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Numerical study of the effects of water drawdown on ground settlement for excavation in residual soils

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Abstract: For deep excavations in residual soils that are underlain by highly fissured or fractured rocks, it is common to observe the drawdown of the groundwater table behind the excavation, resulting in seepage-induced ground settlement. In this study, finite element analyses are firstly performed to assess the critical parameters that influence the ground settlement performance in residual soil deposits subjected to groundwater drawdown. The critical parameters that influence the ground settlement performance were identified as the excavation width, the excavation depth, the depth of groundwater drawdown, the thickness of the residual soil, the average SPT N value of the residual soil, the location of the moderately weathered rock, and the wall system stiffness. Subsequently, an artificial neural network (ANN) model was developed to provide estimates of the maximum ground settlement. Validation of the performance of ANN model was carried out using additional data derived from finite element analyses as well as with measured data from a number of excavation sites.

Keywords: residual soils; braced excavation; finite element analysis; ground settlements; groundwater drawdown; neural networks

1 Introduction

In recent years, a number of deep braced excavation projects have been carried out in residual soils in Singapore for the construction of basements for high rise buildings and underground structures. One major design concern for these excavations which are located in densely built-up areas is to prevent damage to adjacent roads, utilities and buildings from excessive ground movements due to stress relief from the removal of the soil. Consequently, stiff diaphragm walls and bored pile walls with multiple levels of struts are commonly used to minimize the lateral wall movements and ground settlement. However, for residual soils with high permeability overlying highly fissured or fractured rocks, the problem of groundwater drawdown and the associated seepage induced settlement have been observed at a number of sites (Goh et al. 2014).

In this paper, the ground settlements at four recent braced excavation sites (C912, C913, C915 and C916) in residual soils with maximum excavation depths of between 20 m and 24 m are described. Despite groundwater control measures, the groundwater tables behind the retaining walls were observed to reduce progressively with increasing depth of excavation. The groundwater drawdown at these sites ranged from 2 m to 23 m. As a result of the groundwater drawdown, significant ground surface settlements were observed, ranging from 50 mm to 141 mm (Goh et al. 2014; Zhang et al. 2018a). Hence, an accurate prediction of the ground movement can lead to an improved design and mitigate potential damage in the vicinity of the excavation.

In this paper, the ground conditions and the braced excavation systems are presented first. The results of parametric studies using the finite element method are then presented to highlight the main parameters that affect the ground surface settlements. A back-propagation neural network model is then described for prediction of ground surface settlement for braced excavations in residual soil deposits.

2. Subsurface conditions and Excavation support system

Fig. 1 shows the typical subsurface conditions in the central part of Singapore. The groundwater table is typically 1 m to 2 m below the ground surface. There is often a thin layer of fill (not shown) overlying residual soil deposit (denoted as GVI, Bukit Timah Granite residual soil). Some completely weathered soils (GV) may be present above the moderately weathered rocks (GIII). This is underlain by slightly weathered and fresh Bukit Timah Granite rock. This is described in detail in Zhang et al (2018a). Fig. 2 shows a typical soil profile at one site (C915) based on nearby boreholes. The plot of the Standard Penetration Test SPT-N values highlights the heterogeneous nature of the ground conditions that is commonly observed in the granitic residual soils of Singapore. The general trend is for the SPT N values to increase with depth. The SPT N values for the GVI residual soils generally range from 2 to 25, and for the GV soils they range from 30 to 100. The permeability of the GVI residual soil was also very variable, in the range of 10^{-4} to 10^{-8} m/s. For the detailed properties of these geological units, Sharma et al. (1999) is referred to.

Fig. 1. Simplified cross-sectional profile

Fig. 2. Plot of variation of SPT N with depth for C915

For deep excavation projects in these ground conditions, in order to minimize ground movements and damage to adjacent buildings, stiff diaphragm wall or bored pile wall systems are required to be embedded 1 m to 2 m into the GIII material. The excavation geometries and the ground conditions at four different sites that were examined as summarized in Table 1 again highlight the heterogeneous nature of the ground conditions. The retaining systems

adopted for the four sites are also shown in Table 1.

Table 1. A summary of excavation geometries and ground conditions for four sites.

Site	Max excav. Depth H (m)	Excav. Length (m)	Range of Excav. width B (m)	Thickness of GVI T (m)	Depth of GIII (m)	Wall type	No. of strut levels
C912	22	165	30 - 54	2.6 - 11.0	13.0 - 28.0	1.2 m diameter Secant Bored Pile wall	5
C913	20	225	30 - 50	3.0 - 19.0	17.0 - 36.0	1.0 m thick Diaphragm wall	4
C915	24	190	12 - 55	3.0 - 25.0	18.0 - 36.0	1.0 m and 1.2 m thick Diaphragm walls	6
C916	20	225	45 - 70	2.9 - 8.5	9.0 - 30.0	1.2 m diameter Secant Bored Pile wall	4

Prior to the commencement of excavation at sites C912 and C913, fissure grouting was carried out at zones outside the excavation down to an adequate depth below the final excavation level to provide a hydraulic cut-off within the rock mass and to prevent groundwater drawdown. In addition, recharging wells were installed behind the excavation areas for sites C913, C915 and C916 (Zhang et al. 2018a). Despite these groundwater control measures, the groundwater tables behind the retaining walls were observed to reduce progressively with increasing depth of excavation. The groundwater drawdown at these sites ranged from 2 m to 23 m. As a result of the groundwater drawdown, significant ground surface settlements were observed, ranging from $\delta_{vm}/H = 0.09\%$ to 0.90% (where δ_{vm} is the maximum ground settlement and H is the excavation depth) which were much larger than the maximum lateral wall displacements δ_{hm} which ranged from $\delta_{hm}/H = 0.025\%$ to 0.15% as

shown in Table 2. The measured ground surface settlements at these four sites were larger than most of the previously reported excavations in the literature for both soft and stiff soils which typically range from $\delta_{vm}/H = 0.1\%$ to 0.5% , most likely because of the large groundwater drawdown.

Table 2. Summary of range of measured maximum wall displacements δ_{hm} and maximum ground settlement δ_{vm}

Normalized deformation	Range
δ_{hm}/H (%)	0.025-0.15
δ_{vm}/H (%)	0.09-0.90
$\delta_{vm} / \delta_{hm}$	1.0-10.0

3. Finite Element Analyses

The plane strain finite element program Plaxis 2D (Brinkgreve et al. 2017) was used to perform a parametric study to assess the critical factors that influence the ground surface settlements. Fig. 1 and Table 3 show the parameters that were varied. The system stiffness (Clough and O'Rourke 1990) is defined as $S = (EI)_{wall} / \gamma_w h^4$ where $(EI)_{wall}$ is the wall bending stiffness, γ_w is the unit weight of water and h is the average vertical spacing of the struts. The parameter d_G is the depth of the GIII rock layer relative to the final excavation depth with a negative value of d_G denoting the GIII layer is below the final excavation level. In all the analyses, the wall is assumed to be embedded 1 m into the GIII layer.

A typical finite element half-mesh is shown in Fig. 3. The structural elements were assumed to be linear elastic with the wall represented by 5-noded beam elements and 3-noded bar elements were used for the struts. The soil was modeled by 15-noded triangular elements. The struts and wall members have not been shown, for ease of viewing. The nodes along the side boundaries of the mesh were constrained from displacing horizontally while the nodes along the bottom boundary were constrained from moving horizontally and vertically. The right vertical boundary extends far from the excavation to minimize the effects of the boundary restraints. In the analyses, groundwater drawdown was considered.

Table 3. Summary of range of parameters

Parameter	Range of values
Depth of excavation H (m)	17 – 31
Excavation width B (m)	10 – 80
Thickness of GVI layer T (m)	2.6 – 35
Depth of groundwater drawdown d_w (m)	0 – 25
Depth of GIII layer d_G (m)	-18 to +14
SPT N of GVI soil	2 – 36
System stiffness S	181 - 2051

Fig. 3. Finite element mesh

The Hardening Soil (HS) model (Brinkgreve et al. 2017) was adopted in this study. The main input parameters are E_{50}^{ref} , a reference secant modulus corresponding to the reference confining pressure P^{ref} , a power m for stress-dependent stiffness formulation, effective friction angle ϕ' , cohesion c' , failure ratio R_f , E_{ur}^{ref} the reference stiffness modulus for unloading and reloading corresponding to $P^{ref} = 100$ kPa, and ν_{ur} the unloading and reloading Poisson's ratio. The properties of the soils as listed in Table 4 are based on extensive laboratory and in-situ tests that were carried out at the four sites and were validated by finite element back-analyses (Goh and Zhang 2016 and Zhang et al. 2018b).

Table 4. Summary of HS soil properties.

Strata	γ_{unsat}	γ_{sat}	ν_{ur}	c'	$\phi'(^{\circ})$	Stress-dependent stiffness		
	(kN/m ³)	(kN/m ³)		(kPa)		m	E_{50}^{ref} (kPa)	E_{ur}^{ref} (kPa)
GVI	16.0	18.5	0.2	Related to SPT-N		0.6	Related to SPT-N	
GV	17.0	19.0	0.2	0.1	33	0.6	16000	48000
GIII	24.0	24.0	0.2	300	45	0	200000	600000
For GVI, $c_u=5.627N$ for $N < 15$; otherwise, $c_u =84.4+0.508(N-15)$; $c'=20$ kPa and $\phi'=28^{\circ}$ for $N < 15$; otherwise, $c'=17$ kPa and $\phi'=33^{\circ}$; $E_u/c_u = 250$								

For brevity, only one plot of typical back analysis is presented in this paper. Fig. 4 shows the measured and computed wall deflection and the ground surface settlement profiles at the final stage of excavation for one cross section at C913 (Zhang et al. 2018). It is obvious that the computed lateral wall displacements and ground settlements are generally in good agreement

with the measured results.

Fig. 4 Comparison of measured and computed excavation responses

Subsequently, extensive finite element parametric analyses were performed to assess the important factors that affect the maximum ground surface settlement. Fig. 5 to Fig. 10 highlight the general trends that were observed. Fig. 5 shows the influence of the SPT N of the GVI layer and the depth of groundwater drawdown d_w on the maximum ground surface settlement δ_{vm} . It is obvious that the maximum ground surface settlement increases with the increase in the depth of groundwater drawdown. The general trend was for the maximum ground settlement to decrease with the decrease of GVI thickness. In addition, it is obvious that the maximum ground surface settlement increases significantly as the SPT-N value reduces from 15 to 5. The increase in the thickness of the GVI layer T was found to increase the maximum ground surface settlement significantly for SPT N values less than 10 as shown in Fig. 6. Negative values of d_G which denotes that the GIII layer is below the final excavation depth also resulted in increased δ_{vm} compared with the case of the GIII layer above the final

excavation depth (positive d_G) as shown in Fig. 7. The width of the excavation B , the depth of the excavation H , and the wall system stiffness S were also found to influence δ_{vm} as shown in Figs. 8 to 10. This is not surprising, since the increase in B and H , and the decrease in S will lead to increase in the lateral wall deflection and correspondingly increase in ground settlement as a result of undrained shear distortion.

Fig. 5. Plot of δ_{vm} versus d_w ($B = 20$ m, $H = 20$ m, $d_G = -4$ m, $T = 10$ m and $S = 462$)

Fig. 6. Plot of δ_{vm} versus SPT N ($B = 30$ m, $H = 20$ m, $d_G = -4$ m, $d_w = 0$, and $S = 462$)

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Fig. 9. Plot of δ_{vm} versus SPT N ($B = 30$ m, $d_G = -4$ m, $d_w = 0$, $T = 10$ m, and $S = 181$)

Fig. 10. Plot of δ_{vm} versus SPT N ($B = 30$ m, $H = 20$ m, $d_G = -4$ m, $d_w = 0$, and $T = 10$ m)

4. Neural Network Analyses

The finite element analyses in the previous section have highlighted the multiple factors that affect the ground surface settlement. Hence an Artificial neural networks (ANN) back-propagation algorithm was adopted to model the relationship between the various parameters. Artificial neural networks are computational methods that mimic very simplistically the structure and internal information processing operations of the human brain. In general, a neural network is made up of processing units (neurons). Each neuron receives signals, performs a simple computation, and then sends out signals through outgoing connections. The connection between neurons functions like a multiplicative filter with its connection strength or weight. Back-propagation neural networks (Rumelhart, et al. 1986) are multilayer feed forward networks consisting of an input layer of neurons, an output layer, and one or

more hidden layers. Learning in a back-propagation network involves “supervised” learning in which the expected output is included in the training data that the network is supposed to learn. The “training” process involves an iterative process. In each training cycle, signals are propagated forward from the input to the output layer and then the error signals at the output layer are propagated backward, and subsequently the network connection weights are modified through an algorithm that minimizes the sum-squared error using the gradient descent approach. Validation of the performance of the neural network to assess the generalization capability of the trained neural network model to produce the correct input-output mapping even when the input is different from the examples used to train the network, is carried out by “testing” with a separate set of data that was never used in training the neural network. The learning capacity of a back-propagation network depends on the number of neurons in the hidden layer(s) and the connection strength (weights) between the neurons in the adjacent layers. Determining the optimal number of hidden neurons is commonly carried out by a trial-and-error approach through repeatedly increasing the number of hidden neurons until no further improvement in the network performance is obtained.

Neural networks have been successfully used in geotechnical engineering to model problems involving multivariate nonlinear relationships, in place of conventional techniques such as regression analysis. For example, it has been successfully applied to seismic liquefaction (Goh 1994; Juang and Chen 1999; Cabalar et al. 2012, Xue and Liu 2017), constitutive modelling (Banimahd et al. 2005; Ghaboussi et al. 2015), ground property estimation (Goh 1995, Juang et al. 2002, Alavi et al. 2010; Alavi and Gandomi 2011, Afshin et al. 2015), dam

analysis (Kim and Kim 2008, Kang et al. 2015), pile analysis (Jeon and Rahman 2008; Zhang and Goh 2016; Pooya Nejad and Jaska 2017) and tunnelling/underground caverns (Benardos and Kaliampakos 2004; Goh and Zhang 2012; Adoko et al. 2013).

A total of seven input neurons representing the 7 parameters as listed in Table 3 were used in the neural network analysis. The output consisted of the maximum ground settlement. A total of 865 different data patterns were obtained from the finite element analyses described in section 3. Of the 865 data patterns, 694 (i.e. 80%) were randomly selected as the training patterns while the remaining 171 (i.e. 20%) were used for testing purposes. Table 5 shows a summary of some of the training data patterns. The optimal back-propagation neural network model for predicting the maximum ground surface settlement consisted of 36 hidden neurons. The training and testing predictions are shown in Fig. 11 and Fig. 12, respectively. The performance statistics are summarized in Table 6. It is obvious that the neural network model has been able to learn the complicated relationship between the ground settlement and the various geotechnical and excavation parameters. Using the trained neural network model, further validation carried out using measured data from the four sites (Table 7) showed reasonable agreement between the neural network predicted values and the measured ground settlement as shown in Fig. 13.

Table 5. Sample training data.

S	B (m)	H (m)	d_G (m)	d_w (m)	T (m)	SPT N	δ_{vm} (mm)
462	30	20	-4	0	6	2	45
462	30	20	-4	0	10	2	60.7
462	30	20	-4	0	16	2	88.2

462	30	20	-4	0	20	2	101.8
462	20	20	-4	0	10	5	28.3
462	40	20	-4	0	10	5	45.3
1313	30	21	-4	0	10	5	33.6
918	30	17	-4	0	10	8	29.6
1313	30	17	-4	0	10	8	26.2
1313	40	17	-4	0	10	12	21.2
918	30	17	-4	0	10	12	23.4
1313	30	17	-4	0	10	12	20.5
181	30	31	-4	12	10	5	113.7
259	30	31	-4	12	10	5	111.5
405	30	31	-4	12	10	5	108.9
462	20	20	-4	16	10	5	105.4
462	40	20	-4	16	10	5	118.4
462	30	20	-4	16	10	5	112.6

Fig. 11. Plot of predicted versus actual ground settlement (Training)

Fig. 12. Plot of predicted versus actual ground settlement (Testing)

Table 6. Summary of training and testing results.

	Number of patterns	Mean squared error MSE	Coefficient of correlation r
Training data	694	6.200	0.9959
Testing data	171	20.062	0.9853

Table 7. Summary of measured data used in model validation.

S	B (m)	H (m)	dG (m)	dw (m)	T (m)	SPT N	δ_{vm} (mm)
261	50	19.5	-16	15.4	8.5	12.3	40.5
261	50	19.5	-6.5	15.5	9	11	35.1
261	50	19.5	-4.8	15.7	3	12	42
261	40	19.5	-11.5	16.3	15	17.5	48.5
261	30	19.5	1.5	12.4	16	8.4	30.7
261	30	19.5	-6	14.9	14.2	16.2	70.8
261	30	19.5	1.9	14.9	12.2	14.2	28.6
261	30	19.5	-6.7	13.1	10	4.5	71.7
261	30	19.5	-0.5	15.7	14.5	16	72.2
1219	36	24.5	-11	23.4	23	20.6	28.6
705	45	24.5	9.5	15.1	7.5	20	28
1219	55	24.5	-12.3	13	18	15	26.6
1219	55	24.5	-5.8	16.1	13	10.9	69.5
705	12	24.5	6.7	5.8	8.5	5	31.7
1090	54	20	1.7	4.7	2.6	4	48.2
1090	30	20	-7.7	7.7	8.3	12.3	24.3
1090	30	20	0.2	4.4	9	8	33
1219	70	21	0.8	6.5	8.5	18.6	54
1219	45	21	-8.8	4.2	6	15	25

Fig. 13. Plot of predicted versus measured ground settlement

The developed ANN model can also provide the parameter relative importance by partitioning the hidden-output neuron connection weights into components connected with each input neuron (Garson 1991; Goh 1994). Table 8 shows of the relative importance of the 7 input variables for the neural network model. The results indicate that the three most important parameters the affect the ground settlement are the excavation depth H, the SPT N value of the residual soil and the location of the GIII layer.

Table 8. Summary of relative importance of each parameter.

Parameter	Relative importance (%)
H	22.2
N	21.3
d _G	17.8
d _w	12.7
T	12.3
B	7.9
S	5.8

5. Summary and Conclusions

This paper summarizes the general ground conditions and the excavation support systems adopted for four deep excavation sites in granitic residual soils in Singapore. Despite groundwater control measures, the groundwater tables behind the retaining walls were observed to reduce progressively with increasing depth of excavation. The groundwater drawdown at these sites ranged from 2 m to 23 m. As a result of the groundwater drawdown, significant ground surface settlements were observed. Based on extensive finite element analyses, the critical parameters that influence the ground settlement performance were identified as the excavation width, the excavation depth, the depth of groundwater drawdown, the thickness of the GVI residual soil, the average SPT N value of the GVI material, the location of the GIII material and the wall system stiffness S . Subsequently, an artificial neural network model was developed to provide estimates of the maximum ground settlement. Validation of the performance of ANN model was carried out using additional data derived from finite element analyses as well as with measured data from a number of excavation sites.

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Fig. 11. Plot of predicted versus actual ground settlement (Training)

Fig. 12. Plot of predicted versus actual ground settlement (Testing)

Fig. 13. Plot of predicted versus measured ground settlement