-consuming, iterative and of uncertain benefit, thus hindering the method's use to facilitate economical and safe design. With the advancement of numerical modelling, sophisticated back-analyses can now be applied with advanced soil models (e.g. Hardening Soil Model with Small Strain Stiffness (HSS)) and complex boundary conditions, for accurate predictions. Two major advancements are presented in this paper: (1) to perform detailed back-analyses together with comprehensive sensitivity and parametric studies for two key embedded beam walls, utilizing site information and monitoring data from a construction site in central London, and implementing the HSS model for London Clay in PLAXIS; (2) to illustrate in detail the process of automatic back-analysis with PLAXIS automation and implementation of a Bayesian Inference model. The significance of small-strain stiffness within the HSS model on wall deflection prediction is emphasized by the parametric and sensitivity study. The importance of specifying an appropriate in-situ stress state, (i.e. K_0), for an excavation scenario in stiff clay is reaffirmed in this study. The capability of Bayesian inference to deliver prompt results after off-line training and identifying best-fit estimates, enabling more reliable, accurate back-analysis results to be achieved, compared with manual back-analysis is demonstrated. Further development is encouraged based on the success with real site data.

KEYWORDS: Observational Method, automatic back-analysis, Bayesian inference model, embedded beam wall, deep excavation

1 INTRODUCTION

Embedded retaining walls are commonly used to provide crucial lateral support during ground excavation. In densely populated urban cities like London, accurate prediction and continuous monitoring of wall lateral deflection is essential to prevent damage to adjacent structures caused by excessive excavation. The Observational Method (OM) is becoming increasingly important for facilitating performance-based design, ensuring construction safety and controlling impact on the surroundings. To explore fully the potential of OM, prompt real-time back-analysis using high-quality field monitoring data enables the revision of design assumptions and soil parameters to facilitate proactive design modifications, and enhance design efficiency (Hardy et al., 2018). However, three major challenges arise when considering the uncertainties associated with field monitoring data and the complexity of back-analysis: 1. simplified numerical models reduce the accuracy of back-analysis results; 2. tight construction schedules hinder the implementation of iterative, time-consuming back-analysis for design amendments (Eilat et al., 2024); 3. uncertainty with the back-analysed results hinders their adoption under risk-averse situations. Engineering judgment and professional experience in numerical modelling techniques are also crucial for conducting successful back-analyses (Foo et al., 2023).

This research paper targets the challenges in performing successful back-analysis from the following three perspectives.

- The advanced soil constitutive model, Hardening Soil with Small Strain Stiffness (HSS), is explored to better represent soil behaviour for more rigorous predictions.
- An automation program using Python API of PLAXIS (Bentley, 2023), a commercial numerical modelling software widely-used in industry, is developed to demonstrate the benefit of reducing repetitive back-analysis iterations.
- Automatic back-analysis can be achieved by the development of a Bayesian inference model.

This transformative approach enables prompt back-analysis. Probabilistic analysis also enables quantification of uncertainty to facilitate engineering judgment and decision-making (Yang et al., 2024).

This paper streamlines the process of development and application of the automatic back-analysis by: 1. developing a representative numerical model with advanced soil constitutive model e.g. HSS; 2. generating sufficient learning samples automatically; 3. training a multi-stage surrogate model for continuous integration with field monitoring data. With the trained surrogate model, autonomous inference can be performed using monitoring data. This can immediately benefit the forward predictions of subsequent construction and potentially reduce construction costs.

Before training the surrogate model for automation, understanding and identifying critical soil parameters in the constitutive model is essential to capture accurate soil behaviour. This paper provides insight into the benefit of adopting an advanced soil model, namely HSS, for this real case study from a back-analysis stance, given that most published studies focus on the design approach which leads to more conservative input parameters (Chandegra & Kokkinou, 2016; Chambers et al., 2016; Sandström, 2016; Mendis, 2023). This paper also demonstrates the merit of adopting the Bayesian inference framework for a real construction project.

2 STUDY CASE BACKGROUND

2.1 *Background*

In the research reported here, a completed deep basement excavation project located within London was analysed (see Foo et al. (2023) for a detailed description of the site and construction sequence). Walls 2 and 3, shown in Figure 1, were analysed in this research. An extensive review of the monitoring data was undertaken before commencing the back-analysis. Foo et al. (2023) presented detailed and insightful back-analysis results using FREW, a commercial numerical software for analysing the behaviour of retaining structures through limit equilibrium and pseudo-finite element calculation methods. The high-quality monitoring data from inclinometers and total stations provided a good basis for subsequent back-analysis.

Three major construction stages were considered in the model:
Stage 1 - excavation to +1.5 mOD from existing ground level;
Stage 2 - berm in place and installation of raking prop;
Stage 3 - excavation to -5.0 mOD.

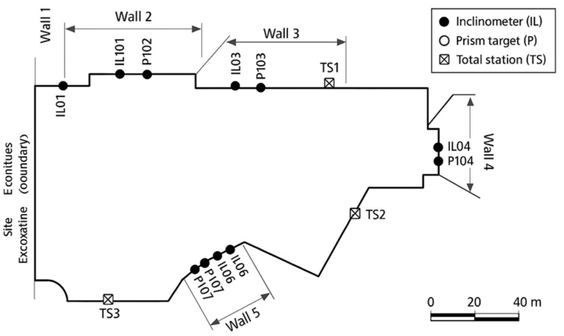


Figure 1. Site plan showing locations of inclinometers, automated total stations and 3D prism targets (Foo et al., 2023)

In this study, two sections of secant pile wall, relating to Walls 2 and 3, as shown in Figures 2 and 3, are analysed. Wall 3 is expected to align more closely to a plane-strain condition owing to its length and the distance between the corners at its ends. Both walls are singly propped with a raking strut and have a soil berm present. Typical London stratigraphy was identified and modelled as shown in Figures 2 and 3.

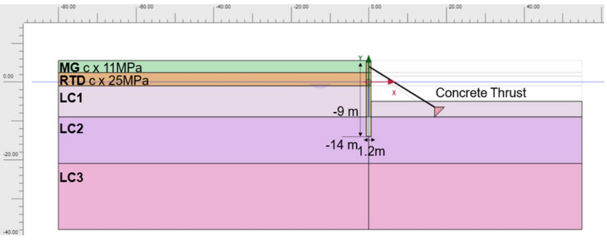


Figure 2. Final Stage cross-section for Wall 2 in PLAXIS

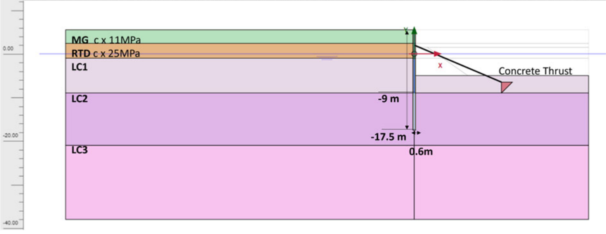


Figure 3. Final Stage cross-section for Wall 3 in PLAXIS

3 METHODOLOGY

A surrogate model was constructed for each of the stages with available data. Analyses were then performed according to the following schema.

1. Establish a representative numerical model using PLAXIS and identify key soil parameters which influence model behaviour through sensitivity analysis using one-factor-at-a-time (OAT);
2. Train an off-line surrogate model using results from the simulator wherein samples are specified from the permissible design space using Latin hypercube sampling and are evaluated and exported via the in-built PLAXIS API.

These procedures were applied to both Walls 2 and 3 and are summarized in flow chart format in Figure 4.

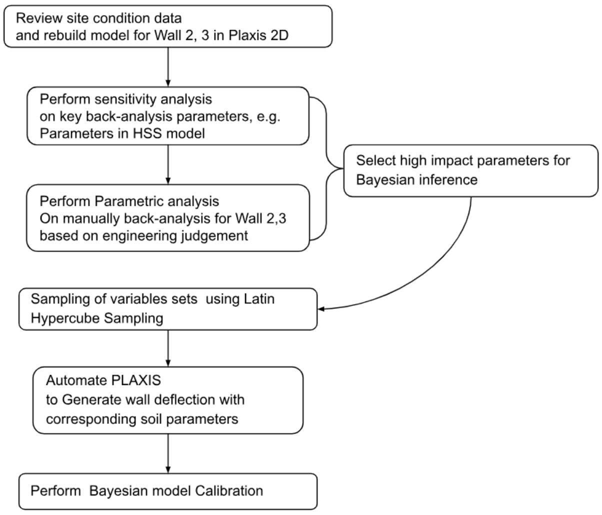


Figure 4. Methodology flow chart

3.1 *Numerical modelling*

The soil constitutive model, HSS, available in PLAXIS is adopted for the London Clay. HSS is advantageous in capturing small strain soil behaviour which is suitable for retaining wall modelling. Foo et al. (2023) previously highlighted the importance of varying soil stiffness with strain level for this project. HSS also provides more realistic unloading predictions by simulating higher unloading stiffness than conventional the Mohr Coulomb model (Eilat et al., 2024; Gouw, 2014). Soil stiffness degradation is primarily controlled by parameters shear stiffness, G_0, and shear strain level at 70% maximum shear stiffness, $\gamma_{0.7}$ (Bentley, 2023).

Baseline PLAXIS models were built following the as-built conditions as described by Foo et al. (2023). The final model set-ups are shown in Figures 2 and 3. In particular, the concrete thrust blocks and secantwalls were explicitly modelled as solid elements rather than beam elements to capture more accurately the wall thickness effect regarding the displacements of the lower part of the walls. Consolidation phases were also modelled. The London Clay was divided into three layers for modelling the depth-dependent K_0 profile with a decreasing trend from the top K_0 value to the bottom layer where $K_0 = 1$.

3.2 *Sensitivity and parametric analysis*

Soil parameters are inter-correlated physically in predicting soil behaviour. Correlations between model parameters are readily available in the literature. To achieve a computationally efficient strategy when constructing the surrogate model, the approach aimed to minimise the number of back-analysed parameters while retaining the model's ability to simulate realistic wall behaviour.

The OAT method is applied to investigate the most impactful variables contributing to the wall deflection, particularly regarding the top of the wall, wall toe and maximum movement. Key parameters including inputs for the HSS model for London Clay, stiffness parameters of the Made Ground and River Terrace Deposits, pile, and props were investigated.

Finally, a parametric study was performed to assess engineering judgement through manual back-analysis, using given field monitoring data from the study case. The parameter set that produced the best fit was taken as the 'best-fit' solution, against which the subsequent Bayesian inference was compared to.

3.3 *Bayesian inference model*

Once the back-analysis model parameters were selected based on the sensitivity analysis. Latin Hypercube sampling, a quasi-random search approach, was used to generate combinations of variables within given ranges (experimental design). Soil parameters were treated as the unknown random variables, with a uniform prior distribution $\pi(x)$ to ensure the high-dimensional space was fully explored. Wall deflections from the combination of variables are evaluated using PLAXIS and stored such that they serve as the training data for the surrogate model.

A trained surrogate model with a custom likelihood function was used to carry out inverse analysis, enabling a prompt and reliable back-analysis workflow. By removing the physics, the empirical surrogate model can provide almost instant estimates of the model output for a given input. This study applies a combination of polynomial chaos expansion (PCE) and principal component analysis (PCA) to construct the surrogate model. Observational evidence is incorporated through a likelihood function, representing the probability of observing data y given x. Finite Element (FE) analyses, $\mathrm{P}(y|x)$, are used to obtain observations i.e. wall deflection, based on sampled combinations of soil parameters. Once actual measurements, $\mathrm{P}(y)$, are obtained, Bayes' Theorem was applied to update the prior into a posterior distribution $\pi(x|Y)$, reflecting revised beliefs about x based on the given observation. The Maximum A Posteriori (MAP) estimate identifies the most probable parameter set. Due to computational demands, the posterior is approximated using Markov Chain Monte Carlo methods. This framework enables probabilistic interpretation of soil behaviour based on observed structural responses. To evaluate the performance of the inverse analysis, the difference between the MAP and 'best-fit' solution as the Mean Absolute Percent Error was calculated to quantify the quality of prediction.

To address uncertainties in field monitoring measurements, a concept called 'Level of Interest' was introduced into the likelihood function within Bayes equation. This approach emphasizes the importance of matching predictions to measurements at specific locations. For instance, top-level measurements—calibrated using total station data—are known to be highly accurate, while critical movements are of high design importance. In contrast, toe movements are less critical. By assigning different levels of interest, the surrogate model is trained to prioritize accurate matching at the upper and critical zones, reducing the influence of discrepancies in less relevant areas. This strategy helps prevent the degradation of the model calibration due to missing or inaccurate physics by focusing on regions of interest, ensuring that the model focuses on the most impactful aspects of wall behaviour, such as maximum wall deflection.

4 RESULT AND DISCUSSION

4.1 *Result and discussion of sensitivity analysis*

This section presents the sensitivity of a select number of parameters required by the HSS constitutive model for calibration. The input variables considered are shown in Table 1.

Table 1. Summary of key parameters for back-analysis

Variables	Wall2	Wall3	Range	Description
K_0	1.05	2.22	1 - 2.28	K_0 value for the first-layer London Clay
G_0 (MPa)	100	80	40 - 180	Max. shear stiffness in HSS input
G_0/E_{50}	2	2	1 - 4	E_{50} can be back-calculated from this ratio for HSS input
PileRF	0.75	0.85	0.7 - 1	Stiffness reduction for pile wall
MG_N	1	0.8	0.5 - 2	Coefficient of the empirical relationship between SPT_N with soil stiffness of MG and RTD

A single, realistic, constant $\gamma_{0.7}$ value was estimated through empirical correlations (Bentley, 2023, Obrzud & Truty, 2018) and laboratory test results (Le, Standing & Potts, 2024) and applied to all soil layers. G_0 was found to have a high impact on the prediction deflection curve. Young's Modulus (E_0, E_{50}, E_{oed}) was set to vary with E_0/E_{50}, which depends on stress history. In this study, E_0/E_{50} was assumed to vary from 3.8 to 16 following Obrzud & Truty (2018). G_0/E_{50} was also allowed to vary in this back-analysis to investigate the influence of stress history.

In-situ stress state, K_0, is another sensitive variable that was found to influence wall deflection. Despite the reduction in in-situ K_0 due to the wall installation effect, the overall soil response at the site is expected to dominate the system's behaviour. Notably, maximum K_0 is capped by the stress path inside the yield surface during initialisation. While the correlation proposed by Vardanega & Bolton (2013) for K_0 and OCR is set as the default in PLAXIS, the relationship proposed by Mayne & Kulhawy (1982), was instead adopted due to its better correlation for London Clay. Interestingly, it was found that for a given K_0, increasing OCR leads to lower wall displacements—the result of which is attributed to a larger yield surface. This effect tends to converge for sufficiently large OCR values, which suggests that the empirical relationship is suitable for accurately quantifying the interaction between OCR and K_0 for this problem.

Preliminary analysis of strength parameters including angle of shearing resistance, cohesion, dilatancy angle, and permeability parameters were found to have limited influence on predicted deflection, thus these were not considered in the back-analysis. Regarding pile and props stiffness, given the as-built conditions described by Foo et al. (2023), only the reduction factor (PileRF) applied in design was reviewed. A consistent trend observed was that higher pile stiffness, (i.e. higher stiffness reduction factor) yields less deflection. To predict the deflection at the top of the wall, soil stiffnesses of the Made Ground and River Terrace Deposits were calibrated against SPT-N values.

In summary, five variables: K_0, G_0, G_0/E_{50}, PileRF, MG_N are considered for inverse analysis with corresponding possible ranges of values. The ranges are bounded by both physical correlations including laboratory test results and soil constitutive model assumptions i.e. yield stress surface cap of HSS (Bentley, 2023).

4.2 *Result and discussion of parametric analysis*

'Best-fit' predictions were determined based on both the deformation shape and magnitude, with the corresponding set of parameters justified through engineering judgment (Table 2). In evaluating the 'best-fit', priority was given to accurately predicting critical movements, as these are of primary concern in engineering design. Upon examining the back-analysed parameters, the input values of G_0 and E_{50} for the HSS model applied to London Clay for both Walls 2 and 3 were expected to be nearly equal. This consistency led to a wider range of variability in the selection of K_0. To match the observed top movements better, the stiffness values for the MG and RTD layers were adjusted accordingly but remained similar for both walls. However, given the uncertainties associated with in-situ pile casting, the pile stiffness for the two walls was allowed to differ. These adjustments enabled the model predictions to align well with the measured deformations, as shown in Figure 5.

Table 2. Key best-fit parameters

	K_0	G_0 (MPa)	G_0/E_{50}	PileRF	MG_N
Wall2	1.05	100	2	0.75	1
Wall3	2.22	80	2	0.85	0.8

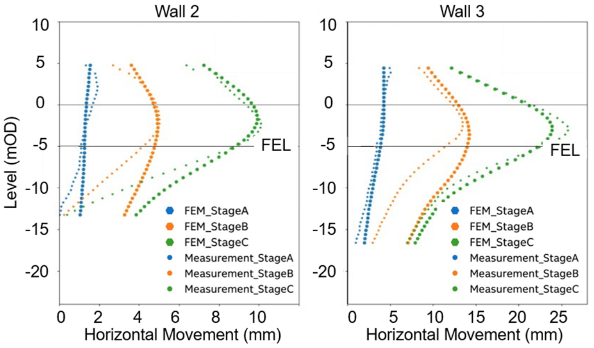


Figure 5. Manual best-fit parameter illustrations and comparison with monitoring measurements (large dot: best-fitted prediction, small dot: measurement results)

Based on site investigation data, the stiffness modulus E_{50} for London Clay was found to be approximately 750×c_u, equivalent to 51 MPa, which closely aligns with the results from the current back-analysis (E_{50}=50 MPa). In contrast, Foo et al. (2023) adopted a significantly higher stiffness value of E=274 MPa for Wall 2 to simulate small-strain stiffness behaviour. However, with the use of advanced soil models and detailed finite element analysis, more realistic and reliable predictions can be anticipated.

Discrepancies are mainly observed at the wall toe, while overall, the prediction for Wall 3 aligns more closely with the monitoring data. These discrepancies may arise from both physical and model-related 'errors'. Physically, site conditions can differ from modelling assumptions. For Wall 2, the corner effect (Emberson, 2022) might justify slightly higher stiffness parameters compared to Wall 3, where lateral movement may have been restrained. Wall 2's limited movement may also be influenced by lateral restraint from Wall 3. Both walls may be affected by neglected 3D effects, such as lateral reactions from concrete thrust blocks, potentially causing overpredicted movements or underestimated soil properties (Emberson, 2022). Additional factors, such as the construction timeline and wall installation effects, were not captured.

Furthermore, significant soil heaving was observed in the excavation mesh. London Clay was modelled as undrained, implying constant volume during loading and unloading. Displacement from the retained side may have caused significant wall toe movement, which appears to correlate with excavation volume—showing notable movement in Stage 2 but minimal change from Stage 2 to 3—differing from field measurements. Therefore, monitoring soil heave during excavation is recommended, as it may also indicate overestimation of wall movement.

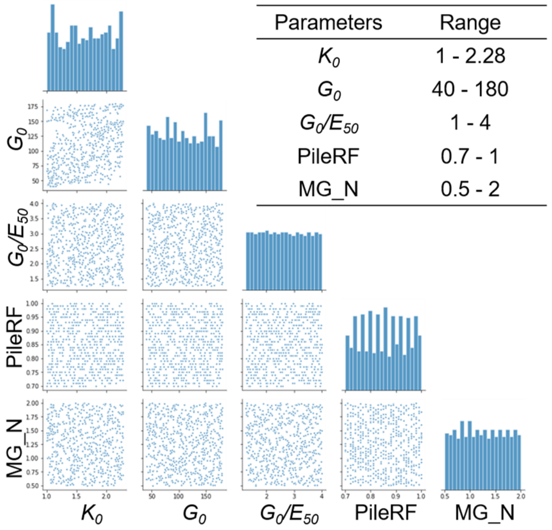
Model discrepancies stem from PLAXIS assumptions, including the stiffness cut-off in the HSS model and isotropic behaviour (Bentley, 2023), which fail to represent London Clay's anisotropy. Additionally, vertical wall movement is not expected and may be caused by numerical issues related to continuous meshing.

4.3 *Bayesian inference result and discussion*

A total of five (5) random variables, as detailed in Section 4.1, were sampled from the experimental design space. Monte Carlo simulations were performed using PLAXIS to model wall deflections. A surrogate model was trained on the resulting data set. Given the 3 stages of monitoring data 3 separate stages of inference were performed. In this section, the inverse analysis for this study will be illustrated in 4 parts: 1. Latin Hypercube Sampling results; 2. Sobol Sensitivity analysis results; 3. Posterior Predictive results of MAP prediction; 4. Parametric calibration.

4.3.1 *Latin Hypercube Sampling*

649 samples of variable combination are obtained using Latin Hypercube Sampling as shown in Figure 6. Each variable was sampled from a uniform prior distribution. Notably, a correlation coefficient of 0.5 was specified between K_0 and G_0 during sampling, reflecting the expectation that higher in-situ horizontal stress (K_0) would correspond to greater shear stiffness (G_0). PileRF was also binned to 0.01 ranges as values are only permissible to two decimal places.



Parameters	Range
K_0	1 - 2.28
G_0	40 - 180
G_0/E_{50}	1 - 4
PileRF	0.7 - 1
MG_N	0.5 - 2

Figure 6. Sampling distribution of key parameters

4.3.2 *Sobol sensitivity analysis*

To make use of the 649 PLAXIS evaluations, a PCE-PCA surrogate model was trained using the numerical output, see Yang et al., (2026) for more detail. Given the use of the PCE model, Sobol indices were trivial to calculate.

Figure 7 illustrates the normalized Sobol indices for each key stage. The level of influence of each parameter contributing to wall deflection versus depth is shown. In general, the Sobol sensitivity results were found to be consistent with the manual analysis performed in above section. Both Wall 2 and 3 were shown to present similar Sobol sensitivity trends throughout construction. Insights offered by calculating the Sobol indices are as follows. The stiffness of Made Ground and River Terrace Deposits layers (MG_N) is important at wall top (around -1 mOD) at cantilever stage (Stage 1). After the installation of props, the structural support begins to dominate over the influence of upper-layer soil stiffness. As excavation progresses, particularly within the London Clay layer, the critical movement intensifies, and the deformation pattern shifts downward. This indicates that the zone of maximum displacement transitions from the upper wall region to deeper levels, reflecting the evolving stress redistribution and changes in the boundary condition. Therefore, increasing influence of London Clay shear stiffness G_0 dominates at later stages and deeper depth. K_0 is of overall high importance especially during Stage 1 and top layer of London Clay. K_0 also exhibits high influence as expected while a decreasing trend of impact from stages and depth can be observed. This reflects the stress redistribution during unloading though stages. For stage 1, it reflects the impact from the variation of K_0 for the three London Clay layers. The pile stiffness reduction factor (PileRF) and the ratio of shear modulus to Young's modulus (G_0/E_{50}) were found to be relatively less significant in influencing the overall deformation shape. This observation is consistent with the manual sensitivity analysis, which indicated that these parameters serve as fine-tuning factors for matching the magnitude of deformation, rather than governing the overall deformation pattern.

Sobol sensitivity analysis highlights the significant influence of K_0 and G_0 on wall deflection predictions. Of these, K_0 stands out as particularly impactful—despite often being preset without thorough site-specific investigation. This finding underscores the importance of carefully evaluating K_0 during model calibration, as its variability can substantially affect deformation outcomes.

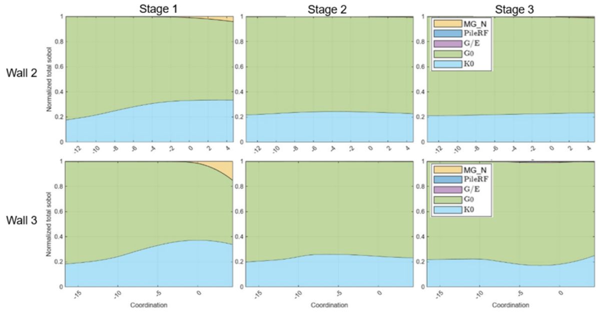


Figure 7. Sobol plot for Wall 2 and Wall 3: normalized total sobol verus depth

4.3.3 *Posterior predictive result*

Performing inverse analyses using Bayesian inference produces parameter estimates in the form of posterior distributions after observation i.e. incorporating field measurements. These posterior distributions can be continuously updated and refined as new data become available or updated in one stage using all the available up-to-date data, allowing the model to evolve with each stage of observation. This research has adopted the use of single stage inference. For each stage, forecasting with current MAP estimates was performed, as such uncertainty of model can be quantified progressively with updated observations. For instance, given stage 1 measurements, first posterior distinction can be obtained together with later stage predictions based on current estimates. Importantly, the probabilistic framework quantified the uncertainties of estimates, facilitating engineers' further decision-making.

In general, the surrogate model can give a good match with the PLAXIS modelling result for the same inputs. Regarding the back-analysis results of Wall 2 and 3, the Wall 3 model shows relatively better agreement between predicted and measured displacements, which aligns with observation from the parametric study. Thanks to the 'Level of Interest' approach, as illustrated in Figure 8, the model progressively achieves good matches in both critical displacement and top-level displacement, reflecting the prioritization of key zones during surrogate model training. For instance, in Stage 2 prediction, the critical movement in this stage can be successfully captured regardless of the severe mismatch of the wall toe. Similarly, for Wall 2, critical movement can be successfully captured.

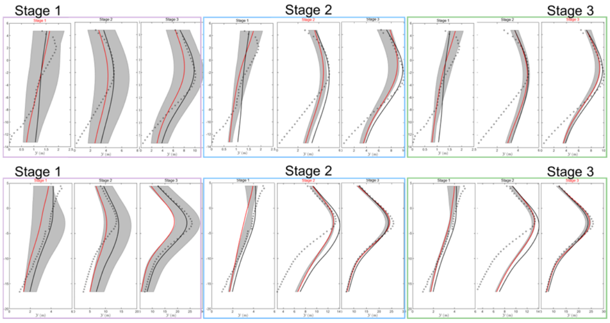


Figure 8. Surrogate model wall deflection prediction: Wall 2 (upper), Wall 3 (lower), dashed line: ground truth measure, red line: surrogate model prediction, black line: manual back-analysis prediction, grey band: uncertainty level

From the corner plots (Figure 9a), the posterior predictive distributions for G_0 and K_0 became increasingly narrow, indicating increased model confidence after incorporating additional observations. These ranges align with expectations from manual analysis: K_0 between 1.5–2 and G_0 around 50–80 MPa. In contrast, the wider distributions for PileRF and MG_N reflect greater uncertainty, probably due to their lower sensitivity in influencing wall deflection behaviour.

4.4 *Calibration of parameters*

Similar to the corner plot, temporal three-sigma plots show the convergence of random variables over successive stages. As shown in Figure 9b (only for Wall 3), a narrowing of the three-sigma range indicates a reduction in uncertainty and improved confidence in the predictions. Generally, MAP result values are within reasonable ranges, regardless of matching between the two walls as in the manual interpretation discussed in Section 3.2. For Wall 3, both K_0 and G_0 show a clear trend of convergence in their posterior predictions, although the MAP estimates remain uncertain. Other parameters exhibit minimal convergence, indicating limited model confidence in their estimates. Similarly, for Wall 2 there are comparable results, but with a less desirable convergence trend overall. This suggests that the model faces greater difficulty in calibrating Wall 2.

5 FUTURE WORK

As this research is aimed at practical applications, four key recommendations are made to facilitate further high-quality probabilistic inverse analysis and support applications of the system to various embedded walls.

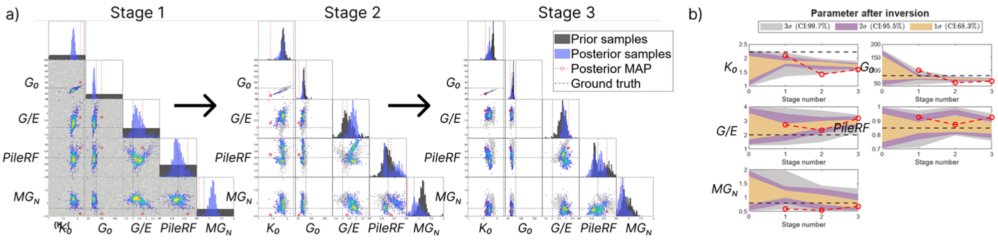


Figure 9. a) Wall 3 corner plot showing distributions for each variable and their interaction; b) Sigma plots used to visualize the confidence in parameter predictions across different observation stages for Wall 3: red dot—MAP results, black line—Manual back- analysis results

1. Baseline numerical analysis can be further refined by studying the corner effect; developing techniques for quantifying the impact of heave induced in the model; controlling wall vertical movement; and related factors.
2. Enhanced inverse analysis requires engineering judgment, and the interaction between walls should be considered. Importance should be placed on the portion of the wall exhibiting greater movement, as indicated by the 'Level of Interest'. Wall installation effects should also be reflected in the determination of K_0.
3. Despite the tailored experimental design, careful thought should be given to defining the prior for the inverse analysis itself. In this study, a simple uniform distribution was adopted for both the experimental design and the prior; this can be refined to reflect on-site investigation and laboratory results.
4. Class C prediction for other walls using the Wall 2 and Wall 3 trained surrogate model can be further explored, especially given the strong correlation observed between wall deflection and piling geometry, similar to the case described by Foo et al. (2023).

6 CONCLUSIONS

This research begins with a detailed review of the studied site, including ground conditions and monitoring measurements. PLAXIS models were then built with careful consideration, and a comprehensive sensitivity study was conducted on key parameters for back-analysing wall deflection—particularly those in the HSS model used for London Clay. A parametric study and Bayesian inference were performed to simulate both manual and automatic back-analysis processes. The major conclusions and recommendations are summarised as follows.

6.1 *Sensitivity and parametric study.*

Proper selection of K_0 is crucial, yet it is often overlooked in design by simply assuming that K_0=1. The observed increase in wall deflection with higher K_0 values highlights the risk of underestimating this parameter during design. In the HSS model, an accurate approximation of the soil degradation curve—particularly parameters such as G_0, $\gamma_{0.7}$, and G_{ur}—has the greatest influence on wall deflection prediction. Determining $\gamma_{0.7}$ is complex; advanced laboratory testing is recommended, or alternatively, verification through multiple empirical relationships from the literature.

6.2 *Automating FE analysis*

Automation with using any finite element program is now very convenient, thereby reducing a significant amount of effort in performing repetitive analysis. Utilizing automation for back-analysis is highly encouraged, even if the Bayesian model might not be available yet.

6.3 *Automatic back-analysis with Bayesian inference*

At the design stage, develop a numerical model capable of capturing the full number of construction stages. Gather Finite Element samples with key parameters and corresponding responses through automation at the design stage. During construction, the initial stage of field monitoring data can be obtained. Perform the inverse analysis with these initial stage measurements to obtain inferred parameters and predictions for future stages. If necessary, carry out additional experimental design to refine further the surrogate model. Inferred parameters and predictions can be used to adjust the design or construction sequence. Models can be reserved in wall prediction for similar design scenarios with continuous updates.

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