Transport and Communications Science Journal, Vol. 77, Issue 7 (09/2026), 955-964

Transport and Communications Science Journal

APPLICATION OF FINITE ELEMENT MODELING AND DEEP LEARNING FOR DISPLACEMENT ESTIMATION IN DEEP EXCAVATIONS

Thanh Sang To*, Tran Kien Tuong

University of Architecture Ho Chi Minh City, Ho Chi Minh City, Vietnam

ARTICLE INFO

TYPE: Research Article
Received: 10/02/2026
Revised: 21/05/2026
Accepted: 10/06/2026
Published online: 15/09/2026
https://doi.org/10.47869/tcsj.77.7.6
* *Corresponding author*
Email: sang.tothanh@uah.edu.vn

Abstract. Accurately predicting excavation-induced displacements remains a critical challenge in geotechnical engineering due to the inherent risks and complex soil-structure interactions during construction. To address this problem, this study proposes a hybrid predictive framework that integrates Finite Element Model (FEM) with Deep Neural Networks (DNN), called DNN-FEM. Initially, parametric simulations are conducted using commercial software in geotechnics, PLAXIS 2D, to simulate various deep excavation scenarios and generate a robust numerical dataset. This dataset is subsequently partitioned, allocating 80% of the data to train the DNN architecture and the remaining 20% to evaluate its predictive performance. The results demonstrate a high degree of agreement between the DNN-predicted displacements and the FEM-calculated values across both the training and independent test sets, as evidenced by R^2 coefficients exceeding 0.99. Ultimately, this research demonstrates that the proposed DNN-FEM approach provides a highly accurate and computationally efficient tool for estimating Diaphragm Wall (DW) and soil displacements in deep excavation projects.

Keywords: Deep Learning, Finite Element Method, Deep Excavation, Diaphragm Wall

1. INTRODUCTION

Underground construction projects generally exhibit higher complexity and are significantly more susceptible to unexpected failures compared to superstructures. Both objective environmental conditions and subjective operational factors remain challenging to control during the design and construction phases. The involvement of highly variable, complex geotechnical parameters further complicates accurate risk assessment. As highlighted by Pan et al. [1], deep excavations pose substantial potential risks to adjacent structures and critical infrastructure.

The design of deep excavations necessitates careful consideration of various soil-structure interaction mechanisms, alongside specific issues related to construction sequencing and soil mechanics. With the rapid advancement of modern computational methods, particularly the Finite Element Method (FEM), the analysis of complex geotechnical problems has been significantly enhanced. Numerous scholars have successfully employed FEM to evaluate the performance of specific excavation scenarios [2-5]. While FEM serves as a highly effective and rigorous design tool, it is imperative to ensure that the numerical model is constructed with an appropriate level of detail. By utilizing FEM, engineers can thoroughly investigate the underlying failure mechanisms of deep excavations, thereby proposing safer and more efficient construction methodologies.

For instance, Do et al. [2] investigated four distinct failure mechanisms of deep excavations using FEM combined with the shear strength reduction (SSR) method, which effectively clarified the root causes of failure during construction. Meanwhile, Dong et al. investigated the required level of detail in finite element models to accurately capture the realistic wall deflections and ground settlements observed during the construction process. However, despite the robust analytical capabilities of FEM, these simulations are highly resource-intensive and computationally expensive. Furthermore, the numerical results computed for one specific project cannot be directly reused or generalized for new excavation geometries or varying geological profiles.

To overcome these computational bottlenecks, the advent of artificial intelligence (AI) has introduced several powerful predictive approaches. Recently, the integration of machine learning algorithms, optimization techniques, and FEM-generated synthetic data has gained considerable traction in geotechnical engineering [6-11]. For example, Wu et al. [12] proposed a predictive framework utilizing recursive feature elimination within a Random Forest algorithm, coupled with Bayesian optimization. Similarly, [13] presented an integrated framework combining in-situ test-based numerical models with data-driven algorithms to evaluate the performance of deep tunnel systems.

Whereas a calibrated framework that integrates 3D modeling using PLAXIS with Genetic algorithm for estimating soil–pile interaction, as proposed by To et al. [5]. Le et al. [14] used FEM updating technique implemented via MATLAB, which interfaced with ETABS software through its Open Application Programming Interface. Subsequently, the authors introduced a surrogate model constructed from the generated FEM data and a deep neural network.

Recognizing the outstanding advantages and synergistic potential of these hybrid computational approaches, this research is dedicated to developing a robust Deep Neural Network architecture specifically designed to predict the lateral displacement of retaining walls induced by deep excavation processes. To achieve this, the study capitalizes on a comprehensive, high-fidelity dataset generated through rigorous FEM simulations, which effectively capture the complex, non-linear soil-structure interactions inherent in geotechnical engineering.

The primary objective of this work is to establish a highly efficient surrogate modeling technique that acts as a reliable surrogate model for traditional FEM analyses. Conventional finite element modeling, while structurally accurate, is notoriously computationally expensive and time-consuming, particularly when iterative evaluations are required for complex ground conditions. By effectively training the DNN on a carefully curated subset of FEM results, the proposed surrogate model aims to drastically minimize the number of direct calls to the computationally intensive FEM software. Crucially, this substantial reduction in computational burden is achieved without compromising the predictive accuracy of the model. The developed DNN surrogate is engineered to preserve the stringent levels of reliability and fidelity strictly required for complex subsequent geotechnical assessments, such as reliability-based design, parametric optimization, or risk analysis during construction phases.

The remainder of this paper is structured into five sections. In which Section 1 serves as the introduction. Section 2 outlines the overall methodology of the proposed framework. Section 3 details the development of the FEM numerical model using PLAXIS 2D. Section 4 describes the architecture and hyperparameters of DNN. Section 5 presents and discusses the predictive results, and finally, Section 6 provides the concluding remarks.

2. METHODOLOGY

Figure 1 depicts the proposed methodological framework for this research. A Deep Neural Network architecture is developed via Python, utilizing input features (X) and target outputs (Y) derived directly from parametric PLAXIS simulations. By training the DNN on this numerically generated dataset, the model is calibrated to predict excavation-induced displacements.

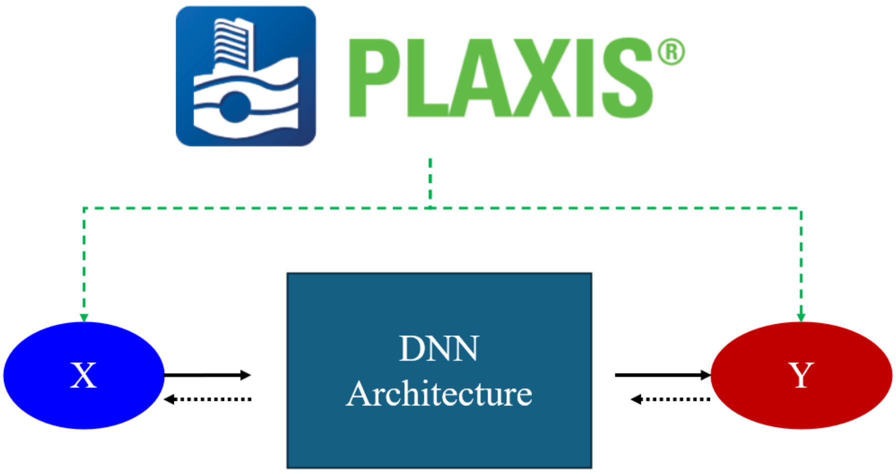

Figure 1. Proposal framework.

3. PLAXIS AND DATA

This section focuses on the simulation and data preparation processes for the deep learning model. Initially, Section 3.1 details the application of PLAXIS software to conduct geotechnical simulations aimed at replicating three-dimensional soil-pile interactions. Subsequently, Section 3.2 outlines the extraction and preprocessing of data derived from these simulation results. The dataset is then partitioned into training and testing subsets to facilitate the development and evaluation of the deep neural network.

3.1. PLAXIS Simulation

This study investigates a submerged deep excavation adjacent to a river, designed to facilitate the installation of immersed prefabricated tunnel segments [15]. The proposed excavation spans 30 m in width and reaches a final depth of 20 m. Given its extensive longitudinal dimension, the problem is analysed under plane strain conditions. Exploiting the inherent geometric symmetry, only half of the cross-section is explicitly simulated to optimize computational efficiency (see Figure 2). The lateral earth support system comprises 30 m deep diaphragm walls, which are braced by horizontal struts spaced at 5 m longitudinal intervals. Adjacent to the pit, a surface surcharge of 5 kPa is applied, extending from a setback distance of 2 m up to 7 m from the wall. The localized stratigraphy consists of an upper 20 m thick deposit of soft soil, simplified as a homogeneous clay layer, overlying a stiff sand stratum that extends to an evaluated depth of 30 m below the clay interface. The detailed geological profiles and soil properties are summarized in Table 1.

Table 1. Detailed soil properties [15].

Engineering geological characteristics	Clay_layer	Sand_layer	Unit
Model	Hardening Soil	Hardening Soil	-
Type	Undrained (A)	Drained	-
γ_{unsat}	16.0	17.0	kN/m³
γ_{sat}	18.0	20.0	kN/m³
c'_{ref}	1.0	0.0	kN/m²
φ'	25.0	32	°
ψ	0.0	2.0	°
ν'_{ur}	0.15	0.20	-
$K0_{nc}$	0.577	0.470	-
k_x	0.001	1.0	m/day
k_y	0.001	1.0	m/day
R_{inter}	0.5	0.67	-
OCR	1.0	1.0	-
POP	5.0	0.0	kN/m²

In the numerical simulation, the diaphragm wall is numerically simulated using isotropic, linear elastic plate elements. The structural capacity of the wall is governed by an assigned axial stiffness (EA_1) of 7.5×10^6 kN/m and a bending stiffness (EI) of 1.0×10^6 kNm²/m. Additionally, the wall element is defined with a unit weight (w) of 10 kN/m/m. The horizontal struts are modeled as linear elastic components. The structural response of these bracing elements is governed by an assigned axial stiffness (EA) of 2.0×10^6 kN. Furthermore, to appropriately account for their discrete longitudinal distribution within the two-dimensional plane strain framework, an out-of-plane spacing ($L_{spacing}$) of 5 m is specified for the strut elements.

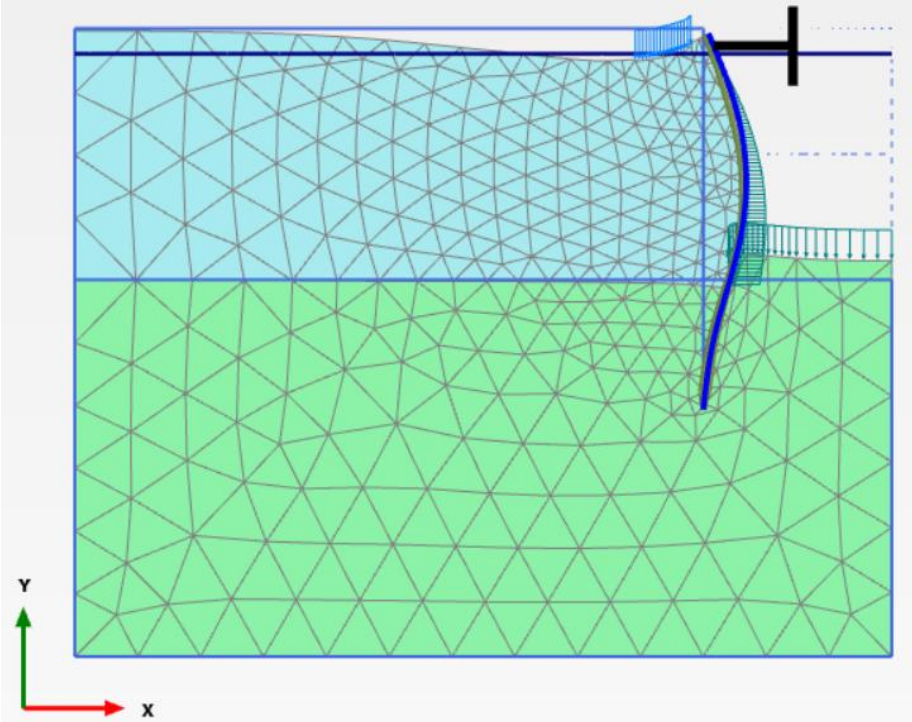

Figure 2. PLAXIS for simulating deep excavation.

Numerically, the construction sequence is phased into three distinct excavation stages as shown in the Table *2*. The diaphragm wall is discretized using plate elements, while soil-structure interaction is captured via interface elements on both sides of the wall, allowing for the specification of a reduced soil-wall friction coefficient. Finally, the horizontal struts are simulated as spring elements governed by a predefined normal stiffness.

Table 2. Excavation stages.

Excavation stages	Describe
First excavation stage	Excavate from the natural ground surface to -2m
Second excavation stage	Excavate from -2m to – 10m
Third excavation stage	Excavate from -10m to – 20m

3.2. Data for training and testing DNN

In the Hardening Soil model, soil stiffness is governed by three fundamental parameters Secant stiffness in standard drained triaxial test (E_{50}^{ref}), Tangent stiffness for primary oedometer loading (E_{oed}^{ref}) and Unloading / reloading stiffness (E_{ur}^{ref}). Because these parameters significantly influence the deformation response of the diaphragm wall, they are selected as the primary variables to investigate soil-structure interaction.

To generate a robust dataset for the machine learning phase, the Finite Element Method (FEM) model described in the previous subsection is employed. A parametric study is conducted by systematically varying the stiffness properties of the upper clay layer, encompassing 50 distinct numerical scenarios with values ranging from very soft to stiff clay. For each scenario, the FEM model computes the corresponding lateral displacements of the diaphragm wall.

Within the Deep Neural Network architecture, these stiffness parameters serve as the input features, while the computed wall displacements are utilized as the target outputs. Finally, the compiled dataset is partitioned, allocating 80% of the data to train the DNN and the remaining 20% to validate its predictive efficacy.

4. ARCHITECTURE OF DNN

Figure 3 illustrates the architecture of the deep neural network utilized in this study. The network comprises three primary sections: an input layer, multiple hidden layers (denoted by the blue circles in Figure 3), and an output layer. The signal propagation through the DNN is governed by activation functions [16-19]. While various activation functions exist with different output ranges and applications, the Sigmoid function has been widely verified as effective for a broad range of predictive problems. Consequently, this study employs the Sigmoid function as the primary activation function for the network. In this study, DNN architecture with 3 hidden layers, each layer consisting of 5 neurons, is adopted.

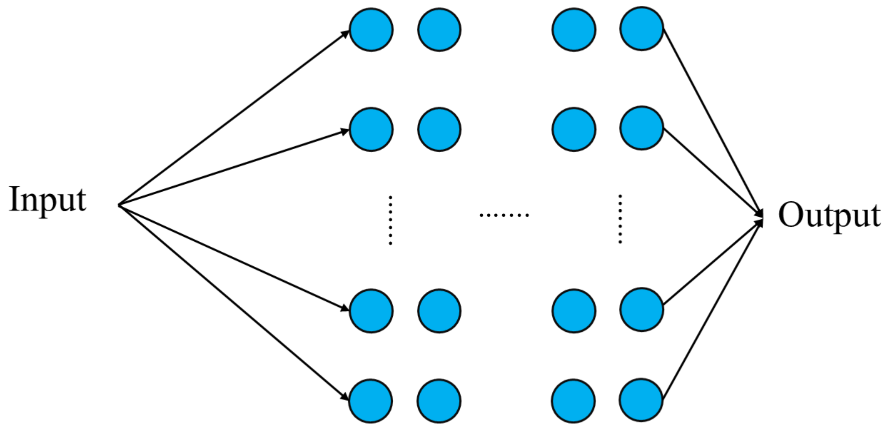

Figure 3. Deep Neural Networks.

The predictive efficacy of the proposed model is quantitatively assessed using the coefficient of determination R^2), root mean square error ($RMSE$), and mean absolute error (MAE), as formulated in Equations (1) to (3).

$$R^2 = 1 - \frac{\sum\left(Y_i - \hat{Y}\right)^2}{\sum(Y_i - \bar{Y})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{3}$$

Where Y_i represents the true target values derived from the numerical FEM simulations, $\widehat{Y_i}$ represents the predicted values generated by the DNN, $\bar{Y}$ is the mean of the true values, and n is the total number of samples.

5. RESULTS AND DISCUSSION

Figure 3 presents the statistical performance metrics for both the training and testing phases of the DNN. The evaluation is based on three primary coefficients. Specifically, the model yields an $RMSE$ of Value and an MAE of 2.18 during the training phase, compared to 6.53 and 3.02, respectively, during the testing phase. These relatively low error margins indicate that the DNN operates stably without significant overfitting. Furthermore, the coefficient of determination (R^2) reaches 0.996 for the training set and 0.999 for the testing set. These values demonstrate that the DNN accurately estimates the lateral displacement of the diaphragm wall, showing a high degree of agreement with the FEM computations.

Table 3. Statistical metrics for train and test.

Statistical metrics	R^2	$RMSE$	MAE
Train	0. 9963	4.081	2.177
Test	0.9992	6.533	3.015

Figure 4 illustrates a comparative scatter plot of the DNN-predicted displacements against the FEM-computed results. The vertical axis represents the predicted values generated by the DNN, whereas the horizontal axis denotes the "true" target values derived from the numerical FEM simulations. The data points are visually categorized: blue circles denote the training set, while green circles represent the testing set. Additionally, a red reference line (representing the ideal 1:1 fit) is plotted to benchmark the accuracy of the predictions. The tight clustering of both datasets along this red line further visually validates the predictive reliability of the proposed DNN model.

The dataset encompasses a broad range of geological conditions, transitioning from very soft to stiff clay, which corresponds to diaphragm wall displacements spanning from approximately 68 mm to 272 mm. Across this extensive parameter space, the predictive performance of the Deep Neural Network was highly accurate. During the training phase, the model achieved an R^2 value of 0.996, indicating a strong agreement between the DNN predictions and the Finite Element Method (FEM) computations. This high level of accuracy is visually corroborated by the data points clustering tightly along the 1:1 reference line. Although minor deviations exist, Figure 4 demonstrates that these errors are negligible and well within acceptable engineering tolerances for complex geotechnical applications.

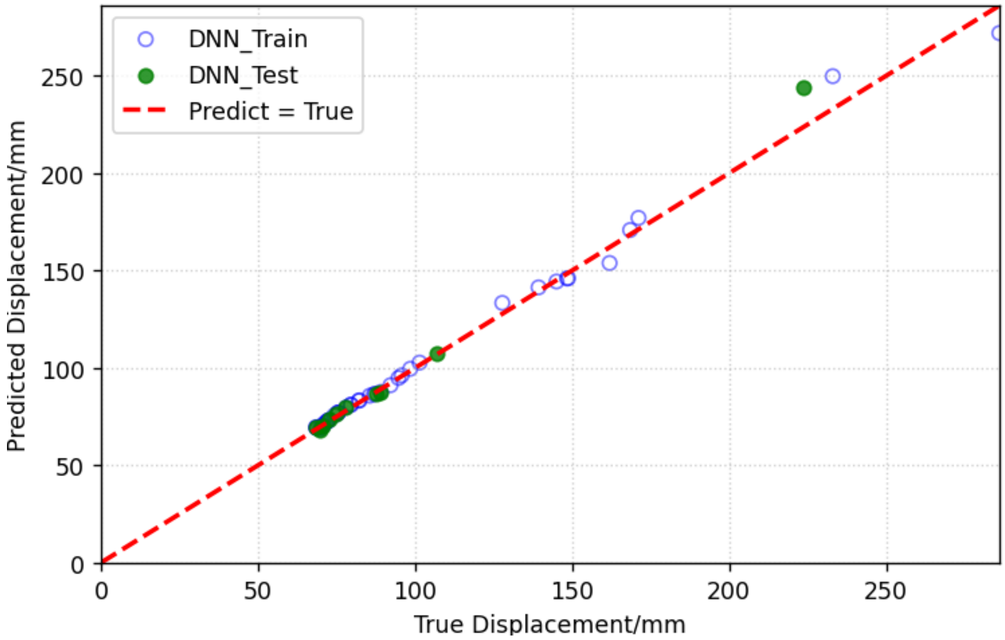

Figure 4. DNN training and testing results.

Regarding the testing set, the model yielded slightly lower values for the RMSE and MAE indices compared to the training phase; however, the R^2 metric indicates that the multi-layer DNN architecture achieved an exceptional fit with the unseen data. Specifically, the model attained an R^2 of 0.999 on the test set, surpassing the 0.996 achieved during training. This performance clearly indicates that the network successfully avoided overfitting and generalized effectively to independent cases. Furthermore, predictions on randomly selected test samples exhibited excellent agreement with the baseline Finite Element Method (FEM) computations. Ultimately, these findings underscore the robustness and efficacy of the proposed deep learning framework for predicting retaining wall displacements in deep excavations.

6. CONCLUSION

This study presents a framework integrating DNN and data from FEM. Based on results obtained herein, several conclusions can be drawn:

In the context of deep excavation design, the coupled DNN-FEM approach emerges as a powerful and highly efficient tool for addressing complex geotechnical challenges. By leveraging rigorous FEM simulations for data generation, the trained DNN model demonstrates exceptional predictive accuracy.

The specific deep learning architecture developed in this study successfully mitigated overfitting, delivering highly reliable performance across both the training and testing datasets. The excellent performance metrics achieved, such as R^{2}, validate the accuracy of the proposed approach, confirming its suitability as a highly efficient replacement for computationally intensive FEM simulations

This research highlights the significant potential of the proposed DNN-FEM framework, paving the way for its application to a broader range of complex geotechnical engineering problems in the future.

ACKNOWLEDGMENT

This research is funded by University of Architecture Ho Chi Minh City under grant number NCKH25-XD05.

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