Proc. of the 8th International Symposium on Geotechnical Safety and Risk (ISGSR)
Edited by Jinsong Huang, D.V. Griffiths, Shui-Hua Jiang, Anna Giacomini and Richard Kelly

doi: 10.3850/978-981-18-5182-7_07-003-cd

ISGSR 2022

The Effect of a Simplified Geotechnical Model for Predicting Surface Settlement Incorporating Bayesian Back Analysis

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Abstract: The intent of this study was to question if a simple geotechnical model could be used to undertake consolidation analysis to an acceptable level of reliability incorporating Bayesian back analysis. Simplification of the ground model is common in geotechnical engineering practice however the use of measured results to verify the model parameters is seldom. Use of a simplified geotechnical model can reduce the amount of computational time required, particularly for Bayesian updating. Oversimplification on the other hand will not capture the appropriate conditions for reliable settlement prediction. Bayesian back analysis can provide a way to update the prior belief of the model and adopted soil parameters using monitoring data. Therefore, a focus on adopting Bayesian updating through back analysis by treating the key parameters of compression ratio, recompression ratio, creep strain and coefficient of consolidation as random variables was considered. A three-layered simplified model was adopted and showed the surface settlement was well predicted using 117 days of observed data. The settlement data was used to update the parameters through Bayesian back analysis to fit the entire time-settlement history. The results of the predictions are discussed in this paper.

Keywords: back analysis; Bayesian updating; consolidation; embankment; settlement prediction

1 Introduction

Settlement prediction is crucial for soft soil projects. Soft soils are typically described as a fine-grained material exhibiting low permeability and high potential for compressibility due to relatively large void ratios. It is this potential for relatively high compressibility under an increased effective stress or deformation under constant effective stress that typify the problems associated with infrastructure built upon them. The key issue in addressing these problems is to adequately characterise the ground conditions and communicate the associated risk implications with a prescribed level of confidence to both technical and non-technical decision makers.

One of the more important considerations when undertaking prediction in geotechnical engineering is understanding the ground conditions and implementing a representative ground model. A representative simplified ground model can provide reasonable predictions even without the use of advanced finite element, numerical methods, or computational software. Simplification of the geotechnical model is common practice in geotechnical engineering however the effect on the field measured results is usually unverified. Monitored data can be used to verify or update the design assumptions including the geotechnical model and parameters selected. Probabilistic methods such as Bayesian updating provide a powerful tool that allows the user to update their initial model or prior belief based on the measured observations (Fenton and Griffiths, 2008). It has been shown that relatively small amount of updated data can produce reliable predictions for a nine layered model for surface settlement prediction (Zheng *et al.*, 2018).

Many studies undertaken have looked at the effects of settlement on soft soils (Kelly *et al.*, 2018) however the effect of using a simplified geotechnical model incorporating the ratio of the compression index to the recompression and creep strain rate has not been as readily discussed. A simplified geotechnical model was used where the soft clay was modelled as a single homogenous layer as discussed in Gong and Chok (2018). The parameters were derived from applying the harmonic mean to the test data, a similar method was adopted for this study. The intent was to demonstrate a useful avenue for the practising engineer to incorporate Bayesian back analysis into their analysis and develop a strategy that incorporates information systematically when predicting long term settlement.

2 Bayesian back analysis

2.1 Multi-step updating of model parameters

For surface settlement prediction the material properties, geometry and loading conditions are considered for Bayesian back analysis. Soil parameters are relatively uncertain when compared to the geometry and loading conditions therefore the focus was on these soil parameters and their modelling as random variables. For this study a Markov chain Monte Carlo (MCMC) algorithm developed by (Vrugt 2016) known as a **D**iffe**R**ential **E**volution **A**daptive **M**etropolis program (DREAM) which incorporates a likelihood function to estimate and update the posterior distribution function (PDF) of the model parameters was used. The posterior probability density function (PDF) was sampled by the algorithm DREAM. The posterior distribution represents the updated knowledge obtained from our observations and incorporates the prior information and the updated information obtained from field monitored behaviour (Kelly and Huang, 2015). The likelihood is assumed to follow a zero-mean Gaussian distribution and can be modelled explicitly through PDF. A more detailed description of the algorithm implemented is discussed in Zheng *et al.* (2018) and Zeng *et al.* (2019).

3 Embankment prediction

3.1 Ground Model and Loading

The test embankment located to the east of the Ballina township was constructed on typical 'Ballina clay' (Pineda *et al.*, 2016) which is an estuarine soft clay with high to extremely high plasticity, low permeability and extremely compressible from the Richmond River valley. The typical delineation of the subsurface soil profile is generally as topsoil or crust approximately 0.2 m thick underlain by Alluvial sandy clayey silt approximately 1.0 to 1.3 m thick. Estuarine silty clay with high plasticity approximately 8.8 to 9 m thick, clayey Sand transition zone with increasing sand content with depth approximately 4 m in thickness followed by fine grained sands approximately 5 m thick underlain by a stiff to hard Pleistocene clay layer to a depth of 38m which represents the limit of the field investigation. The test embankment constructed was over an area approximately 16 m wide and 80 m in length along the crest with a height of about 3 m. Ground investigation data was provided through the Centre of Excellence for Geotechnical Science and Engineering (CGSE) with interpreted laboratory results performed and outlined in (Pineda *et al.*, 2016).

The ground model adopted for this study consists of three layers, that being an alluvial crust underlain by a soft estuarine silty clay transitioning into a soft to very stiff sandy silty clay. The medium dense sand and stiff Pleistocene silty clay were ignored as consolidation of these layers is expected to be negligible relative to the soft estuarine clay and low thickness of the fill embankment. The drainage is assumed to be free draining at the top and impermeable at the base. The water table adopted was 1.5 m below ground with no assumed rise in ground water considered that may reduce the applied effective stress. The model is ideally represented in Figure 1. The construction time, loading stage time and vertical pressure from the low embankment are summarised in Table 1.

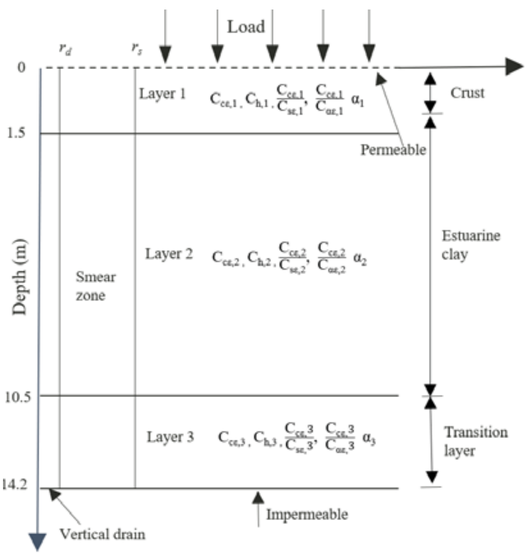


Figure 1. Simplified soil profile with random variables adopted shown in each layer

Table 1. Simplified embankment construction, stage time and vertical pressures

Stage	Description	Time (days)	Total pressure (kPa)
1	Fill platform to 0.6m	1	0
2	Consolidate	12	12.6
3	Install drainage layer	20	12.6
4	Consolidate	50	21.6
5	Fill to 3.0m	60	21.6
6	Consolidate	974	61.5

3.2 Geotechnical parameters

The deformation parameters adopted for the one-dimensional model are the compression ratio ($C_{c\varepsilon}$), the recompression ratio ($C_{s\varepsilon}$), the creep strain rate ($C_{\alpha\varepsilon}$). The rate of consolidation parameter adopted is the coefficient of consolidation in the horizontal direction (c_h). The vertical coefficient of consolidation (c_v) was taken as equal to c_h for the Ballina site. The values of equivalent radius (r_s), smear zone ratio (r_m/r_s) and permeability ratio (k_s/k_m) are described in Table 3. The initial compression ratio have been derived from laboratory testing, review of the literature and engineering judgement. For the simplified ground model adopted these geotechnical parameter values were assigned for the prior prediction based on the ground model. For geotechnical application the harmonic average is of particular interest due to it having a strong low-value dominated characteristic (Fenton and Griffiths, 2008). It was shown that harmonic means for the Ballina site could mitigate the effects of abnormal test data and be applied for the statistical analysis to take into account the natural spatial variability of the soil parameters (Gong and Chok, 2018). For this study the harmonic means calculated in (Zheng *et al.*, 2018) and (Gong and Chok, 2018) were used to simplify and refine the parameter values from a nine layered model to three layers.

The recompression ratio and creep strain rate were derived using a ratio from the compression ratio. The prior values for the recompression ratio were initially taken as $C_{c\varepsilon}/5$ for and $C_{c\varepsilon}/15$ for the creep strain rate. The factor of compression ratio over recompression ratio ($C_{c\varepsilon}/C_{s\varepsilon}$) and compression ratio over the creep strain rate ($C_{c\varepsilon}/C_{\alpha\varepsilon}$) were deemed to be uniformly distributed with a range of 5 to 10 and 15 to 25 respectively. $C_{c\varepsilon}$ and C_h were deemed to be statistically lognormally distributed to ensure the random variable remained positive (Huang and Griffiths, 2010). The yield stress (σ'_p) across the whole profile was multiplied by a universal alpha (α) factor to account for the rate-effect and was deemed to be uniformly distributed with a range of 0.6 to 1.3. Therefore, each soil layer had five parameters that were treated as random variables $C_{c\varepsilon}$, c_h, $C_{c\varepsilon}/C_{s\varepsilon}$, $C_{c\varepsilon}/C_{\alpha\varepsilon}$ and α. Any correlations among random variables for simplicity are not considered in this study. Further research could consider a soil model incorporating the correlation between $C_{c\varepsilon}$, $C_{s\varepsilon}$ and $C_{\alpha\varepsilon}$. The stochastic material parameters are shown in Table 2 and the parameters associated with a one-dimensional model are summarised in Table 3.

Table 2. Stochastic material parameters adopted

Parameter	Properties	Distribution	COV $\left(\frac{\sigma}{\mu}\right)$
Compression ratio ($C_{c\varepsilon}$)	$C_c(1+e_o)$	Lognormal	0.3
Coefficient of horizontal consolidation (c_h)	m^2/yr	Lognormal	3.0
Ratio of Recompression to compression ratio ($C_{c\varepsilon}/C_{s\varepsilon}$)	$C_s(1+e_o)$	Uniform	$0.19\left(\frac{1.43}{7.5}\right)$
Ratio of Creep strain rate to compression ratio ($C_{c\varepsilon}/C_{\alpha\varepsilon}$)	$C_\alpha(1+e_o)$	Uniform	$0.14\left(\frac{2.88}{20}\right)$
alpha (α) for preconsolidation	-	Uniform	$0.21\left(\frac{0.2}{0.95}\right)$

Table 3. Prior parameters of soils and vertical drains adopted a three-layered model.

Parameter	Properties	Crust	Soft estuarine clay	Stiff clay
		1	2	3
Layer thickness	H (m)	1.5	9.0	4
Over-consolidation ratio	OCR	4.8	1.7	2.5
Unit weight of soil	γ (kN/m^3)	18.75	15.2	19.0
Compression Index	C_c	0.36	1.56	0.61
Recompression Index	C_s	0.07	0.31	0.12
Compression ratio ($C_{c\varepsilon}$)	$C_c(1+e_o)$	0.2	0.45	0.40
Ratio of Recompression to compression ($C_{c\varepsilon}/5$)	$C_s(1+e_o)$	0.04	0.09	0.08
Ratio of Creep strain ratio to compression ($C_{c\varepsilon}/15$)	$C_\alpha(1+e_o)$	0.0056	0.017	0.016
Coefficient of horizontal consolidation (C_h)	m^2/yr	50	3	100
Ratio of horizontal to vertical consolidation	c_h/c_v	1	1	1
Pre-consolidation pressure	kPa	67.5	89	237.5
Coefficient of Variation	$[C_{c\varepsilon}, C_{s\varepsilon}]$	0.3	0.3	0.3
Coefficient of variation	$[C_{\alpha\varepsilon}]$	3.0	3.0	3.0
Drain spacing	S_p (m)	1.2	1.2	
Drain pattern	-	Square	Square	Square
Drain radius	r_s (m)	0.025	0.025	0.025
Ratio of smear to drain radius	r_m / r_s	5	5	5
Permeability ratio	k_s / k_m	5	5	5

3.3 Numerical model

Numerical consolidation analyses were carried out using a finite difference numerical solution of one-dimensional equations for **C**onsolidation **A**nalysis **O**f **S**oils (CAOS) developed by Poulos (2008). The program implements a forward marching finite difference procedure to solve the consolidation equations for one dimensional consolidation, radial consolidation with wick drains and combined vertical and radial consolidation. The program has been successfully benchmarked against analytical solutions for vertical, radial and combined consolidation (Kelly, 2008). Creep settlements are implemented by Bjerrum's concept (Bjerrum, 1967) modified by the creep transition equation (Wong, 2006).

3.4 Prior prediction

Based on the mean values of the prior distributions adopted in Table 1 the surface settlements were computed using the numerical model. The prior prediction was made prior to any Bayesian back analysis with the model adopted in Table 3 and are usually referred to as the design model or 'first pass'. The prior prediction showed a deviation from the observed settlement in both overall prediction and shape of the curve. The prior prediction for the model adopted in this study overpredicted the surface settlements.

3.5 Prediction incorporating Bayesian back analysis

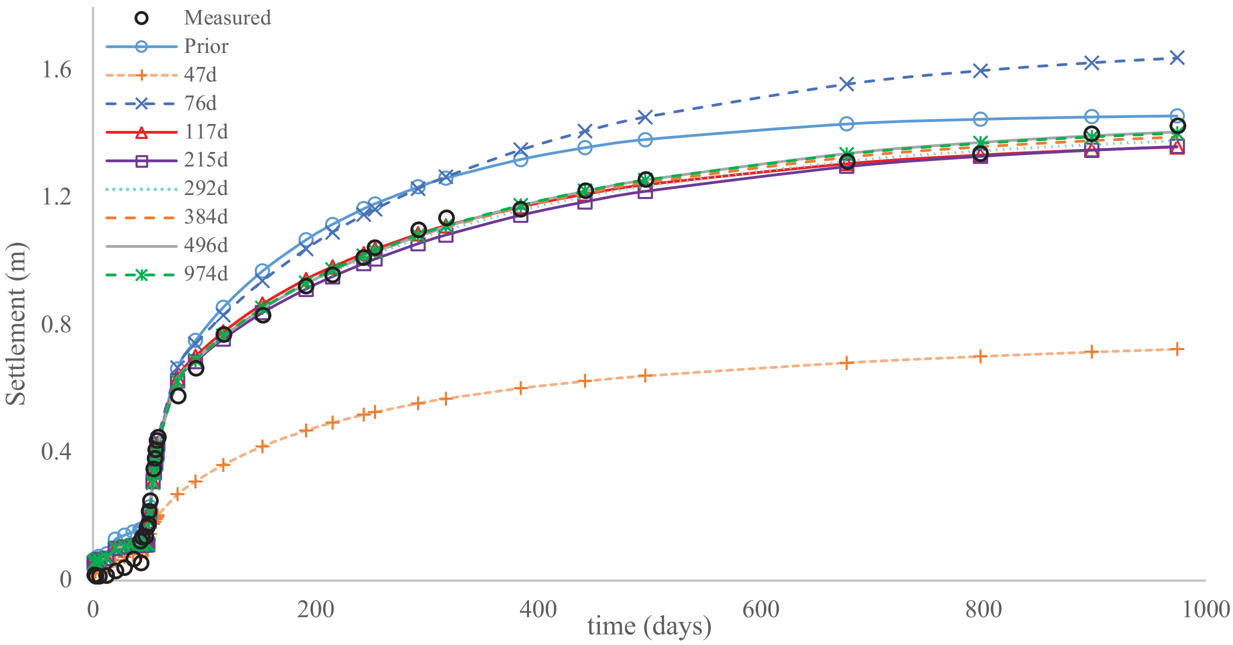
The inclusion of observed surface settlement results allows the designer to update their initial prediction. The back analysis, for the purpose of updating the prior soil parameters were performed for a period of days starting from 0 to 47 days through to 0 to 974 days using the observed settlements for that period. The period from 0 to 47 days is denoted as '47d' as shown in
Table *4* and Figure 2 below. Following each time period, a prediction was made with the updated posterior values shown in
Table *4*. When the monitored data from 0 to 47 days was used for prediction on the 974th day the mean settlement was 0.72m which is about half of the measured settlement of 1.427m and shows a clear deviation between the predicted and measured results. Two more iterations were incorporated one from 0 to 76 days and 0 to 117 days before the prediction converged with the measured results. 0 to 76 days showed an over prediction of 1.53m however 0 to 117 days showed a prediction of 1.41m which compares well with the measured result of 1.427m. The accuracy of the prediction based on the soil parameters increased with an increased amount of monitored data. The mean values of posterior distributions are presented in
Table ***4***.

Table 4. Mean values of updated soil properties using monitored surface settlement data

Dimension	Parameter	Properties	Prior	Posterior (mean)

ID				47d	76d	117d	215d	292d	384d	496d	974d
1			0.20	0.087	0.236	0.247	0.253	0.244	0.237	0.256	0.25
2	$C_{c\varepsilon}$	$C_c(1+e_o)$	0.45	0.668	0.325	0.257	0.206	0.214	0.228	0.211	0.228
3			0.40	0.430	0.704	0.727	0.728	0.733	0.722	0.735	0.738
4			0.137	0.188	0.047	0.057	0.054	0.089	0.157	0.061	0.074
5	c_h	m^2/day	0.008	0.011	0.012	0.014	0.014	0.014	0.012	0.012	0.013
6			0.274	0.337	0.467	0.450	0.483	0.489	0.491	0.484	0.484
7	$C_{c\varepsilon}/C_{s\varepsilon}$	-	5	6.800	5.141	5.281	5.117	5.111	5.089	5.119	5.262
8	$C_{c\varepsilon}/C_{\alpha\varepsilon}$	-	15	19.32	21.15	20.90	20.78	18.78	19.82	18.86	19.95
9	α	-	1	0.846	1.086	1.094	1.080	1.075	1.069	1.069	1.073

Figure 2. Updated surface settlements using different numbers of monitored settlements based on prior values in Table 3.



4 Discussion

For this study a simplified geotechnical model was updated using observed data incorporated by Bayesian back analysis to update the parameters and surface settlement over time. This method is useful in predicting long term surface settlement performance of embankments built on soft soils. It demonstrates the use of an advanced method such as Bayesian back analysis in combination with a simplified geotechnical model can produce a reliable predictive model. It shows that approximately 117 days of monitored data is required for a prediction that converged to the field data which is similar to the results obtained for a nine layered model (Zheng *et al.*, 2018). Predictions prior to the construction phase being completed, in this case up to about 60 days may not produce reliable results for settlement prediction as shown by the 0 to 46 day prediction result. Therefore about 60 days of post construction data was required for reliable prediction for the three-layer model adopted for this case.

This method presents a step toward reducing the highly subjective process of parameter selection for prediction of surface settlement. It also demonstrates the use of random variables for the compression ratio, recompression ratio, creep stain rate and permeability. The method used the ratio of the compression index to recompression and creep strain as a mean of reducing the parameters required. This type of back analysis is well suited for soft soils due to the amount of literature and lab data for prior predictions to fit a suitable distribution with reasonable boundary conditions. The method employed in this study can be implemented with a basic understanding of programs such as excel and MATLAB©. Further studies could focus on adapting the one-dimensional parameters to isotropic consolidation parameters.

5 Conclusion

Bayesian back analysis has been successfully applied to predict the long-term surface settlements. Based on the results the following conclusions can be made:

(1) The recompression ratio and creep strain rate taken as ratios of the compression index can yield reasonable surface settlement predictions.

(2) The harmonic mean was a useful technique for prescribing prior parameters from laboratory data and reduced the number of sublayers required for a simplified model.

(3) Reliable surface settlement predictions can be made with a simplified ground model incorporating Bayesian back analysis with around 117 days of measured field data which is similar to the results outlined for the nine layered model.

(4) Bayesian back analysis undertaken after the construction phase produced better long-term surface settlement predictions.

(5) Parameters for the compression ratio tend to be slightly higher than realistic values.

(6) Settlement prediction can be improved by incorporating additional field monitoring data progressively into the Bayesian back analysis using the DREAM algorithm.

Credits and authorship contribution

Merrick Jones: Methodology, software, formal analysis, writing, original draft and data curation.
Shan Huang: Software implementation, data curation, review and editing.
Jinsong Huang: Conceptualisation, methodology, resources, review, editing and supervision.

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