Case studies of prediction of excavation response using learned excavation performance

Abdolreza Osouli, *Graduate Research Assistant, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 North Mathews, Urbana, IL 61801; e-mail: aosouli2@illinois.edu*
Youssef M. A. Hashash, *Professor, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 North Mathews, Urbana, IL 61801: Tel.: 1-217-333-6986; Fax: 1-217-333-9464; e-mail: hashash@illinois.edu*

ABSTRACT: *Inverse analysis approaches are increasingly used to learn from instrumented excavations with the aim of predicting excavation performance in similar stratigraphy. This paper demonstrates the capabilities and limitations of a recently developed inverse analysis approach, SelfSim, to predict excavation performance using soil behavior learned from measured excavation response in similar soil stratigraphy. Self-Learning Simulation (SelfSim) inverse analysis approach utilizes continuously evolving soil models to extract soil behavior from measured displacements and loads due to excavation. SelfSim learning and subsequent prediction of excavation performance is applied to three sets of case studies in Texas, Shanghai and Taipei separately. The difficulties associated with the use of measured excavation response that is incompatible with recorded construction activity, and the importance of engineering judgment in preparing measurement data for inverse analysis are discussed. In the Texas A&M full scale model wall, the soil behavior extracted from field measurements of a two-level tieback section is used to predict the lateral deflections of inclinometers at the wall and behind the wall with a single tieback level. The limitations of inverse analysis in modeling the slippage of the wall and predicting settlements are described. In Shanghai Metro Station Excavation, the predicted wall deflections and surface settlements at various sections along the station are in general agreement with the measured values. In Formosa deep excavation in Taipei, the lateral wall deflections and surface settlements are predicted reasonably well after learning from measurements at an excavation that is nearly 2 km away.*

KEYWORDS: Excavations, soil behavior, inverse analysis, case study

SITE LOCATION: IJGCH-database.kmz (requires Google Earth)

INTRODUCTION

Urban underground facilities are often constructed in heavily built environments, confined areas, difficult soft ground conditions, and adjacent to structures that can tolerate only minimum disturbance. It is necessary to predict and control the magnitude and distribution of ground movements that result from creating such underground space. In addition to local empirical experience, engineers can use semi-empirical methods (Clough and O'Rourke, 1990; Peck, 1969) and numerical simulations (Clough and Tsui, 1974; Finno and Calvello, 2005; Finno and Roboski, 2005; Finno and Harahap, 1991; Whittle and Hashash, 1994, 1996; Hashash, 1992; Hsi and Small, 1993; Kung et al., 2009; Kung et al., 2007; Mana and Clough, 1981; Ou et al., 2000; Ou et al., 2008; Ou et al., 1996; Ukritchon et al., 2003; Whittle et al., 1993; Wong, 1970) to estimate excavation induced ground deformations.

Instrumentations are installed to monitor excavation performance and take corrective action during construction if needed. In many major urban areas, there are a number of well documented excavation case histories that are used by engineers to estimate performance of new excavations in similar soil stratigraphy. Learning from precedent represents a classic inverse analysis problem aimed in part at interpreting the soil and stress response implied by field observations. Numerical modeling is a powerful tool that can be used in solving inverse analyses. The simplest form of an inverse analysis is ad-hoc material model parameter adjustment. Systematic material model parameter optimization (Gioda and Sakurai, 1987;

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Ledesma et al., 1996; Pal et al., 1996; Samarajiva et al., 2005) are also widely used in solving this inverse analysis problem (Briaud and Lim, 1997, 1999; Calvello and Finno, 2004; Finno and Calvello, 2005; Levasseur et al 2008; Ou and Tang, 1994; Rechea et al., 2008). Calvello and Finno (2004) calibrated the Hardening-Soil (H-S) model (Schanz et al., 1999) for four layers of Chicago glacial clays using triaxial test results. Since the calibrated model could not accurately predict the lateral wall deformations of a subway station excavation in Chicago, they had to recalibrate the model using inclinometer data that recorded the displacements. Finno and Calvello (2005) used the inclinometer data from stage 1 of excavation to recalibrate the H-S model and could predict the measured lateral deflections for later stages reasonably well. However, their study was limited to prediction of lateral wall deflections. While parameter optimization approaches are very powerful, they are constrained by prior assumptions regarding the material constitutive model and thus unable to learn new material behavior. For example as illustrated in Rechea et al. (2008) this approach is unable to capture the measured surface settlement distribution due to inherent limitation in the H-S soil model.

Hashash et al. (2006) introduced a novel inverse analysis approach, Self-Learning Simulation (SelfSim), to extract soil behavior from field measurements such as wall deformations and surface settlements in a supported excavation. SelfSim is an inverse analysis framework that implements and extends the autoprogressive algorithm proposed by Ghaboussi et al. (1998). It extracts behavior of materials through the use of continuously evolving Artificial Neural Network (ANN or NN) material models, rather than calibrating properties of conventional constitutive models. The use of a NN material model provides a versatile capability to learn new aspects of soil behavior such as small strain nonlinearity and anisotropy. More details on NN material models used in this study is found in cited papers. Hashash et. al. (2010) provide a comparison between SelfSim and parameter optimization inverse analysis approaches for an excavation case history. Additional background on SelfSim is provided in the next section.

This paper demonstrates the use of a relatively new inverse analysis technique, SelfSim learning, using several excavation case studies in Texas, Shanghai, and Taiwan and the potential for tighter integration between field case histories and numerical modeling. At each of these locations an instrumented excavation is used in learning of the relevant underlying soil behavior. The learned soil behavior is then used in a finite element analysis to predict the performance of another excavation in similar stratigraphy that was not used in the learning process. It is important to note that any inverse analysis technique is only applicable for cases where a reasonable consistency exists between observed excavation behavior and reported construction activity. Therefore, for cases where the cause and effect is not known or some field data are questionable, any inverse analysis or field calibration approach cannot be properly applied since the cause and effect are unknown.

The case histories used in this paper have been published elsewhere in the literature and the original references are cited. The interested reader can refer back to these original sources for full details of the case histories and their geotechnical information. In this paper we only reproduce data relevant to the numerical simulations. Details of the original development of SelfSim can also be found in original sources cited in this paper and are not reproduced here.

SELF LEARNING SIMULATIONS

The SelfSim framework is illustrated in Figure 1. In SelfSim, two complementary finite element analyses are performed at a given excavation stage using continuously evolving NN soil models. The NN soil model input is the current state of stress and strain and the output is the updated state of stress and stiffness matrix. The model learns the soil behavior through a training process using available information on soil stress-strain behavior. Details of implementing a NN soil model in numerical analysis can be found in Hashash et al. (2004).

In the first finite element analysis, the excavation construction sequence is imposed as a force boundary condition in finite element (FE) simulation using NN material (2a in Figure 1). Given equilibrium consideration, it is assumed that the stress distribution within the FE mesh correctly approximates the actual stress distribution and the stresses are extracted from the analysis.

In the second finite element analysis, the measured field deformations (displacement boundary) are imposed as displacement boundary conditions in the FE simulation (2b in Figure 1). Given compatibility requirements, it is assumed that the strain distribution within the FE mesh correctly approximates the actual strain distribution, and strains are extracted.

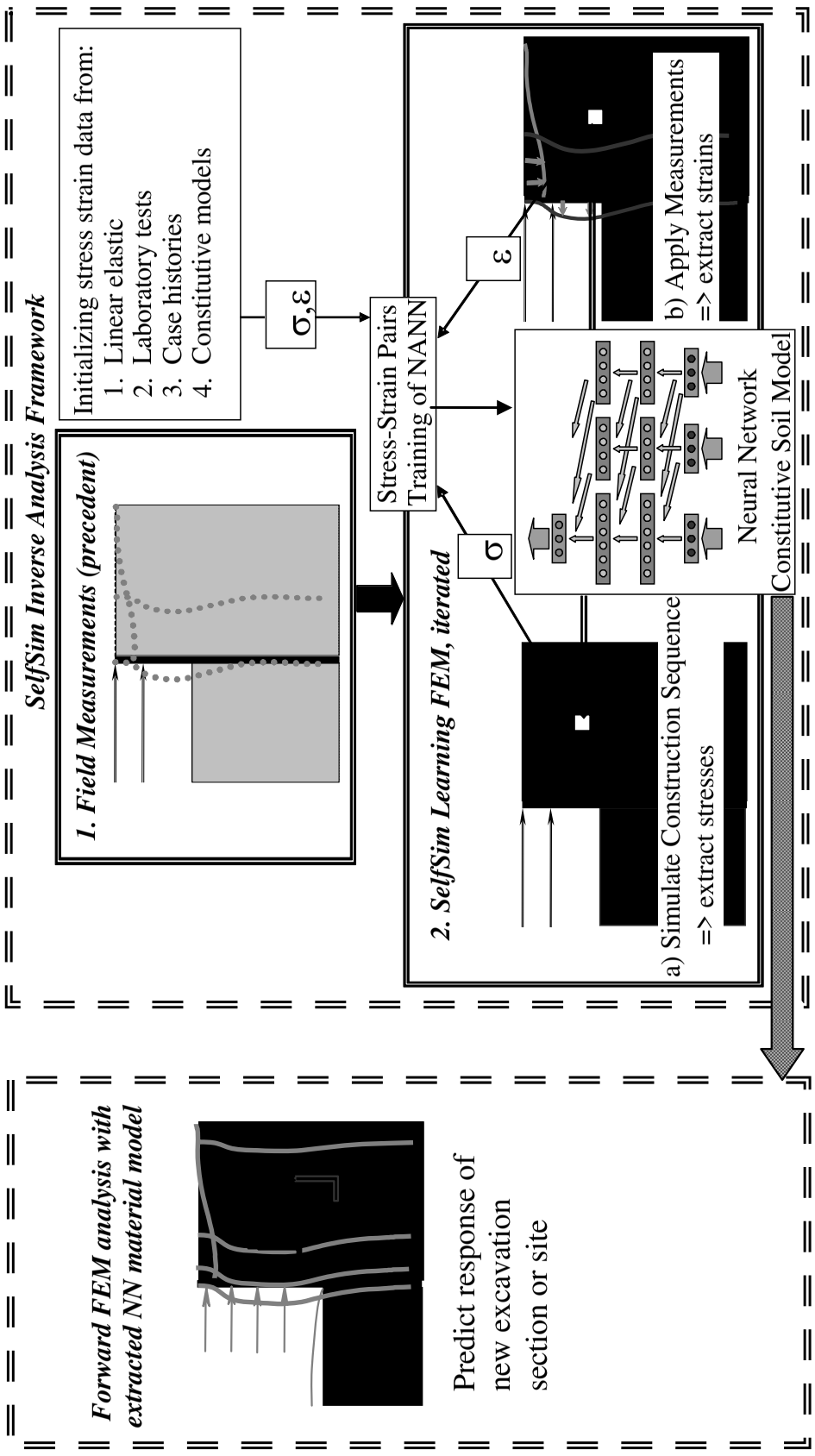


Figure 1. Application of SelfSim inverse analysis framework to predict ground response at a new excavation section or site.

The extracted stresses from the first analysis and the strains from the second analysis provide stress-strain pairs used to re-train the NN material models. This process is repeated using all excavation stages and until the two parallel analyses provide similar results that match field measurements well (Hashash et al., 2006; Marulanda and Hashash, 2007). The extracted NN material models can be used in a forward analysis to predict excavation response of a new excavation with similar ground conditions.

In order to start the SelfSim learning process, there is a need to initialize the NN material models. In this paper we initialize the material models to represent linear elastic behavior over a small strain range. However, once the learning process is initiated, this behavior is lost in favor of new information on soil behavior implicit in the newly extracted stress-strain pairs. Hashash et al. (2006) describe the initialization process and the evolution of the material models during learning to represent soil small strain nonlinearity essential for capturing surface settlement distribution around an excavation.

Hashash et al. (2006) demonstrated the SelfSim learning capacity and the ability to predict performance of a new excavation using numerically simulated excavation case histories. Three different simulated case histories were developed within a fictitious urban area where the geologic profile is similar but not identical at all three sites. The subsurface profiles assumed for the three simulated case histories had slight variations in properties (different overconsolidation ratios OCRs) and strata thickness. SelfSim learning was conducted using wall deflections and surface settlements behind the wall from all three cases. The extracted soil model from the three case histories was then used in the FE analysis of a new hypothetical excavation to correctly predict the ground movements. This finding demonstrated that it is possible to predict excavation performance of a new case study after learning soil behavior from previous case studies that have similar soil stratigraphy. However, the findings of Hashash et al. (2006) are limited to simulated excavations using synthetic measurements. The following sections describe a similar application but now to actual excavation case histories in three different regions. This discussion includes the challenges encountered using field data.

FULL SCALE MODEL WALL IN SANDY SOILS AT UNIVERSITY OF TEXAS A&M

Site Description

The Texas A&M full scale model wall was constructed and tested as a part of research performed to improve the design of permanent ground anchor walls for highway applications (Weatherby et al., 1998). A 7.5-m-high, instrumented, full-scale, tiedback, H-beam and wood lagging wall was constructed in an alluvial sand deposit to study various aspects of the behavior of anchored walls. Figure 2 shows the location of the site at Texas A&M University Riverside campus.

The schematic plan view, instrument locations and elevation view of the Texas A&M wall are shown in Figure 3. The wall which is supported by pressure-injected ground anchors has two sections. Piles 1 through 12 have lighter sections (HP8x36, HP6x25) and two levels of tiebacks are used. Piles 13 through 22 have a heavier section (HP10x57, HP12x53, HP10x42) and a single tieback level is used. Soldier beams 7 to 10 in the two levels of tieback section and soldier beams 13 to 16 in the single tieback level section are instrumented with inclinometers and surface settlement points, Figure 3. There are 6 inclinometers in the retained soil. Inclinometers I-1, I-2 and I-3 are in the two-level tieback section of the wall and located behind soldier beam 10 at distances of 0.7m, 1.5m, and 4.5m behind the wall, respectively. The corresponding surface settlement points for these inclinometers are located behind soldier beam 9. Inclinometers I-4, I-5, and I-6 are in the single tieback level section of the wall behind soldier beam 14 at distances of 0.7m, 1.5m, and 4.5m from the wall, respectively. The corresponding surface settlement points for these inclinometers are located behind soldier beam 15.

The cross sections of the wall with soil stratigraphy are shown in Figure 4. The soil profile consists of fill overlying loose clayey sand followed by medium dense clean sand, and medium dense clayey sand. The fill composes of silty and clayey sand, which was placed in 15 to 22 cm lifts. The water table is at El. -7.0 m. The friction angle of the loose clayey sand and medium dense sand layers was estimated to be between 30 to 32 degrees using a correlation developed by Trofimenkov (1974). The relative densities of the layers vary from 40 to 60 percent.

Learning Soil Behavior from Two-Level Tieback Section of the Wall

SelfSim learning is conducted using inclinometer measurements from the two-level tieback section. The extracted soil models are used in a finite element analysis to predict the excavation performance in the single tieback section of the wall. Figure 5 summarizes the construction activities for the two-level tieback section of the wall. The deformation measurements are available at stages 2, 4, and 7 for the two-level tieback section. The full scale model wall is simulated

using solid element with a bending stiffness equivalent to that of the soldier-pile wall. The tiebacks are simulated by elastic spring elements. The excavation is modeled as a 2D symmetric excavation with large half width of 20m with dimensions of 85m and 18m in horizontal and vertical directions respectively. Individual soil layers are represented via corresponding NN3 based material models.

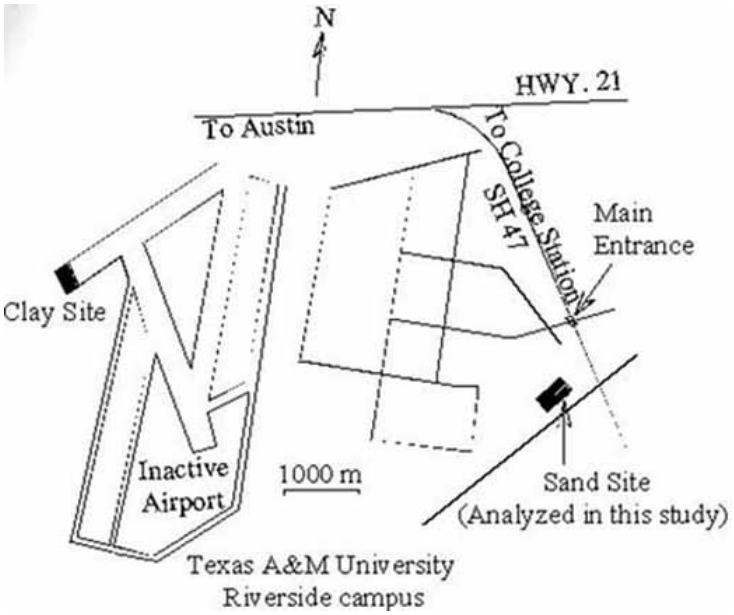


Figure 2. Location of sandy site at Texas A&M University campus, modified after Benoit and Lutenegger (2000).

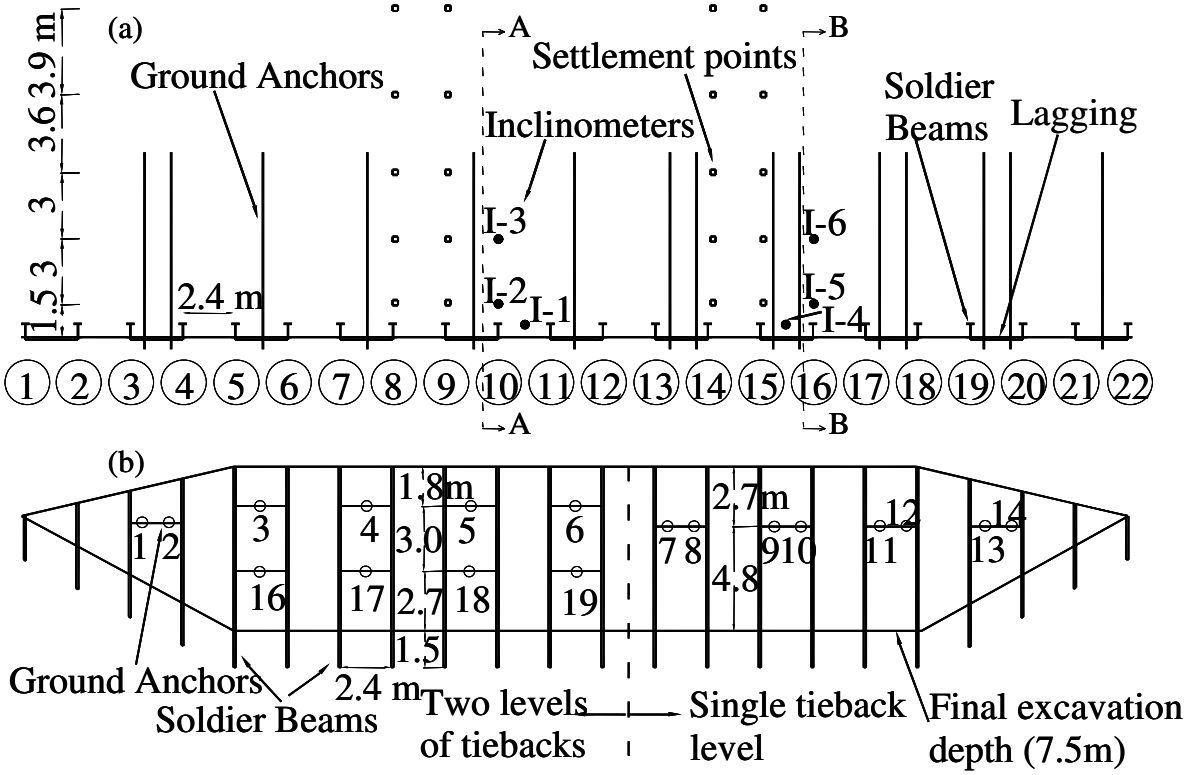


Figure 3. Schematic of Texas A&M University full scale model excavation site showing a) plan view and instrument locations, b) elevation view of the wall, inclinometer labels introduced in this study, modified after Weatherby et al. (1998).

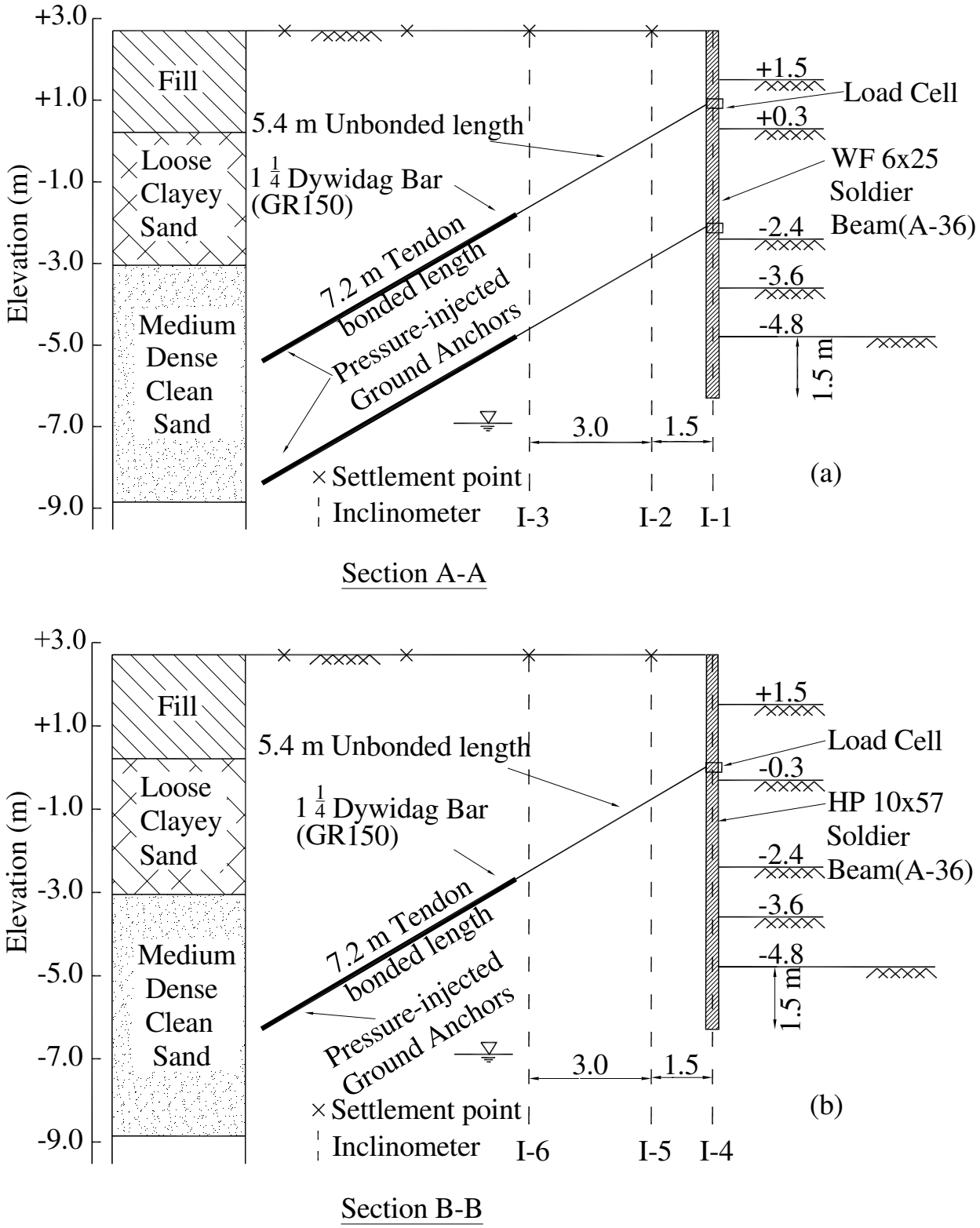


Figure 4. Sections of the Texas A&M University full scale model wall: a) two-level tieback, b) one-level tieback, modified after Weatherby et al. (1998).

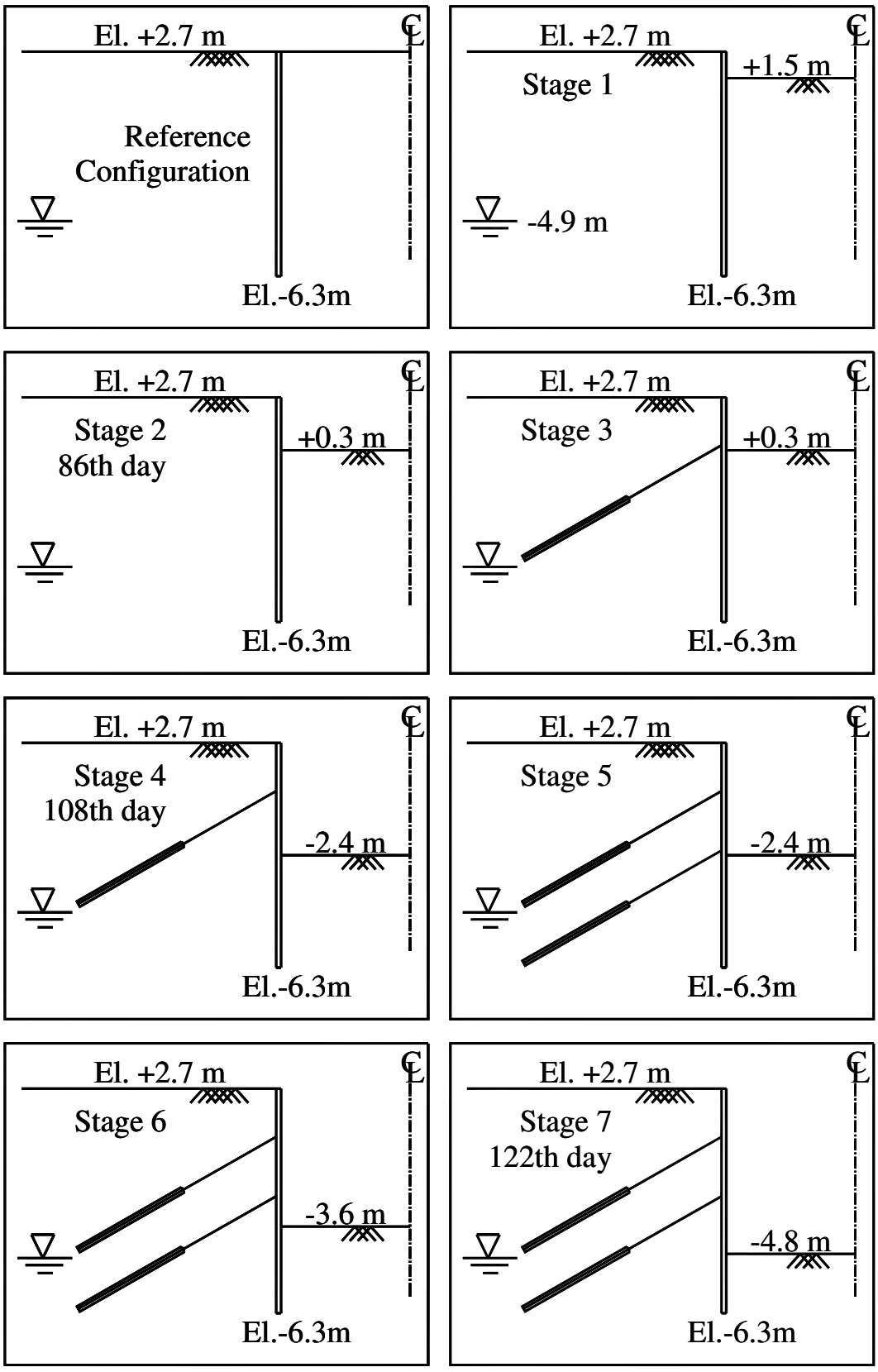


Figure 5. Construction sequence for two level tieback section of the Texas A&M University full scale model wall.

Prior to any SelfSim learning, NN is initialized with linear elastic response within a very small strain range. During the SelfSim analysis, NN loses this linear elastic response and learns the characteristics of soil extracted directly from global measurements. Figure 6 shows the computed deformations prior to SelfSim learning. The surface settlements and lateral deflections of I-1, I-2, and I-3 are underestimated. In the last stage of full scale model wall construction (i.e. 122nd day), the soldier beam piles appear to have settled/slipped. The measured subsurface settlement behind the wall reflects this observation, Figure 6a. The wall slippage induced large settlements behind the wall and is not represented in the inverse analysis.

Various instrument combinations are used in SelfSim learning to explore the extent of learning and the ability to predict excavation response. Initially, SelfSim learning was conducted with wall deformations (I-1) only then using wall deformations (I-1) and I-3. Finally SelfSim learning analysis is conducted using the wall deformations (I-1), lateral movements of inclinometer I-3, and tieback loads. This last analysis provided the best match with measured response. Figure 7 shows the computed excavation response. The computed lateral movements of the wall (I-1) and inclinometer I-3 compare well with measured deflections. Surface settlements near the wall which are affected by wall slippage are under-predicted. It is worth noting that measured wall deflections for inclinometer I-2 at stage 7 exceed those for inclinometer I-1 at stage 7. This behavior is unexpected as I-1 is closer to the wall and should experience larger deformations than I-2. This measured data is inconsistent from the 2-D inverse analysis point of view as it provides contradictory information. Therefore inclinometer I-2 is not used in learning.

Figure 8 compares measured and computed tieback loads. When only wall deformations (I-1) are used in SelfSim learning, the computed tieback loads are overestimated. The computed loads are improved by using both wall deformations (I-1) and lateral deflections of inclinometer I-3. The computed tieback loads after learning with wall deformations (I-1), lateral deflections at inclinometer I-3 and tieback loads provide the best agreement with the measured loads.

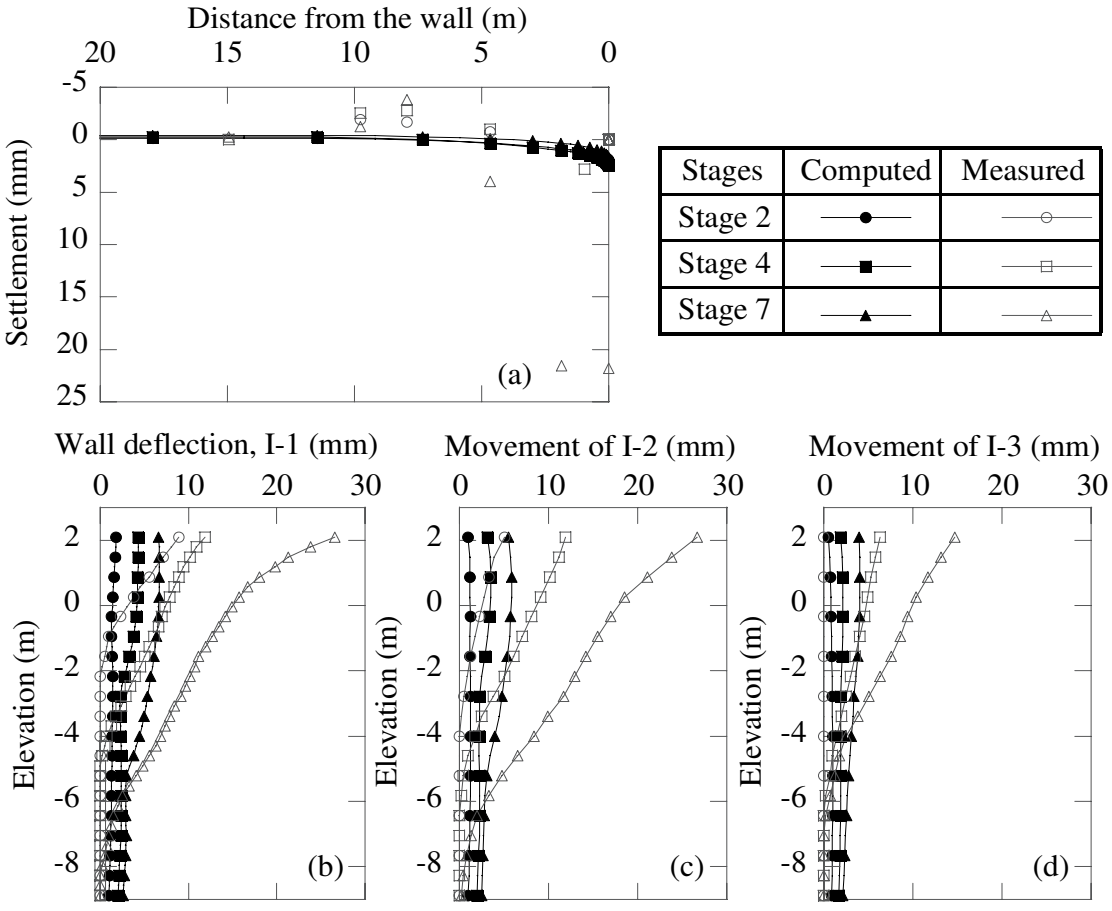


Figure 6. Computed response in two anchor section, Texas A&M excavation, prior to SelfSim learning.

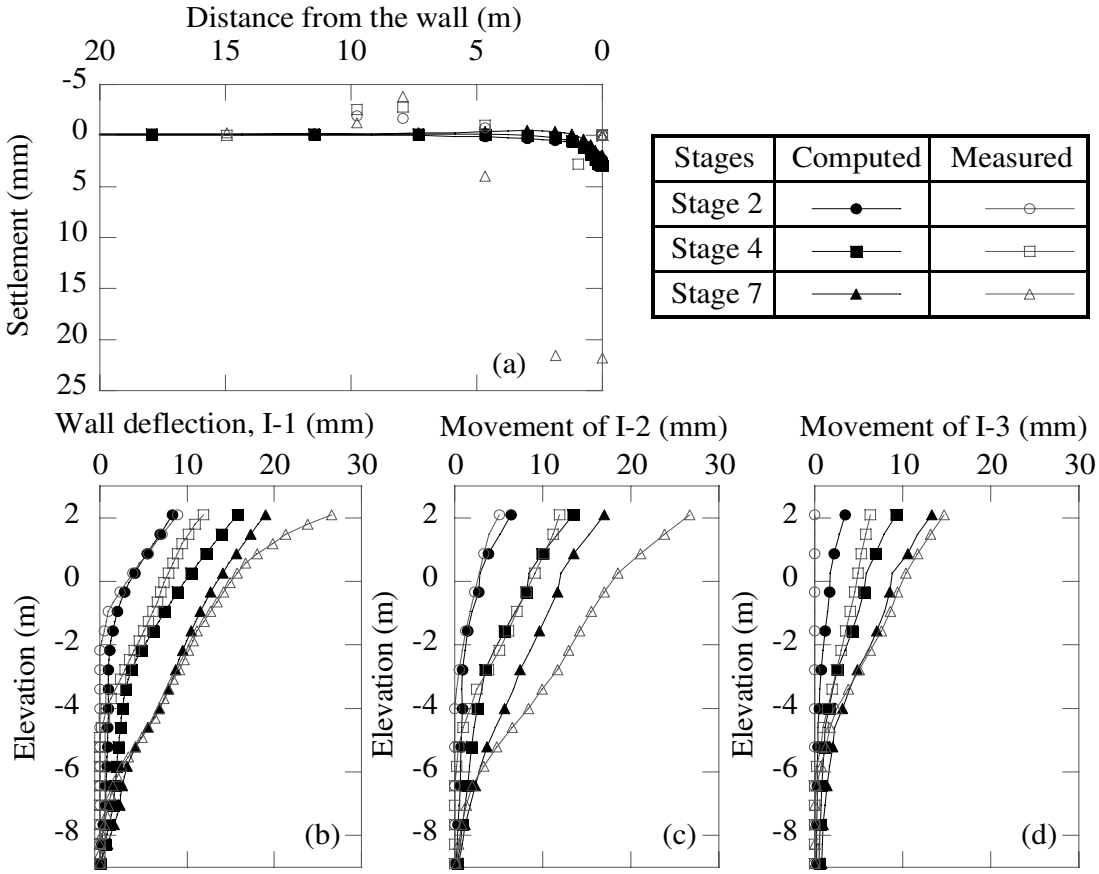


Figure 7. Computed response, two anchor section, Texas A& M excavation, after six passes of SelfSim learning with wall deformations (I-1), lateral movements of inclinometer I-3, and tieback loads.

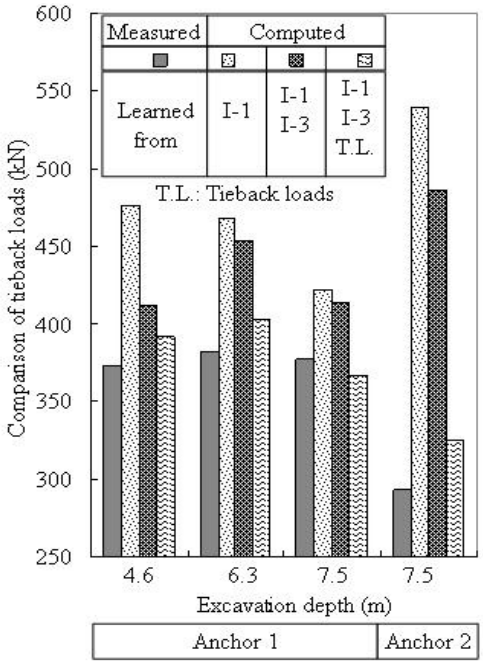


Figure 8. Comparison of measured and computed tieback loads in two-level tieback section of the wall, Texas A&M excavation.

The developed models from the SelfSim learning of the two-level tieback section are used to predict the soil behavior in the one-level tieback section of the wall. The wall length and excavation depth are the same as those for the two-level tieback section (Figure 4), but larger soldier beams sections are used. Figure 9 shows the construction sequence for the one-level tieback section of the wall.

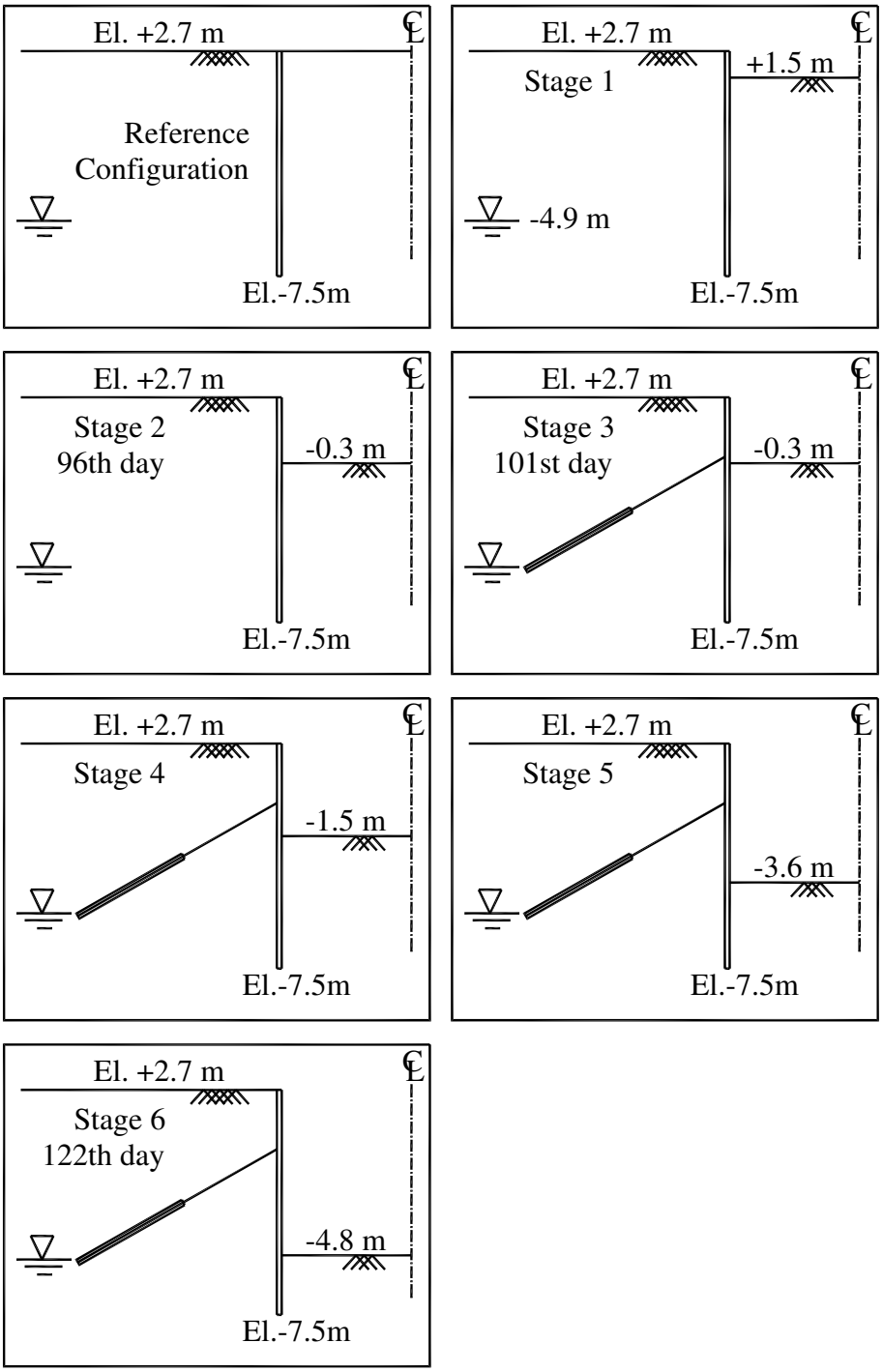


Figure 9. Construction sequence for single tieback section of the wall, Texas A& M excavation.

Figure 10 shows the predicted excavation response using the developed soil models after SelfSim learning with wall deformations (I-1), lateral deflections of I-3 and tieback loads of two-level tieback section. The predicted lateral deformations of inclinometers I-4, I-5 and I-6 are in good agreement with measured values. Similar to the two-level tieback section of the wall, the slippage of the wall induced large surface settlements behind the wall in single tieback level section. Therefore, the surface settlements near the wall which are affected by wall slippage are not modeled in this simulation and are under-predicted.

Figure 11 compares measured and predicted tieback loads in one-level tieback section of the wall. The predicted tieback loads using extracted model after SelfSim learning with wall deformations (I-1), lateral deflections of I-3 and tieback loads of the two-level section of the wall are in reasonable agreement with measured values, for one out of the three construction stages. The predicted tieback loads using extracted soil models after SelfSim learning with wall deformations (I-1) only or wall deformations (I-1) and lateral deflections of I-3 of the two-levels tiebacks section consistently overestimate the measured loads.

This case study demonstrates that lateral deformations at the wall and at distances from the wall in the single tieback level section can be predicted using the soil model extracted from field observations in the two-level tieback section of the wall. However, the surface settlements are not well predicted due to the wall slippage effect which caused large settlements behind the wall and was not simulated in the inverse analysis.

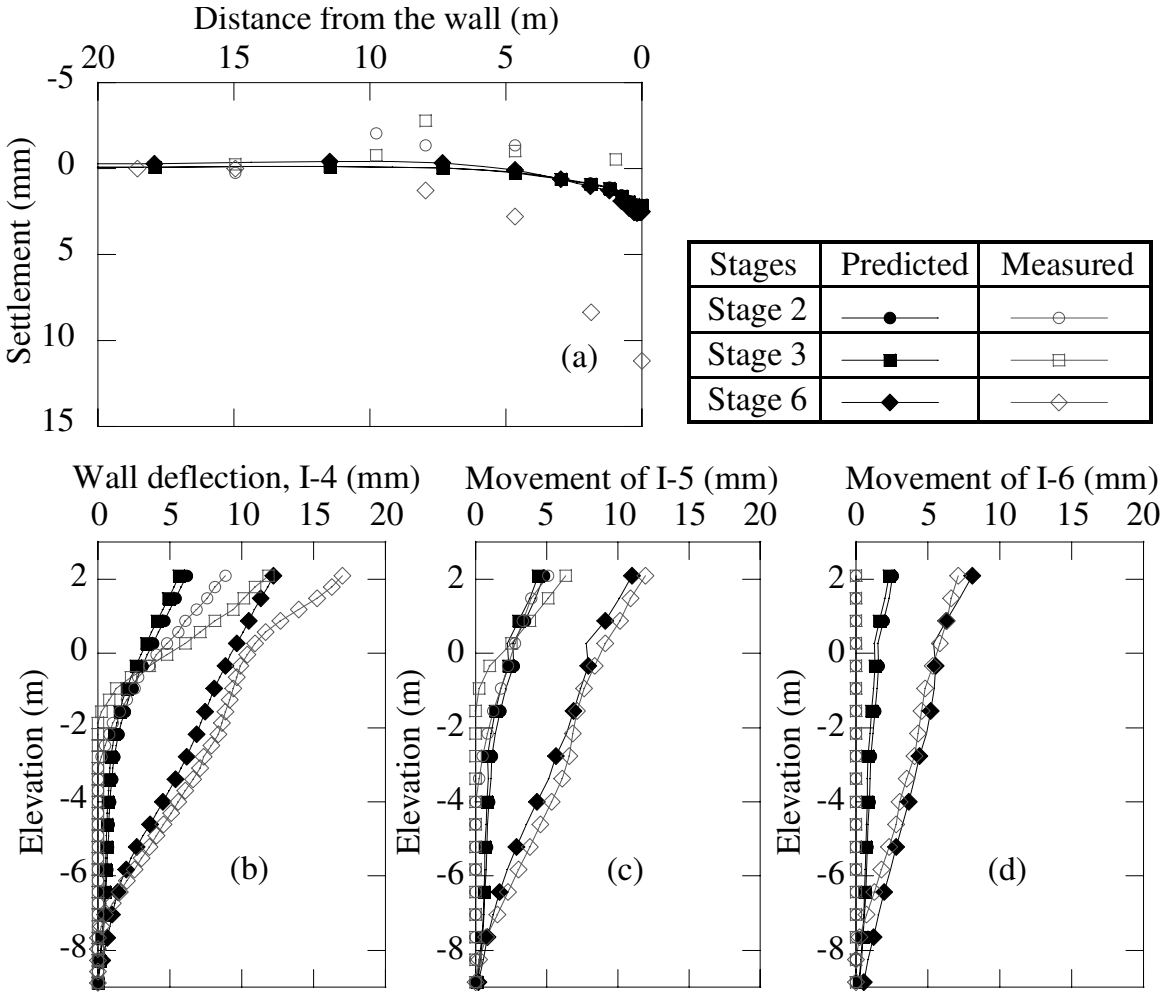


Figure 10. Predicted excavation response in single tieback level section, Texas A& M excavation, using developed model from learning wall deflections (I-1), lateral movements of inclinometer I-3 and tieback loads in two-level tieback section of the wall.

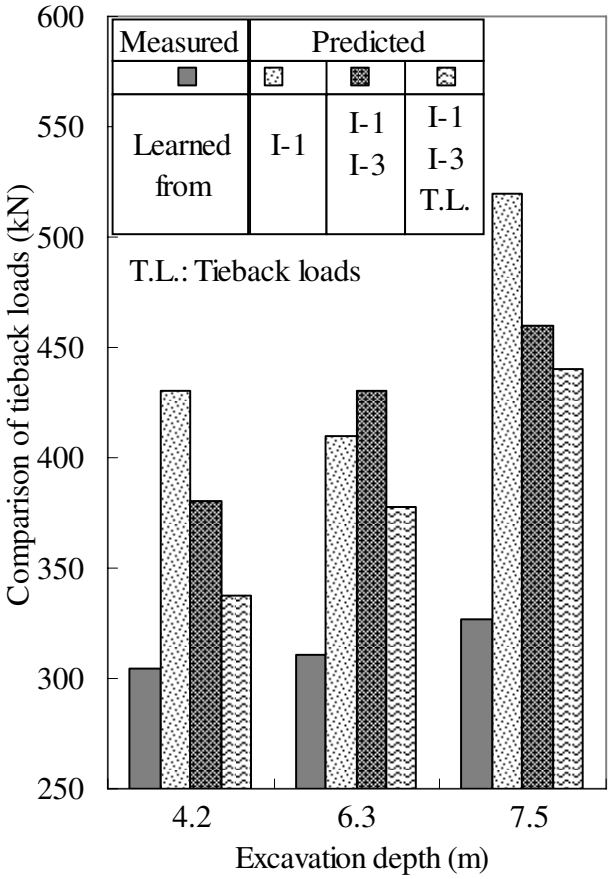


Figure 11. Comparison of measured and predicted tieback loads in single tieback level section of the wall, Texas A&M excavation.

BOTTOM-UP EXCAVATION IN SOFT CLAYS OF A METRO STATION IN SHANGHAI

Site Description

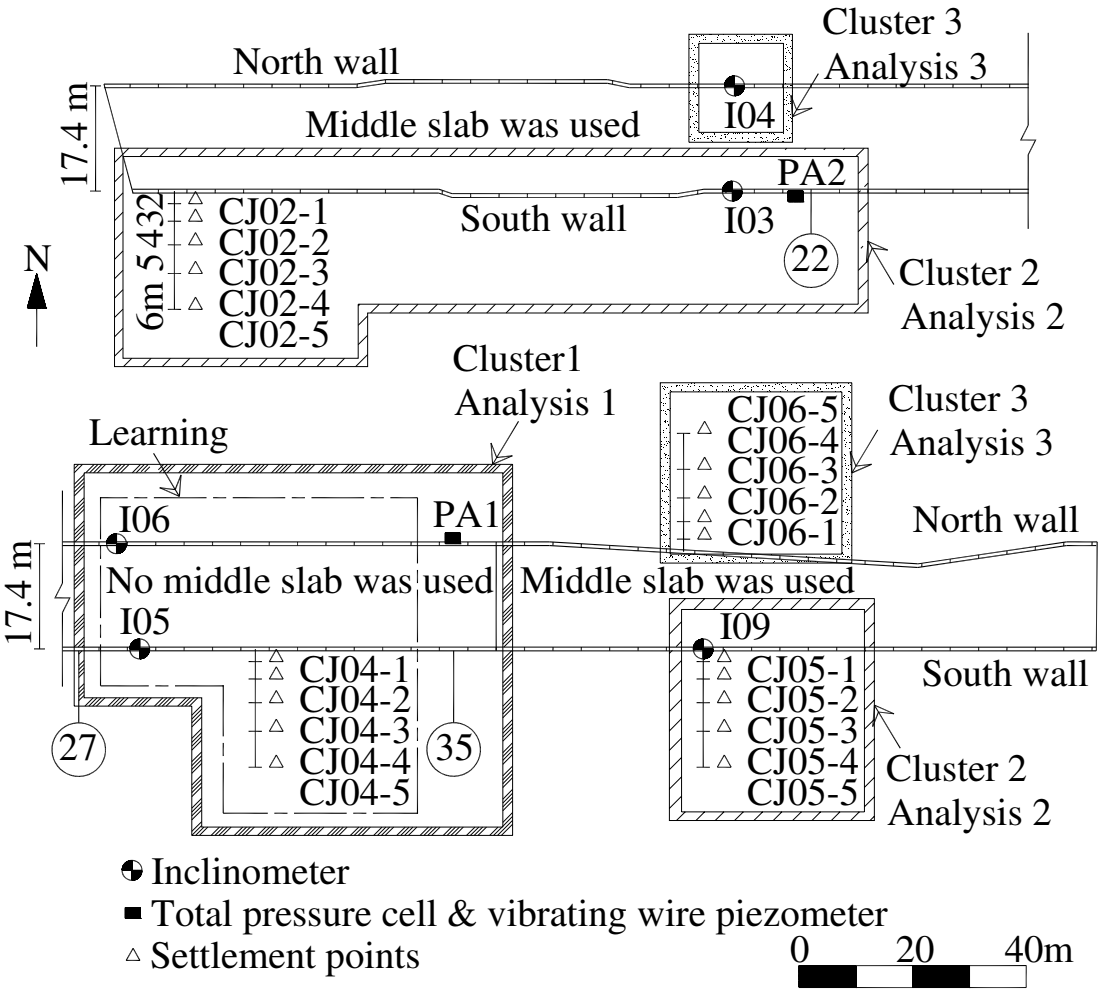
The Yishan Road metro station, located in southwest Shanghai, is a, 17.4 m wide and 335 m long excavation in Shanghai soft clays at Pearl II metro line (Liu et al., 2005). The site was instrumented to monitor wall deflections, total earth pressures at the wall, pore-water pressures, and vertical ground movements. Figure 12 shows the plan view of Yishan Road metro station and instrument locations along the project line. The groundwater table is at about 1 m below the ground level. Figure 13 shows the soil stratigraphy and typical cross section of the excavation site. The site is underlain by thick, relatively soft to medium soft clay deposits. The uppermost clay layer is desiccated and has lower water content but higher shear strength than underlying marine deposits (i.e., soft silty medium clays). The shear strength profiles were obtained from in situ vane shear tests and are in the range of 100 to 200 kPa. The permeabilities of shallow sedimentary marine soft silty clays and marine medium clays were 10^{-8} and 10^{-9} m/s, respectively. Generally the water content of each soil lies close to the liquid limit and the soils have a relatively high void ratio and hence high compressibility (Liu et al., 2005).

The Yishan Road metro station excavation was supported by a 0.6 m thick concrete diaphragm wall. The wall length between Panels 27 and 35 was 28 m and in the remaining panels was 28 m along the north side and 34 m along the south side of the station. The deeper wall in the south side was placed to minimize the effects of the station excavation on adjacent light-rail line running parallel to the wall about 20-30 m away. Prior to the excavation, the soils inside the excavation at depths between 8.6 and 10.6 m and between 16.6 and 19.6 m below the ground surface were treated by compaction grouting at 3 m horizontal spacing after the construction of the diaphragm wall. The measured wall deflections did not show a restraining effect at the levels of the compaction grouting, thus it appears that the grouting was ineffective. The excavation was conducted from the two ends towards the center of the station.

Reinforced concrete struts of 800 mm width and 1200 mm thick were installed 1.2 m below ground surface at 6 m horizontal spacing. Pre-stressed steel pipes 609 mm in diameter (external) and 16 mm in thickness were used at other levels at 3 m horizontal spacing to support the diaphragm wall. Each pre-stressed strut was periodically adjusted to maintain the pre-stress load to be not less than 0.7 times the estimated total vertical stress (Liu et al., 2005). Prior to excavation to a depth of 12.5 m, a 0.6 m thick reinforced concrete middle slab was constructed except for the section between Panels 27 and 35. After construction of middle slab, 60 days were allowed for concrete curing. Liu et al. (2005) indicates that no significant creep effect could be identified over the 60 days curing of the middle slab.

A jump in lateral wall deflections was reported from excavation depth of 12.5 to 15.5 m, which was not consistent with reported excavation and construction activities. Liu et al., (2005) indicated that this was probably because of the relatively shorter wall or insufficient application of pre-stress struts. Therefore, the reason for such observation was not known. Without a clear cause and effect relationship between measured performance and construction activity it is not possible to reliably learn the excavation behavior or for that matter perform conventional model calibration. Therefore, the metro station excavation was simulated down to 12.5 m excavation depth only.

Based on the support system configuration and construction activities three analysis clusters are defined in Figure 12. In cluster 1 the wall length for north and south walls of the excavation is 28 m. The middle slab was not used in this cluster. In cluster 2 the middle slab and wall length of 34 m are used. In cluster 3 the middle slab and wall length of 28 m are used.



Note: These were the only instruments used in this study.

Figure 12. Plan view of Yishan road metro station and instrument locations, Shanghai excavation, modified after Liu et al. (2005).

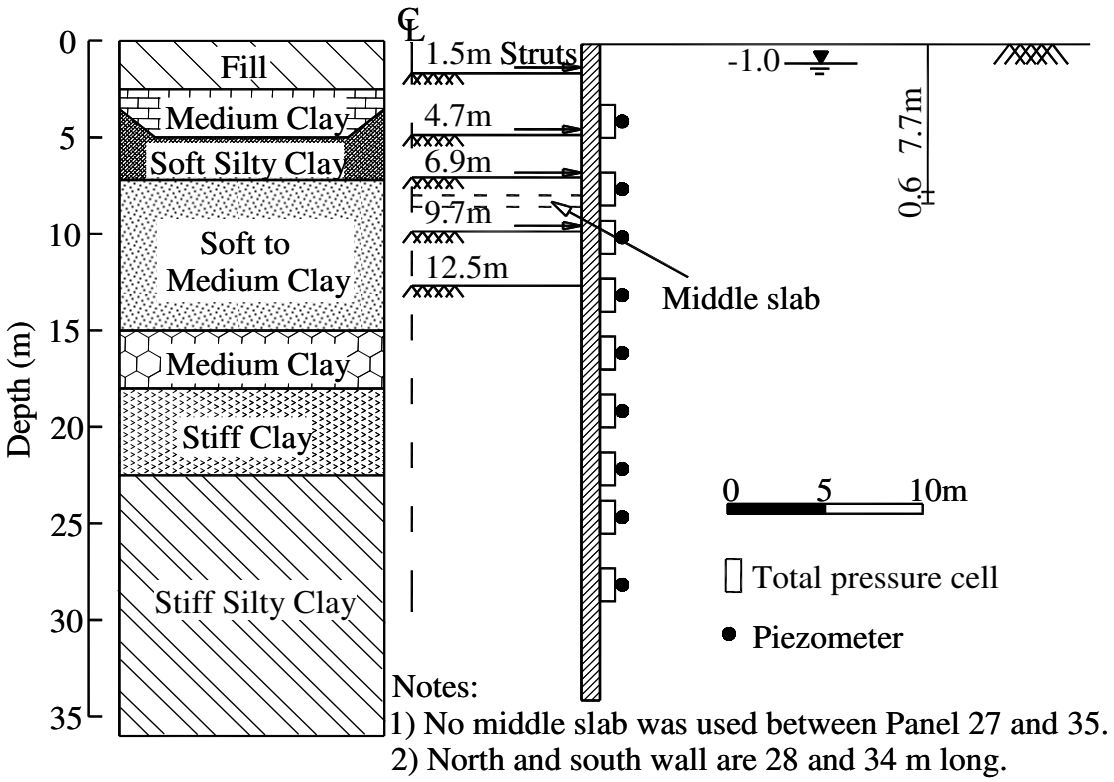
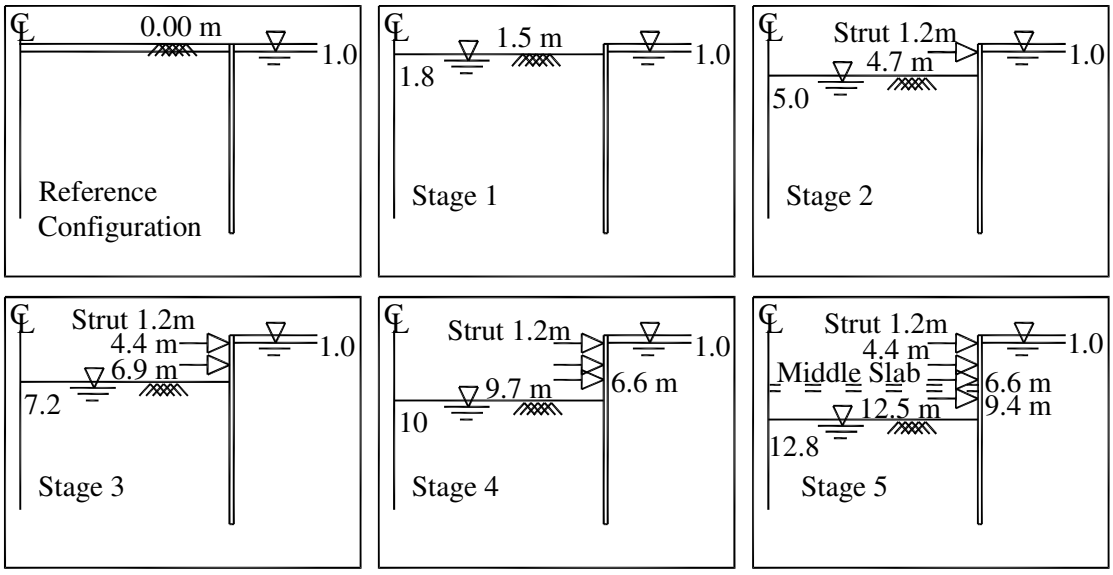


Figure 13. Typical cross section of the Yishan road metro station, Shanghai excavation, modified after Liu et al. (2005).



Cluster	Instruments	Middle Slab	Wall length	
			North	South
1	I05, I06, CJ04, PA1	No	28m	28m
2	I09, CJ05, I03, CJ02, PA2	Yes	----	34m
3	I04, CJ06	Yes	28m	----

Figure 14. Construction sequence for different clusters, Shanghai excavation.

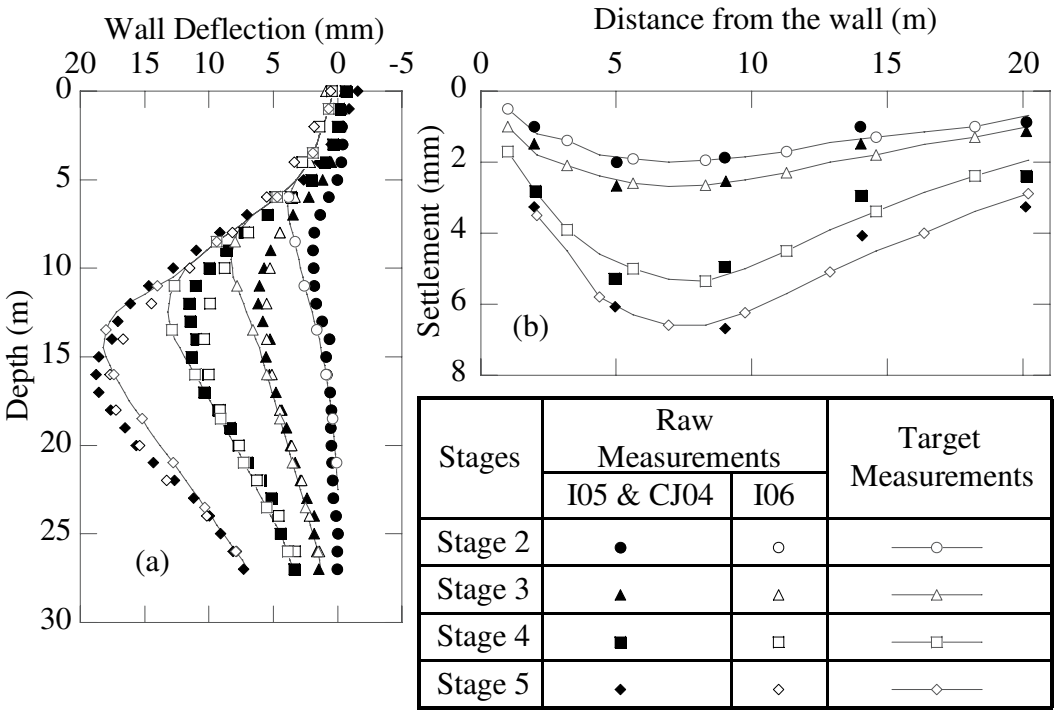


Figure 15. Original and target measurements for inverse analysis for a) lateral wall deflections of I05 & I06, and b) surface settlements CJ04, Shanghai excavation.

The construction sequence and wall length of excavation for clusters 1, 2, and 3 is illustrated in Figure 14. SelfSim learning is conducted using measurements of inclinometer I05, inclinometer I06, and settlement line CJ04 in cluster 1 to extract the underlying soil behavior. The measured deflections in the first excavation stage were not reported, hence the measurements of stages two to five are used for SelfSim learning. The extracted soil models are used in finite element analyses to predict the excavation response in clusters 2 and 3.

Figure 15 shows the reported measurements of inclinometers in Yishan Road station for inclinometer I05 & I06, and surface settlements CJ04 (Cluster 1, Figure 12). Inclinometer data of I05 and I06 are similar. Inclinometer I05 shows movements into the retained soil that cannot be explained by the idealized construction sequence shown in Figure 14. This movement might be due to unreported and thus unknown excessive pre-stressing of the bracing. Inverse analysis requires that appropriate cause and effect linkages exist between measurements and construction sequence. Therefore the target measurements used in the inverse analysis are adjusted to eliminate the slight outward movement of the wall (Figure 15). A continuous surface settlement profile is also developed from the reported measurements at discrete points (Figure 15).

Learning Soil Behavior from Measurements in Cluster 1

The support wall for the deep excavation is simulated using solid elements with a bending stiffness equivalent to that of 0.6 m thick concrete diaphragm wall. The soil profile in the analyses is represented with five NN material models to represent layers: (1) for top fill layer, (2) for medium clay, soft silty clay, and soft to medium clay between depths of 2 m and 15 m, (3) for medium clays between depths of 15 m and 18 m, (4) for stiff clays between depths of 18 m and 23 m, and (5) for stiff silty clays at depths below 23 m. The Shanghai deep excavation is modeled as 2D symmetric excavation with half width of 8.7 m. The model dimensions are 130 m and 70 m in horizontal and vertical directions, respectively.

The computed deformations prior to SelfSim learning significantly underestimate the measurements (Figure 16). SelfSim learning is then conducted using target measured wall deformations of inclinometer I05 & I06 and surface settlement points CJ04 (for locations see cluster 1 in Figure 12). Computed and target measured deformations of the excavation after six passes of SelfSim learning are shown in Figure 17. The difference between measured and computed deformations except for wall movements in the fifth stage of excavation, are generally less than 2 mm, which indicates a reasonable match. The lateral deformations in the fifth stage are underestimated.

The predicted pore water pressures at different depth at location PA1, located in cluster 1, are shown in Figure 18. No pore water pressure data was used in SelfSim learning. The trends of predicted dissipation of pore pressures are in general agreement with measured values for PA1.

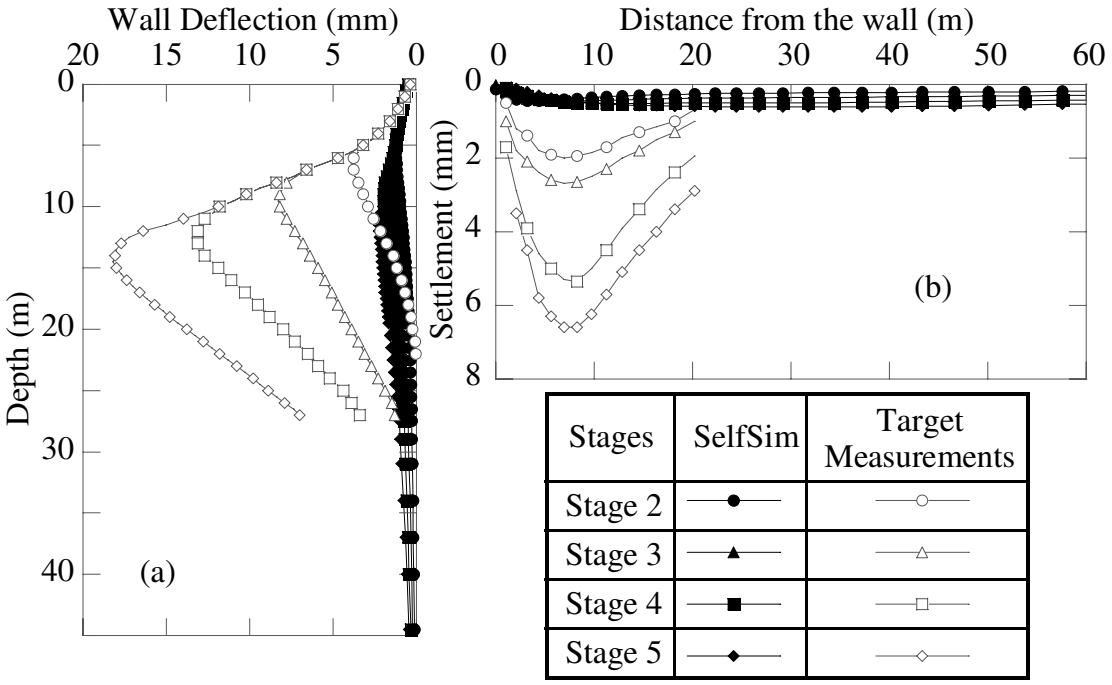


Figure 16. Computed deformations in Cluster 1 prior to SelfSim learning; a) wall deformations, and b) surface settlements, Shanghai excavation.

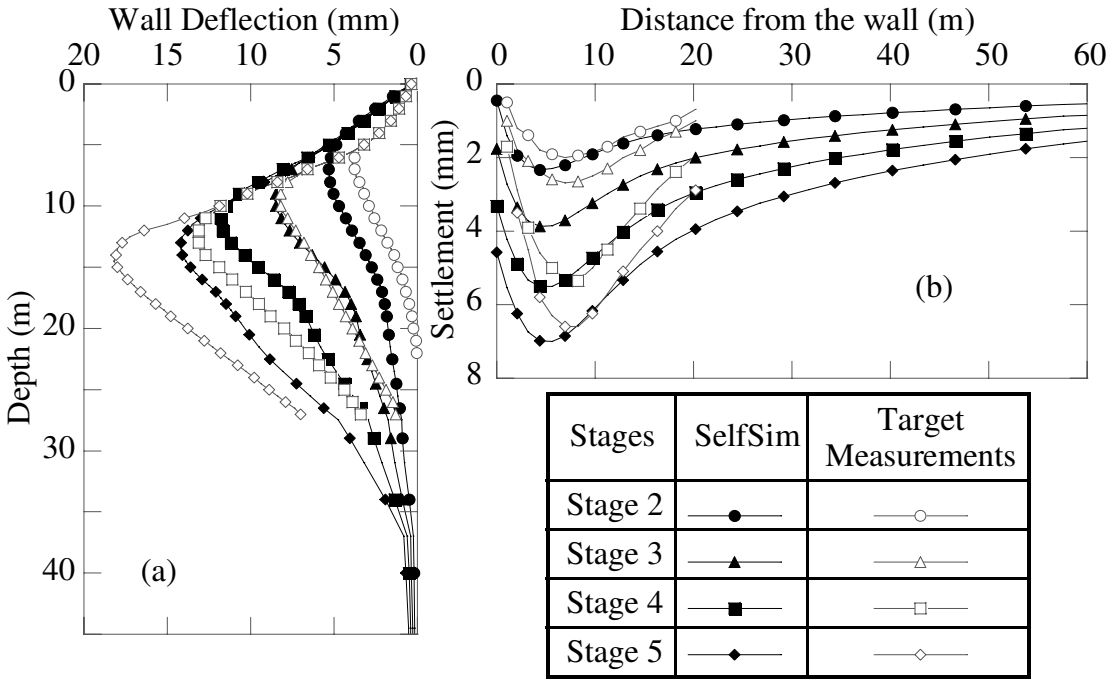
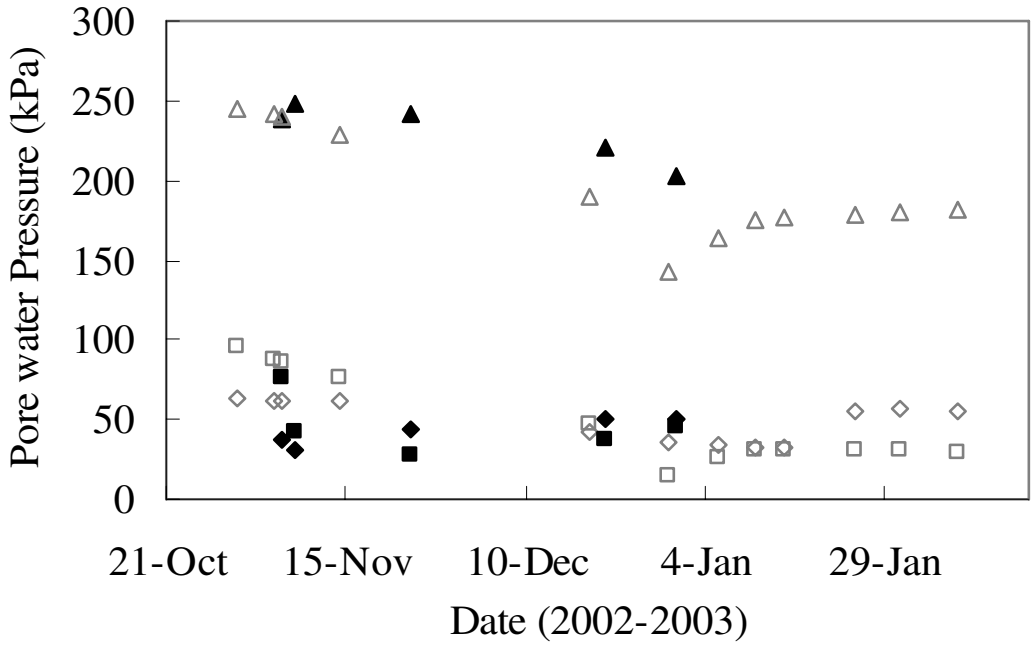


Figure 17. Computed deformations in Cluster 1 after six passes of SelfSim learning with Cluster 1 measured deformations; a) wall deformations, and b) surface settlements, Shanghai excavation.



Depth (m)	Predicted	Measured
7.25	◆	◇
10.5	■	□
25.5	▲	△

Figure 18. Comparison of predicted and measured pore water pressures for PA1 in cluster 1, Shanghai excavation.

Predicting Excavation Response in Clusters 2 and 3

The extracted soil models after SelfSim learning with measured wall deformations and surface settlements in Cluster 1, are used in finite element analyses to predict excavation response in Clusters 2 and 3 shown in Figure 12.

Prediction for Cluster 2

The predicted wall deformations of I03 and I09, and surface settlements CJ02 and CJ05 in cluster 2 are shown in Figure 19. The lateral deformations of I03 and I09 are less than the measured deflections of I05 and I06 due to use of middle slabs. The predicted wall deformations in stages 3 and 4 are in reasonable agreement with the measured deflections. The wall deflections and surface settlement for stage 5 are underestimated. It is unclear why a sudden increase in measured settlements occurred between Stage 4 & 5 which cannot be explained by the known construction sequence. It is possible that an unrecorded deviation from the construction sequence caused this sudden increase.

The predicted pore water pressures at PA2, cluster 2, at different depths is shown in Figure 20. There is a general agreement between measured and predicted porewater pressures.

Prediction for Cluster 3

The predicted wall deformations of I04 and surface settlements CJ06 in cluster 3 are shown in Figure 21. The lateral wall deflections for stages 3, 4, and 5 of the excavation match reasonably well with the measured values. The settlements also are in reasonable agreement with measured values for stages 3, 4 and 5. Measured settlements along line CJ06 don't show the large settlements at Stage 5 seen in Cluster 2 for lines CJ02 and CJ03 (see Figure 19).

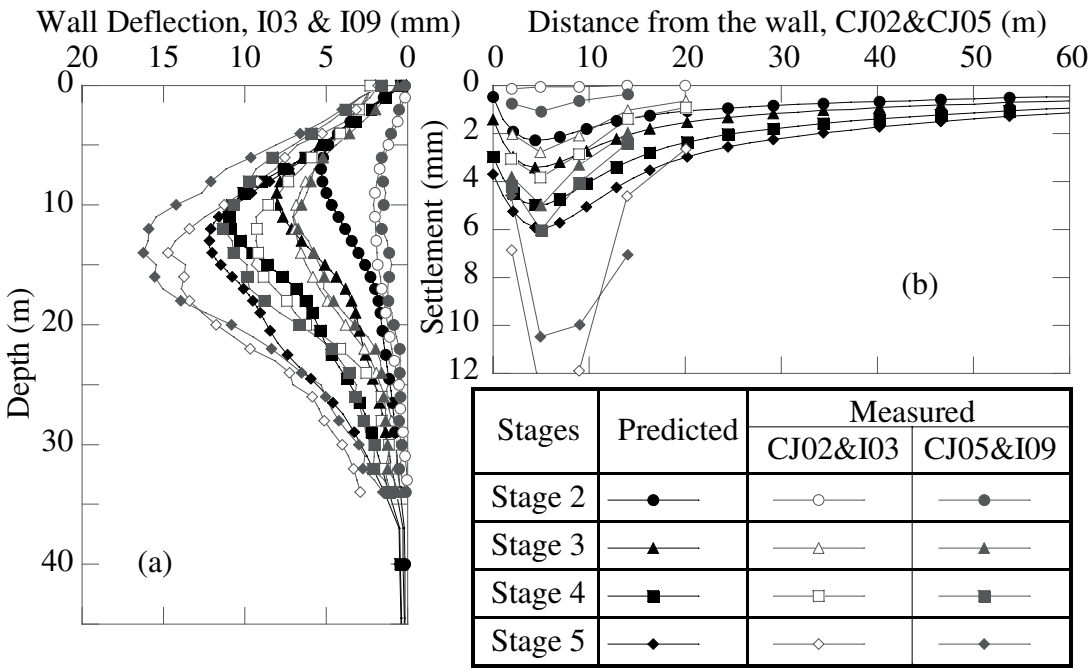


Figure 19. Predicted deformations in cluster 2 after six passes of SelfSim learning with Cluster 1 deformations; a) wall deformations (I03 and I09) and b) surface settlement CJ02 and CJ05, (middle slab was used), Shanghai excavation.

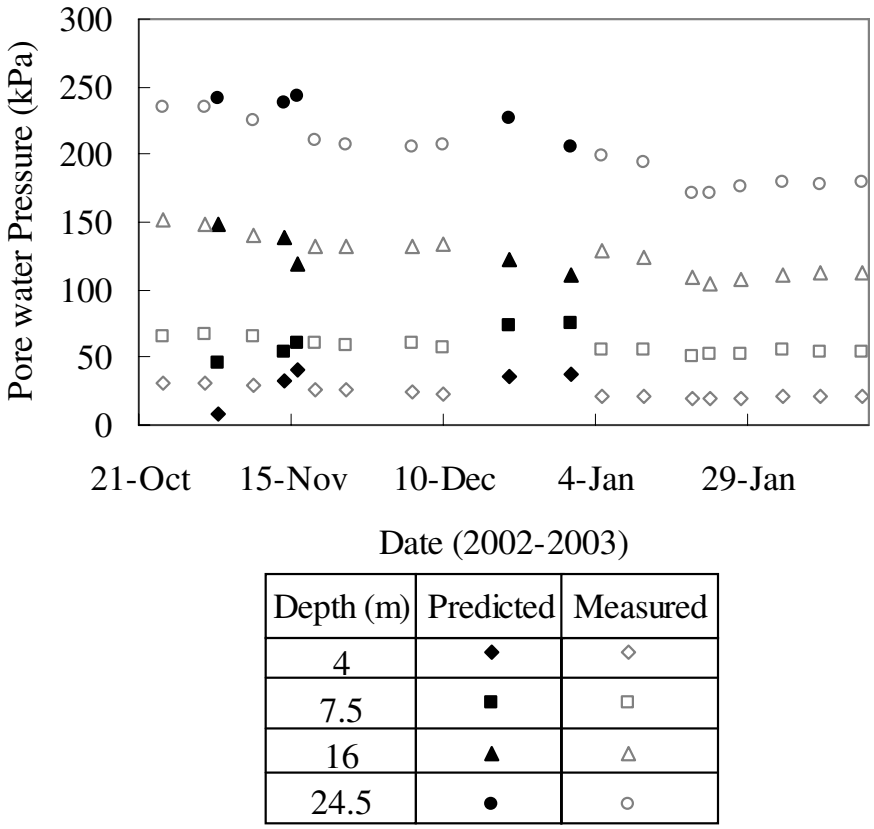


Figure 20. Comparison of predicted and measured pore water pressures for PA2 in cluster 2, Shanghai excavation.

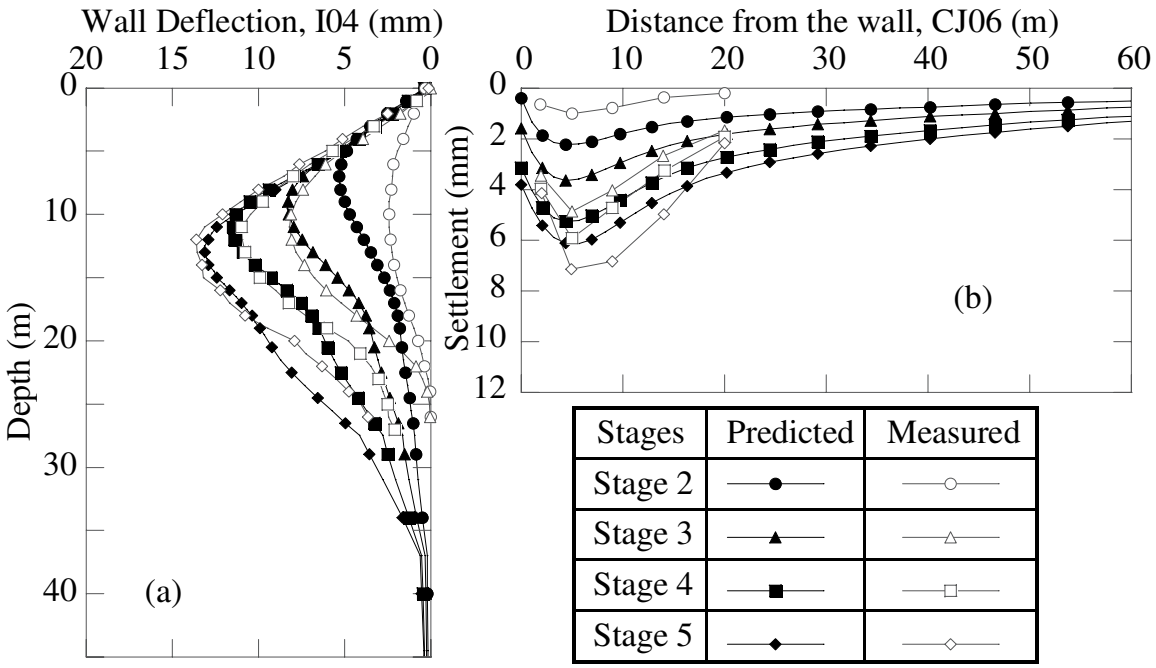


Figure 21. Predicted deformations in cluster 3 after six passes of SelfSim learning with cluster 1 deformations; a) wall deformations (I04) and b) surface settlement CJ06, (middle slab was used), Shanghai excavation.

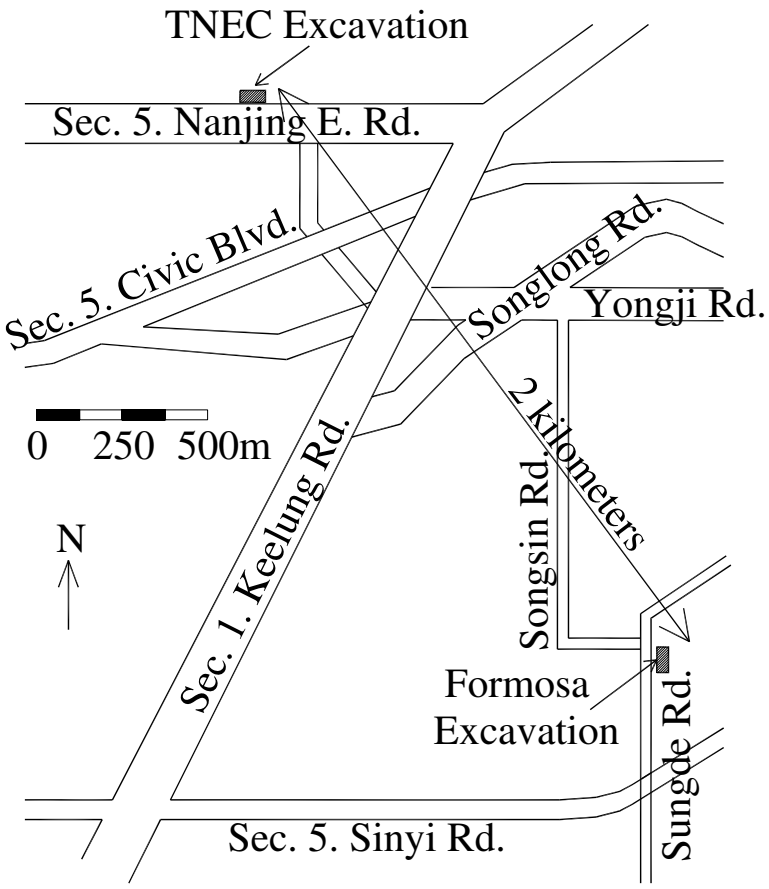


Figure 22. The location of TNEC and Formosa excavation sites in Taipei.

Two excavation sites in Taipei, shown in Figure 22, are employed in the inverse analysis and prediction exercise. The Taipei National Enterprise Center (TNEC) and Formosa deep excavation sites are about 2 kilometers apart. Inclinometer measurements from the TNEC excavation are used in SelfSim inverse analysis to extract the underlying soil behavior. The extracted soil models are then used in a finite element analysis to predict the performance of the Formosa deep excavation.

Site Description

TNEC Excavation Case Study

The Taipei National Enterprise Center (TNEC) is an 18-story building with five basement levels constructed using a top-down construction techniques (Ou et al., 1998). The site plan view which occupies an area of about 3500 m^2 is illustrated in Figure 23. The excavation site was extensively instrumented using earth pressure cells on the wall, rebar stress meters on the reinforcement cage, piezometers, inclinometers, heave gauges and settlement gauges.

A cross section of the excavation is shown in Figure 24. The excavation site consists of six layers of alternating silty clay and silty sand deposits overlying a thick gravel formation. The first and second layers consist of silty clay (CL) and silty sand (SM), respectively. The third layer is a 26-m-thick silty clay (CL), and it is mainly this layer that controls the excavation response. The fourth and fifth layers are medium dense fine sand and silty clay mixed with silty sand, respectively. A gravel formation is located 45 m below the ground surface. Prior to excavation, the ground water table was 2 m below the ground surface. A 90-cm-thick and 35-m-deep diaphragm wall was used as the earth-retaining structure. The construction sequence of TNEC excavation is shown in Figure 25.

Formosa Excavation Case Study

Figure 26 shows the plan view of the project and instrument locations (i.e. inclinometer and surface settlement points). The cross section of the wall and soil layers is shown in Figure 27. The soil profile is a typical soil profile of Taipei and consists of mainly clayey layers at the top 26 meters. Underneath the clay layer is a combination of silty sand and clayey silt followed by a gravel layer (Ou et al., 1993). The excavation is supported by a 31 m long wall and 0.8 m thick diaphragm wall braced by the struts at 3 m spacing. The ground water table is 2 m below the ground surface. The idealized construction sequence of the excavation is shown in Figure 28.

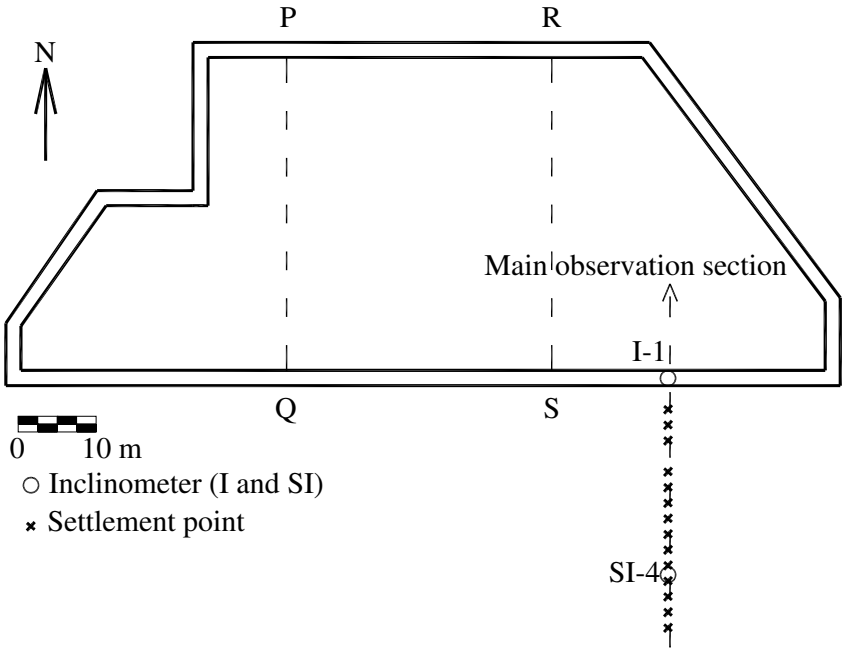


Figure 23. Plan view and instrument locations in TNEC excavation, modified after Ou et al. (1998).

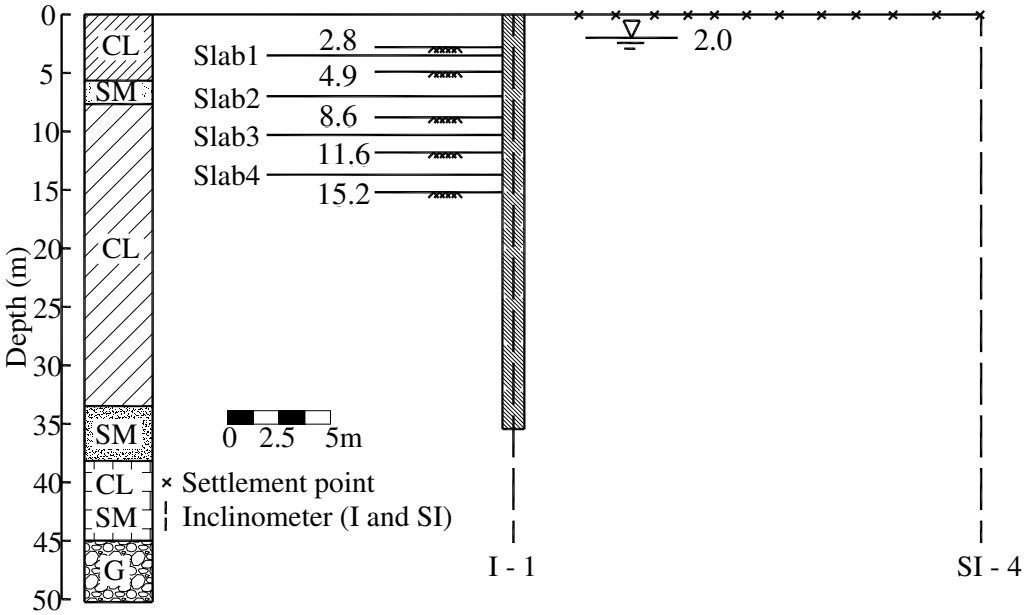


Figure 24. Excavation section view of TNEC excavation, modified after Ou et al. (1998).

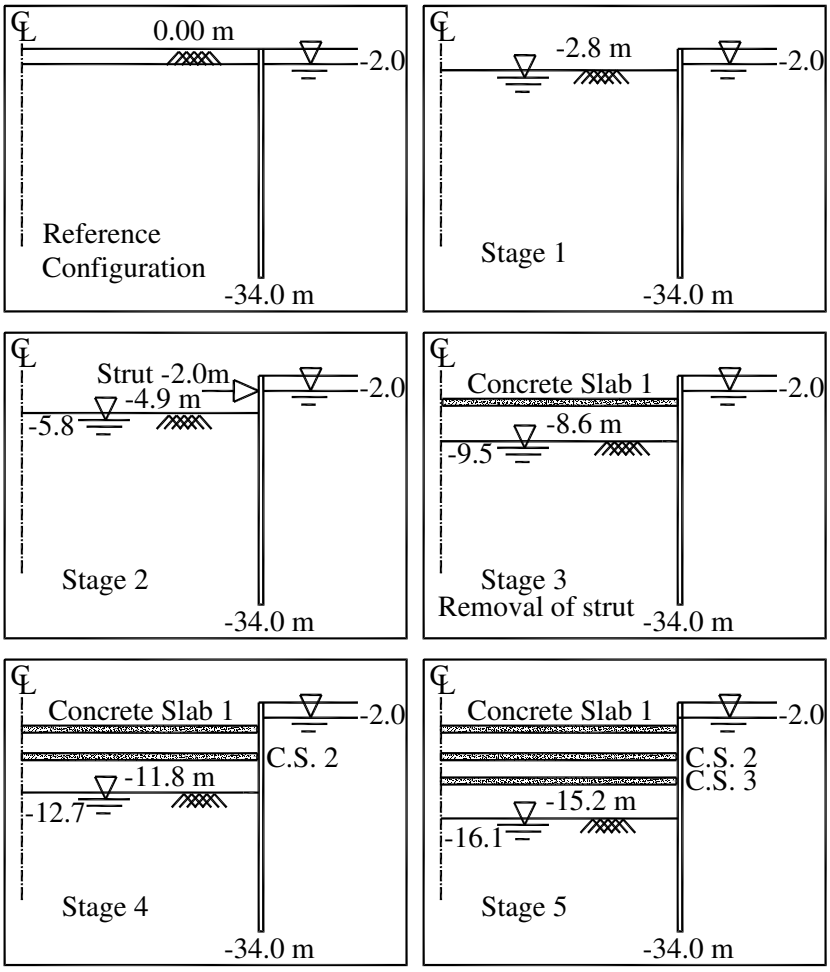


Figure 25. Excavation sequence in TNEC excavation in Taipei.

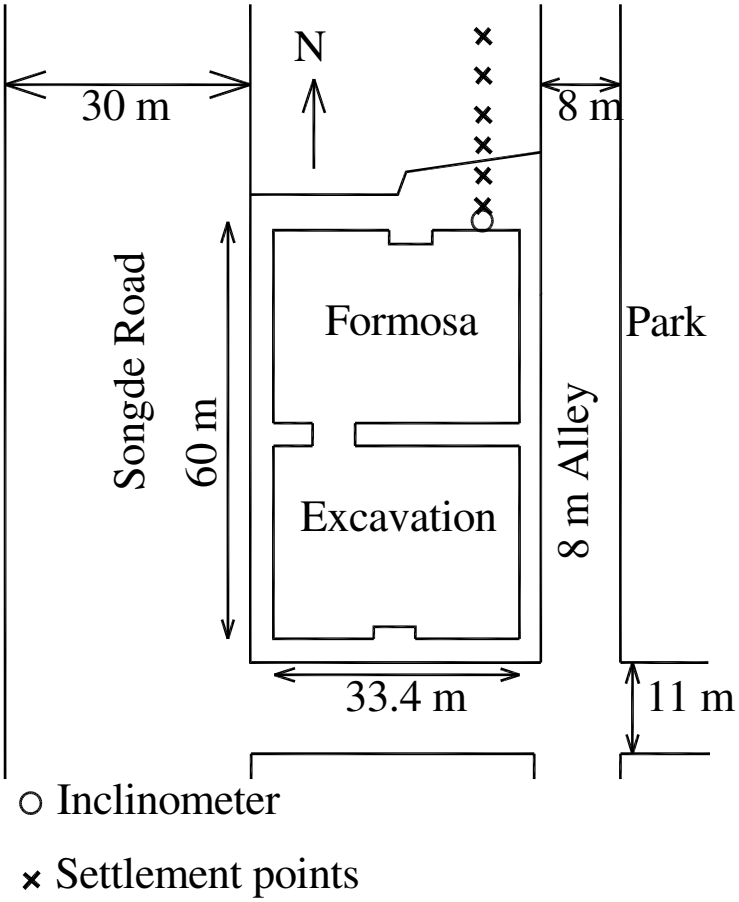


Figure 26. Plan view of Formosa excavation and instrument locations.

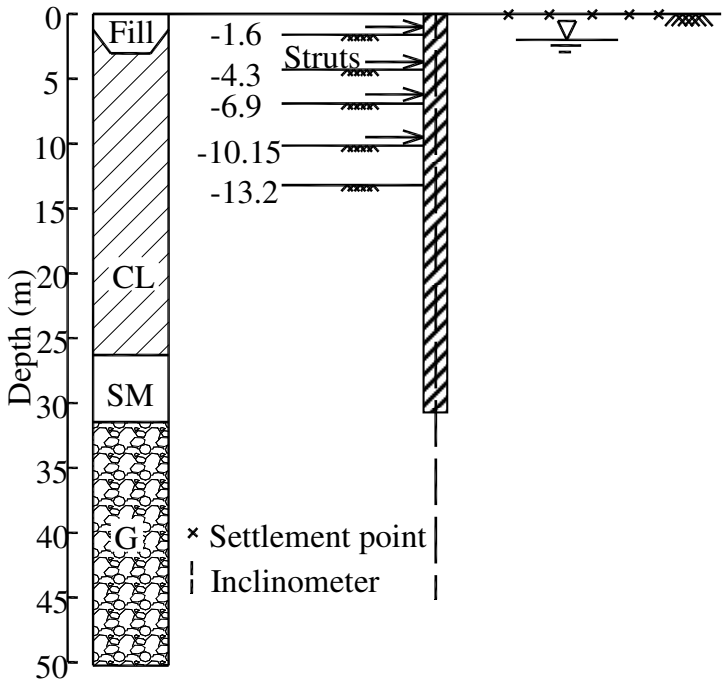


Figure 27. Cross section of the wall and soil layers in Formosa excavation.

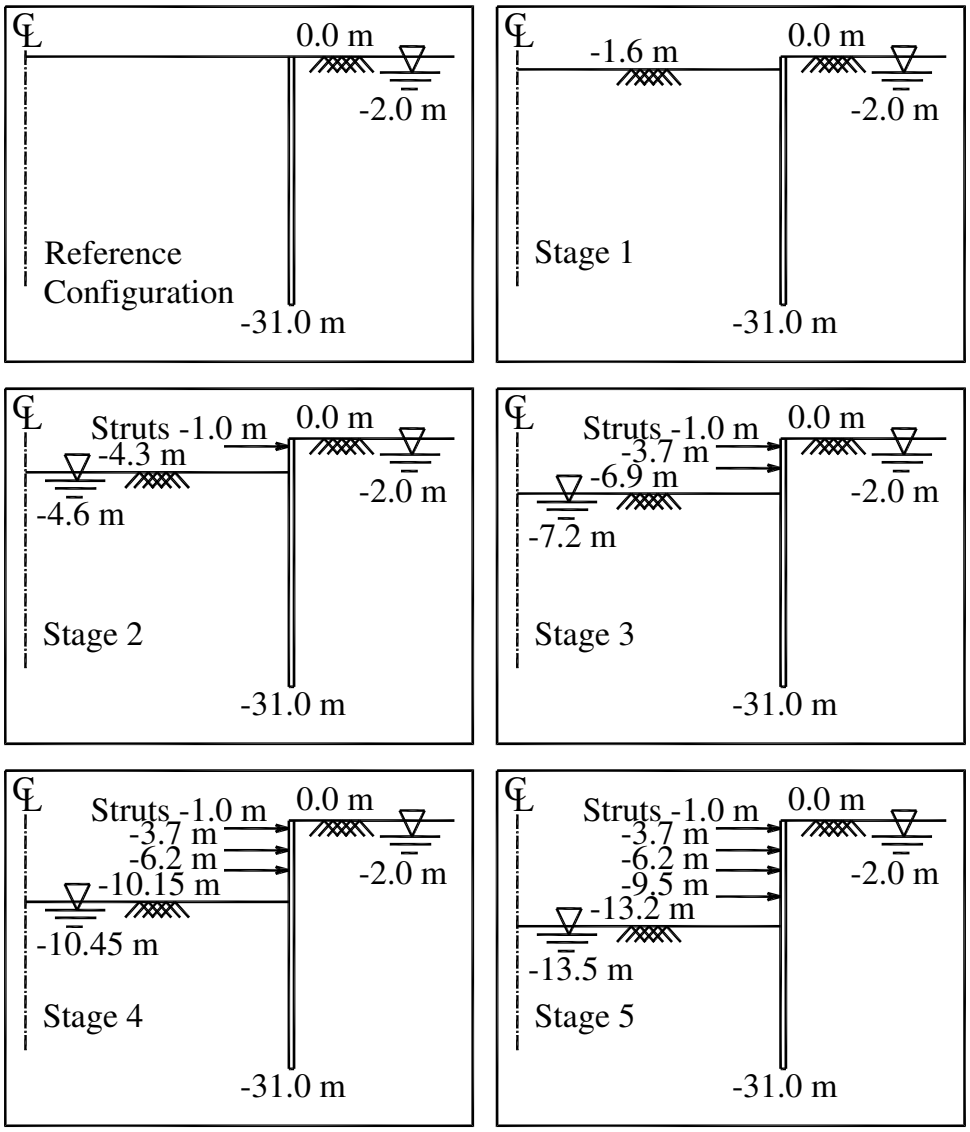


Figure 28. Construction sequence of Formosa excavation.

Learning Soil Behavior from Measurements of TNEC Excavation, Taipei

The support wall for the TNEC excavation is simulated using solid elements with a bending stiffness equivalent to that of a 90-cm-thick concrete diaphragm wall. The soil profile is represented with four NN material models to represent layers: (1) for top 6 m silty clay and 2 m silty sand (NN1-TNEC), (2) for silty clays between depths of 8 m and 16 m (NN2-TNEC), (3) for silty clays between depths of 16m and 24m (NN3-TNEC), and (4) for silty clays between depths of 24 m and 34 m (NN4-TNEC). Elastic material model with Young modulus of E = 16.6 MPa is assigned for soils below a depth of 34 m. TNEC excavation is modeled as a 2D symmetric excavation with a half width of 25 m. The model dimensions are 170 m and 70 m in horizontal and vertical dimensions, respectively.

A set of SelfSim analyses was conducted using wall deformation measurements (I-1) only (Osouli, 2009). SelfSim learning could not proceed beyond stage three of the excavation. This might be due to a limitation in the information contained in these additional stages. Therefore, inclinometer measurements SI-4, 22 m away from the excavation wall are added to the wall deformation measurements as part of further SelfSim learning down to the fifth excavation stage. Figure 29 shows the measured and predicted wall deformations, lateral deflections of inclinometer SI-4 and surface settlements after six passes of SelfSim learning. The computed lateral deformations of wall (I-1) and inclinometer SI-4 are in close agreement with the measured values. The settlements (not used in SelfSim learning) are also reasonably predicted.

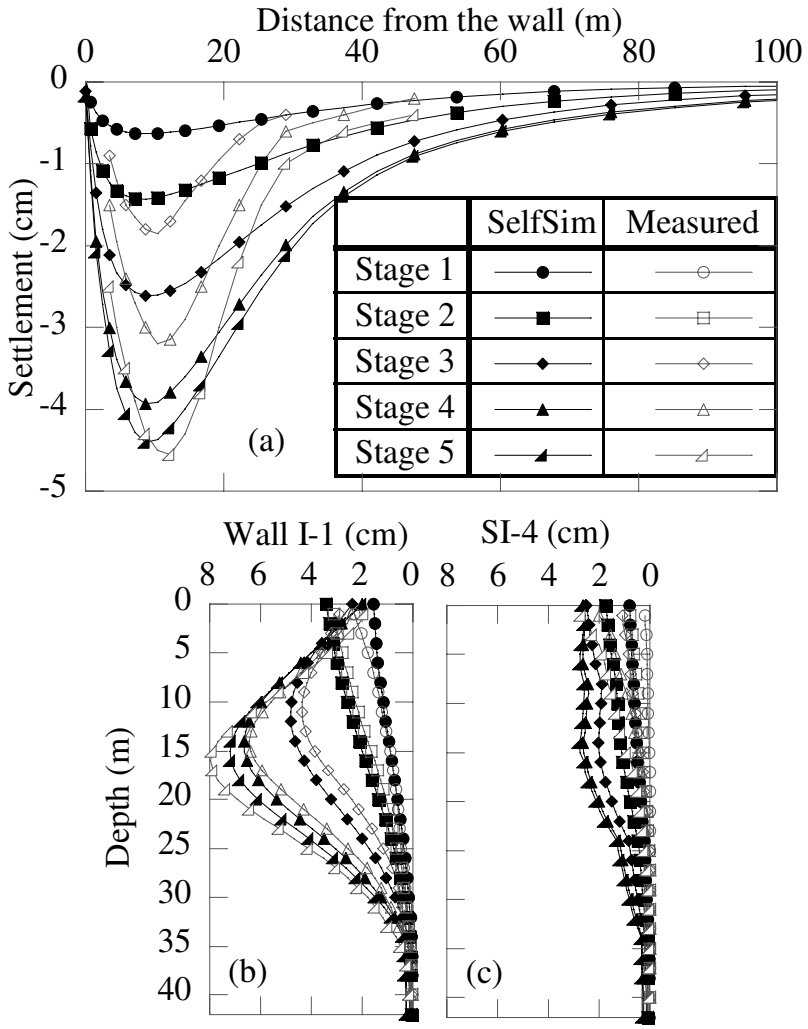


Figure 29. Computed response after six passes of SelfSim learning with wall deformations (I-1) and inclinometer SI-4 at 22 m distance from the wall, down to fifth stage of the excavation using the database of SelfSim learning with wall deformations only down to stage 3; (a) surface settlements, (b) wall deflections (I-1), (c) lateral movement at SI-4 in TNEC excavation.

Predicting the Excavation Response in Formosa Excavation, Taipei

The SelfSim extracted soil models from the TNEC exacation are used in a finite element analysis to predict the wall deflections and surface settlements in Formosa excavation.

The support wall for Formosa deep excavation is simulated using solid elements with a bending stiffness equivalent to that of a 0.8-m-thick diaphragm wall. The soil profile in the analysis is represented with three extracted NN material models from TNEC excavation. The represented soil layers are: (1) NN1-TNEC soil model for top 1 m fill, (2) NN2-TNEC soil model for clays between depth of 1 m and 12 m, (3) NN3-TNEC soil model of TNEC for clays between depth of 12 m and 26 m. An elastic material model with Young's modulus of E = 16.6 MPa is used for soil below 26 m. The Formosa deep excavation is modeled as a 2D symmetric excavation with half width of 15m. The model dimensions are 120 m and 70 m in horizontal and vertical dimensions, respectively.

Figure 30 shows the predicted and measured deformations of wall deflections and settlement points. The predicted wall deformations reasonably match the measured values. The surface settlements are also reasonably predicted up to 10 m from the wall but are slightly overestimated at farther distances from the wall. It should be emphasized that no measurements from the Formosa excavation case study were used in SelfSim learning and the computed values are true predictions.

The TNEC and Formosa case studies show a successful application of SelfSim learning whereby extracted soil behavior from an excavation site provides a reasonable prediction of wall deformations and surface settlements at another excavation site with similar soil stratigraphy.

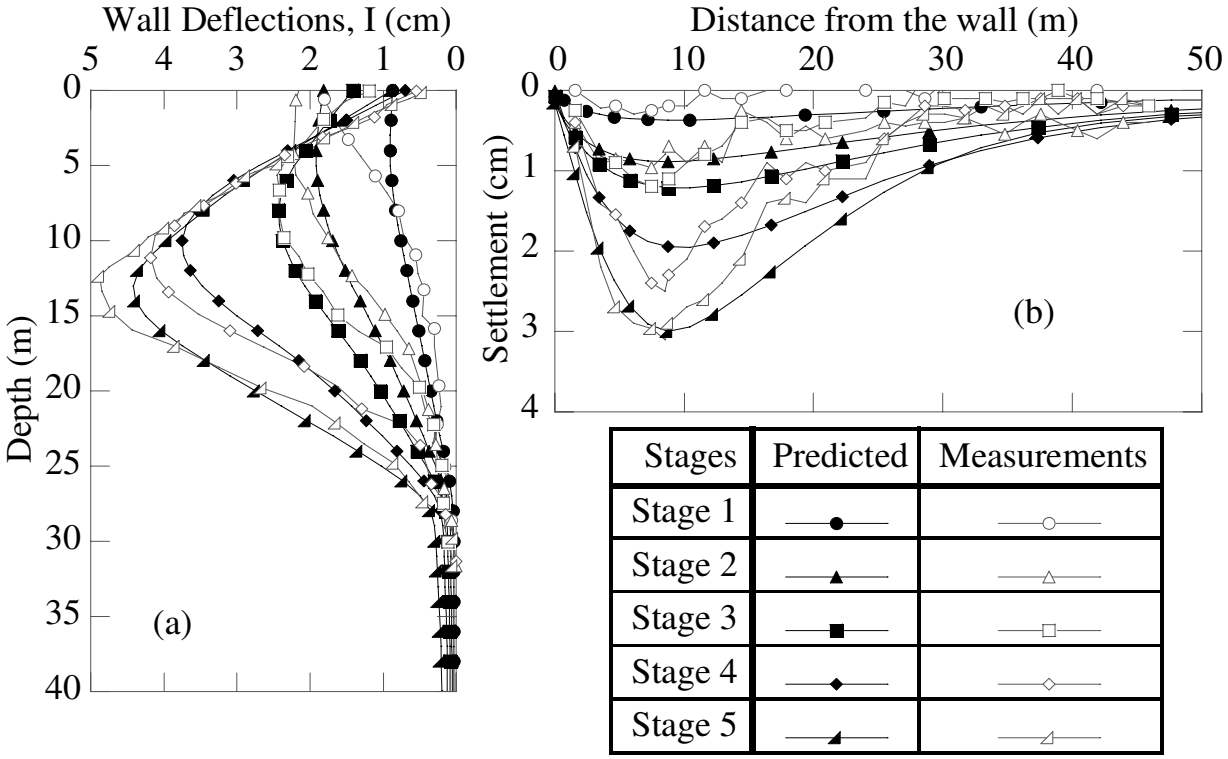


Figure 30. Predicted and measured excavation response for a) lateral wall deflections, b) surface settlements in Formosa excavation.

CONCLUSIONS

This paper demonstrates that inverse analysis can be a suitable approach to predict the excavation performance in urban areas after learning from precedent case histories or local experience.

The extracted soil behavior from the two-level tieback section of the wall in the Texas A&M case study in sandy soil could reasonably predict wall deformations and lateral deformations at distances from the wall by one-level tieback section of the wall. The extracted soil behavior from instrument measurements in cluster 1 of the Yishan Road metro station case study provides a reasonable prediction of wall deformations and surface settlements in clusters 2 and 3 along the 335 m length of the station. Predicted pore water pressures are in agreement with the measured values. Use of extracted soil behavior from TNEC project to predict the excavation behavior in Formosa case study in soft clays of Taipei shows a successful application of SelfSim framework whereby excavation performance can be predicted after learning from a precedent.

While the SelfSim inverse analysis approach provides significant flexibility in learning soil behavior beyond more conventional model calibration approaches it has some limitations that require further development. The analyses can be time consuming and require significant user expertise. The initialization of the evolutionary material models require care to ensure that they represent reasonable material behavior. The overall robustness of the approach can be improved by further application of the approach to additional case histories in addition to development of software tools to make it user friendly. The paper highlights the importance of having reliable measurements that can be clearly related to specific construction activities (cause and effect). Therefore it is not sufficient to rely on measurements of quantities such as deformations and pressures, but there is a need to develop a detailed record of construction.

In the future, the proposed inverse analysis approach can be used with available measurements to develop numerical and soil models with "local experience". Available excavation performance data sets can be used to develop area-specific soil models. The developed soil models can be used to provide acceptable predictions of excavation-induced ground deformations for new excavations constructed in these locals.

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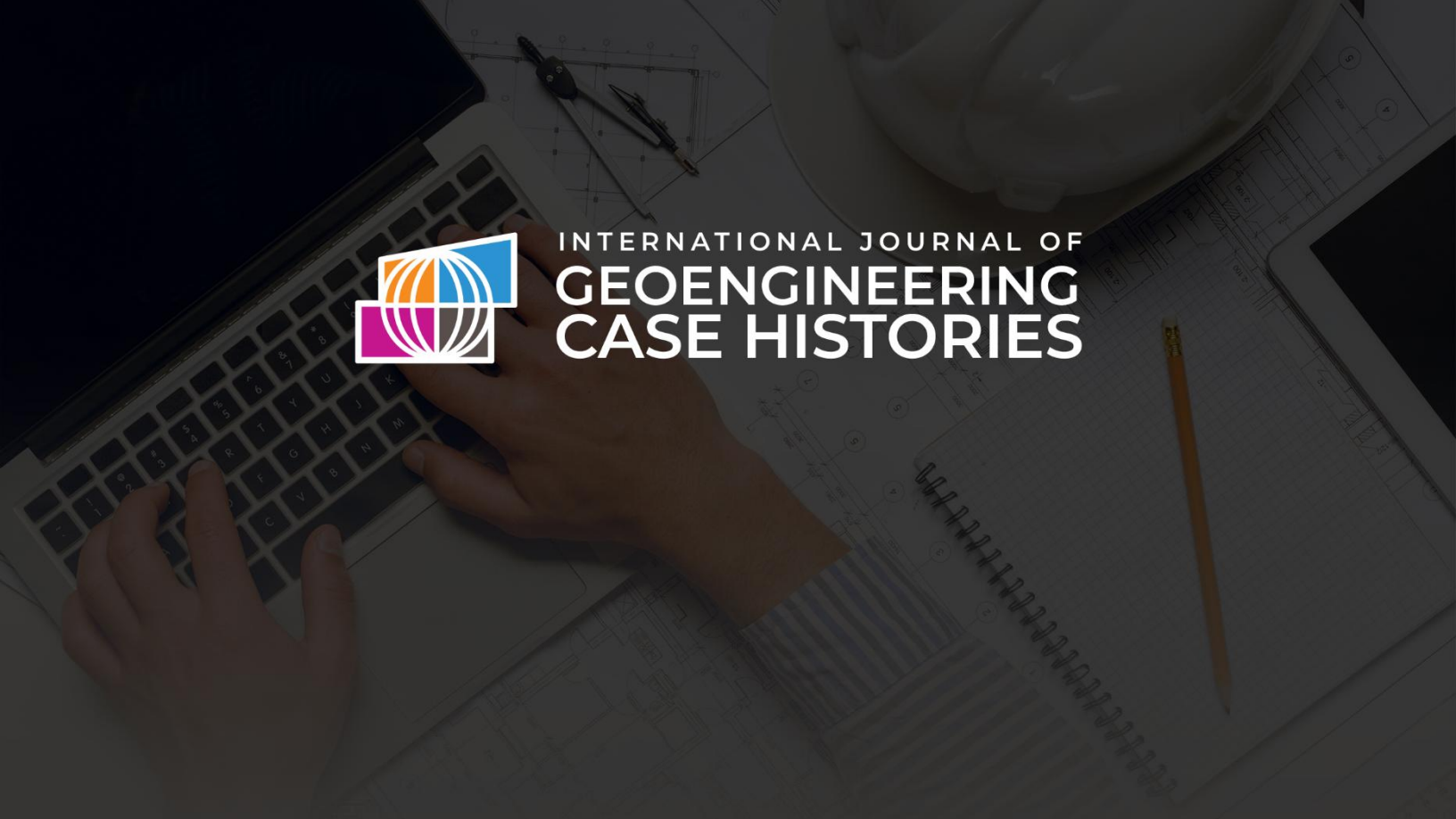
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