Geomechanics and Engineering, *Vol. 34, No. 3 (2023) 329-339*
https://doi.org/10.12989/gae.2023.34.3.329

Development of stability evaluation system for retaining walls: Differential evolution algorithm–artificial neural network

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(*Received March 23, 2023, Revised June 22, 2023, Accepted July 14, 2023*)

Abstract. The objective of this study is to develop a Stability Evaluation System for retaining walls to assess their safety in real-time during excavation. A ground investigation is typically conducted before construction to gather information about the soil properties and predict wall stability. However, these properties may not accurately reflect the actual ground being excavated. To address this issue, the study employed a differential evolution algorithm to estimate the soil parameters of the actual ground. The estimated results were then used as input for an artificial neural network to evaluate the stability of the retaining walls. The study achieved an average accuracy of over 90% in predicting differential settlement, wall displacement, anchor force, and structural stability of the retaining walls. If implemented at actual excavation sites, this approach would enable real-time prediction of wall stability and facilitate effective safety management. Overall, the developed Stability Evaluation System offers a promising solution for ensuring the stability of retaining walls during construction. By incorporating real-time soil parameter analysis, it enhances the accuracy of stability predictions and contributes to proactive safety management in excavation projects.

Keywords: artificial neural network; digital twin; management; numerical analysis; safety factor

1. Introduction

Excavation works during the construction of buildings at present tend to involve greater and deeper construction sites compared with the past. The retaining wall technique has been used in various applications, such as deep excavation, the reduction of sediment runoff from embankments, and the defense of structures from rising seas or rivers. Although the construction technology for retaining walls has advanced significantly for deep excavation works in urban areas, it still has several drawbacks, including wall cracks and ground sinking, which can damage nearby structures and underground utilities. Furthermore, as compared to ground structures, there are several variables related to underground structures such as earth pressures, ground movements, and ground water changes, making it difficult to estimate precisely at the design stage (Li *et al.* 2016). Therefore, the safety of retaining walls during construction should be carefully monitored (Park *et al.* 2019, Woo and Chung 2020). Although ground parameters are evaluated during the ground investigation in the planning process for retaining structures, The investigated soil volumes constitute just a modest portion of the volume susceptible to stress change in situ, and the results of laboratory experiments are mostly influenced by sampling and specimen preparation errors (Cherubini 2000). To analyze the stability of the wall in real time, it is important to identify and quantify the uncertainty of the ground to reflect the actual condition of the ground (Zevgolis and Bourdeau 2010). The back analysis method has recently been used to determine the condition of the actual ground (Zhong *et al.* 2020, Zhao *et al.* 2021, Vila *et al.* 2021, Barani *et al.* 2018). In these studies, back analysis was mostly performed using the trial-and-error method with limited variables. However, the back analysis method needs to be considered for multiple variables because the strata are not uniform and the actual ground parameters vary.

The artificial neural network (ANN) developed by McCulloch and Pitts (1943) is a machine-learning algorithm that imitates the structure and principle of a human neural network. Recently, the stability or action for ground and design of retaining walls have been analyzed by using ANN methods (Xiang *et al.* 2021, Armaghani *et al.* 2020, Gordan *et al.* 2019, Chen *et al.* 2019, Mohamed *et al.* 2019, Gao, and He 2017, Javadi and Rezania 2009). In most studies, the stability of the wall can be judged by using the ground parameters during the design of a retaining wall as an input when conducting ANN learning. However, this value may not be the same as the stability of the actual wall.

To optimize a continuous spatial function that is nonlinear and nondifferentiable, Storn and Price (1997) suggested the differential evolution algorithm (DEA), which is an optimization algorithm. The DEA has the advantage of having a reasonably short convergence time because the number of parameters used for the calculation is limited and the mathematical operation is simple, although it follows the flow of the calculation process similar to the genetic algorithm (Shon *et al.* 2013). The components of each generation are developed into the next generation based on the distance and direction information of the object vector. This algorithm is appropriate for

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http://www.techno-press.org/?journal=gae&subpage=7
ISSN: 2005-307X (Print), 2092-6219 (Online)

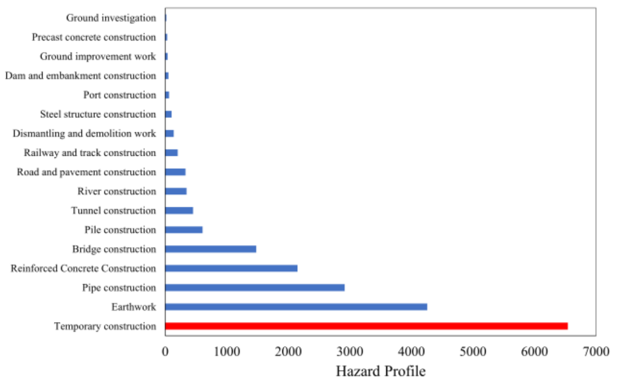


Fig. 1 Current status of the derivation of risk factors based on construction type (CSI, 2022)

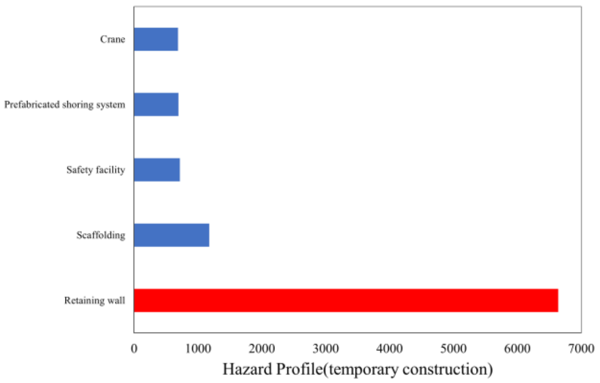


Fig. 2 Current status of the derivation of risk factors for temporary construction (CSI, 2022)

parallel processing based on the characteristics of the evolutionary program (An 2016). In this study, the effect of ground parameters on the wall was analyzed by performing a sensitivity analysis on retaining walls. The back analysis was conducted using the DEA, and the real-time stability of the wall was determined using the modified variables of the ground obtained through the back analysis as the input in ANN machine learning.

Because of overcrowding in downtown areas, the importance of underground space is increasing. Consequently, the importance of excavation into considerable depths near structures is also increasing. The risk factors in construction sites in downtown areas need to be monitored and predicted because the risk elements are increasing because of the expansion or deepening of excavation works (Lee *et al.* 2021).

Construction safety management integrated information (CSI) in Korea provides statistics on the risk factors of each type of construction by identifying the potential risk factors that lower the safety of construction objects, surrounding buildings, temporary structures, and workers in the field. As shown in Fig. 1, the construction of temporary structures is categorized as the most dangerous work (6,541) with 19,728 risk factors among 17 types of construction work.

As shown in Fig. 2, the retaining wall has the most risk factors at 6,639 cases among the temporary constructions based on the categorization of the risk factors into five groups according to the construction equipment and method. Delayed cases occur frequently during temporary construction; therefore, the cost can increase rapidly because of the identification of the cause and management. In Korea, 24 accident cases were investigated to determine the reason for retaining wall accidents. Insufficient ground investigations, nine accidents owing to temporary structural instability, and nine accidents owing to inadequate groundwater level management were found (Seong *et al.* 2011). Therefore, in this study, we propose a retaining wall safety evaluation system to account for the stability of retaining walls in various scenarios.

2. Wall stability evaluation systems

2.1 Working space

We have derived an algorithm, as depicted in Fig. 3, to develop a stability assessment system for retaining walls. The selection of the initial site determines the construction of the actual ground and the ground system. The target site focuses on excavated grounds, and various support methods such as soil nailing, cantilever walls, braced walls, raker walls, and anchor walls can be applied. The applicable wall types include steel sheet piles, H-piles, cast-in-place (CIP) walls, and continuous underground wall methods, which can be employed for various types of earth-retaining structures. By investigating the information regarding the site's methods and processes, it is incorporated into the system, ensuring alignment between the construction information at the site and the numerical analysis system.

2.2 Model setup

By conducting a site investigation on the selected ground site, we can obtain information about the ground parameters. The Standard Penetration Test (SPT) provides the N-value of the ground, which helps assess the soil's bearing capacity and estimate various parameters. Additionally, boring is performed to examine the soil distribution, and through sampling, various soil tests such as specific gravity tests, soil compaction tests, particle size distribution tests, permeability tests, unit weight tests, consolidation tests, liquid limit tests, compaction tests, and shear tests are conducted using the obtained soil samples. These tests provide information about the ground parameters, strength characteristics, and other properties that can be applied in the stability analysis system.

2.3 Slope displacement analysis

A ground investigation is typically conducted during the design process to gather parameters for the numerical analysis system established in Section 2.1, which calculates the behavior of the retaining wall within the system. However, the stability of the retaining wall may be compromised due to sudden changes in groundwater levels during construction or uncertainties in the ground parameters resulting from the ground investigation process. Moreover, the specified ground parameters from the investigation may differ from the actual ground parameters due to inherent uncertainties in the ground.

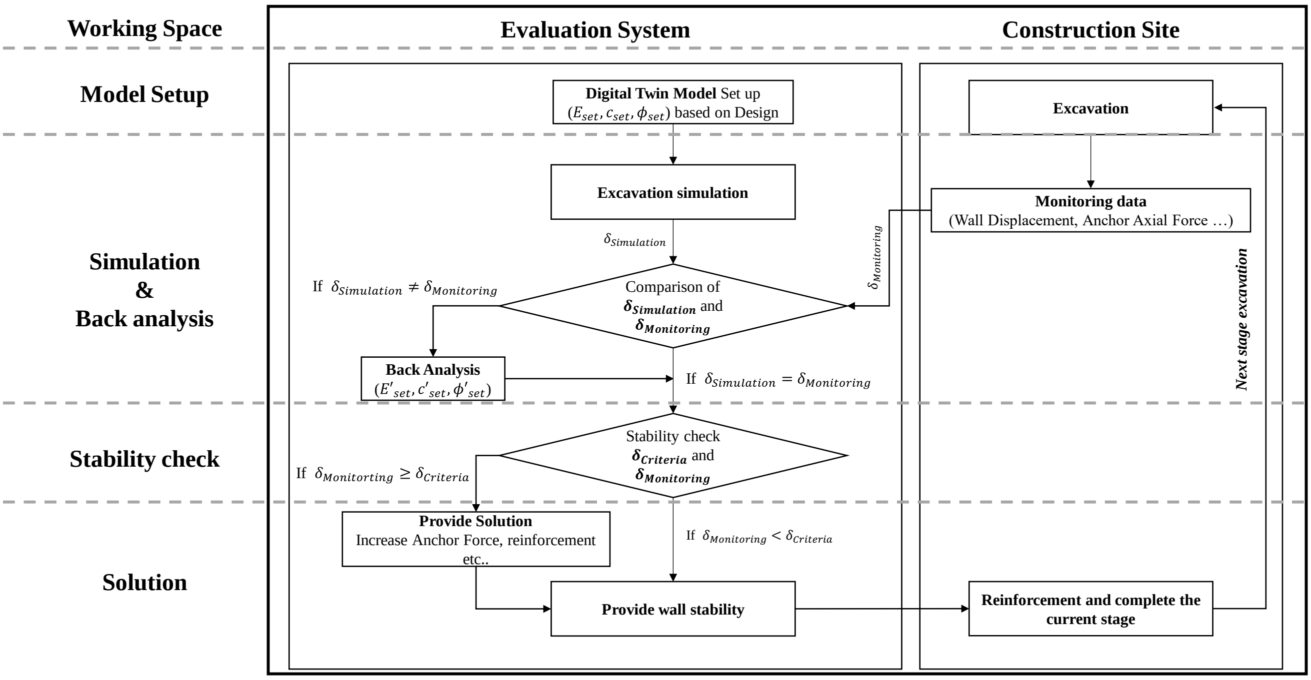


Fig. 3 Wall stability evaluation systems

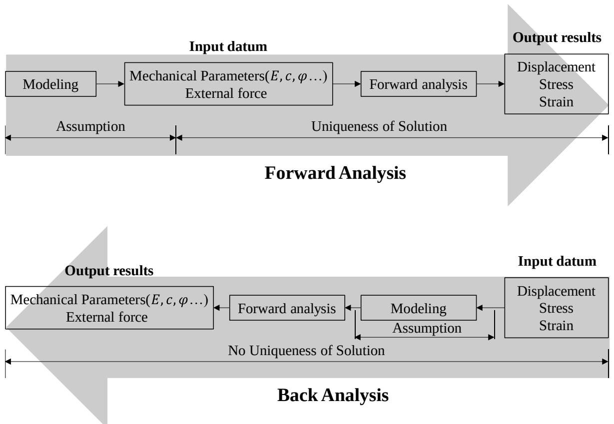


Fig. 4 The procedure of forward analysis and back analysis (Sakurai 1997)

To address these challenges, the back analysis process is employed. Back analysis is a method that derives the design values of a model from measured displacements or stress results, contrary to the forward analysis conducted during the design phase. Sakurai (1997) defines back analysis as an interpretation in the opposite direction of the forward analysis based on the input values. Fig. 4 illustrates the concept of back analysis.

Through back analysis, the actual properties of the ground are determined, and numerical analysis is conducted based on these properties to analyze the behavior of the retaining wall.

2.4 Stability check

By utilizing back analysis, the obtained ground parameters and measured data can be used as inputs for artificial intelligence (AI) learning, enabling real-time assessment of the stability of retaining walls. Temporary structures' measurements, obtained at regular intervals through smart monitoring sensors, can be used for back analysis to estimate the actual ground parameters. These estimated parameters are then fed into a trained AI model to estimate the stability of the retaining wall.

The use of AI for assessing the stability of structures allows for considering various variables, inferring the stability of the wall, making real-time judgments, and providing high accuracy through extensive data training.

2.5 Solution

If the stability of the retaining wall is found to be compromised, the system's solution algorithm can be employed to address the issue. By applying the solution to a numerical analysis model, the stability can be assessed, and once deemed safe, the solution can be implemented on-site during the construction process. This enables a holistic approach to the long-term safety management of the retaining wall.

3. Select of target variable for ground

3.1 Shapely value

The Shapley value is employed to calculate the contribution of each player in a game. In other words, it is a method for determining the influence of a given parameter by comparing the results obtained when all relevant combinations are considered. However, no consistency can be found in the contributions, and the calculation procedure is complicated. SHAP, a Python module, was used to perform sensitivity analysis with the modified Tree-SHAP

Table 1 Unit and range of input parameters in the sensitivity analysis

N value	Soil packing	Parameter	Unit	Range
4–10	Loose	Young's modulus (E_s)	MPa	4.12–10.3
		Friction (ϕ)	Degree	25.4–25.8
		Poisson's ratio (ν)	-	0.105–0.110
		Unit weight (γ_d)	kN/m^3	17–18
10–30	Compact	Young's modulus (E_s)	MPa	10.3–30.9
		Friction (ϕ)	Degree	25.8–27.4
		Poisson's ratio (υ)	-	0.110–0.129
		Unit weight (γ_d)	kN/m^3	18–19
30–50	Dense	Young's modulus (E_s)	MPa	30.9–51.5
		Friction (ϕ)	Degree	27.4–29
		Poisson's ratio (υ)	-	0.129–0.148
		Unit weight (γ_d)	kN/m^3	19–20
-	-	Cohesion (c)	kPa	7–37

model (Lundberg *et al.* 2018). A sensitivity analysis was performed with five ground parameters: Young's modulus, cohesion, friction angle, Poisson's ratio, and the unit weight of soil.

3.2 Sensitivity analysis case

The sensitivity of the ground properties was analyzed by applying FLAC3D, an analysis program that uses the finite difference method. Fig. 5 shows a schematic of the numerical analysis model. The figure shows five stages of excavation, four stages of anchors, and the employed H-pile + Timber method. For the friction angle of the ground where the anchor was installed, the free length and installation angle were simulated such that they behaved similarly to the actual excavation site. The ground differential settlement, wall displacement, and axial force of the anchor were monitored. The sensitivity analysis was performed assuming a single stratum condition (not considered as multistrata) and without considering the groundwater level.

The sensitivity analysis was performed on weathered soil in Korea. Gang *et al.* (2018) proposed empirical equations, Eqs. (1) and (2), based on the N value obtained from the standard penetration test (SPT) for the Young's modulus (E_s) and friction angle (ϕ) utilized in Korea. They claimed that the range of ground cohesion (c) does not vary with the N value and lies between 7 and 37 kPa. Kulhawy and Nayne (1990) presented empirical equations, Eqs. (3) and (4), for the Poisson's ratio (ν) determined by using the direct shear test for soil with an internal friction angle greater than 25°. Meyerhof (1956) categorized soil softness based on the N value. In addition, the unit weight of the soil was calculated based on the consistency of regularly utilized soil. In this study, the sensitivity of the ground properties of cohesion, friction angle, Young's modulus, unit weight of weathered soil, and Poisson's ratio was analyzed for the retaining wall.

$$E_s = 1.030N(MPa) \tag{1}$$

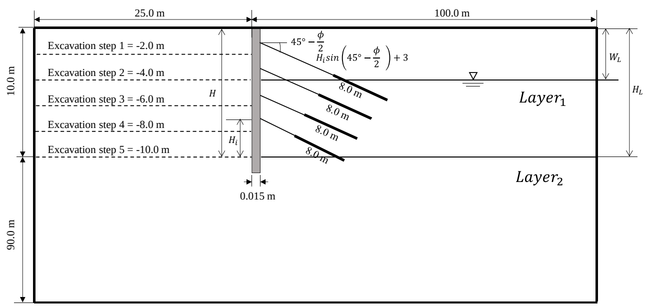


Fig. 5 Numerical analysis modeling

$$\phi = 0.08N + 25 \tag{2}$$

$$\nu = 0.1 + 0.3\phi_{rel} \tag{3}$$

$$\phi_{real} = \frac{\phi - 25}{45 - 25} \tag{4}$$

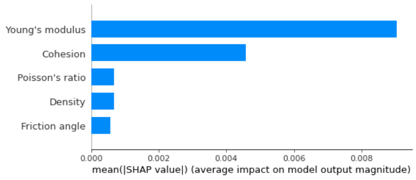
The soil was classified into three types based on consistency (Table 1), and the ranges of the Young's modulus, friction angle, and Poisson's ratio for each type were determined by using Eqs. (1)–(4). The cohesion and unit weight range were defined regardless of the soil consistency. The sensitivity analysis was conducted for 3,000 cases by performing 1,000 analyses for each type of soil while changing the variables.

3.3 Result of sensitivity analysis

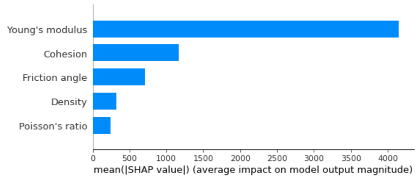
The results of the sensitivity analysis in Fig. 6 show the SHAP value of all the variables for the dense differential settlement case and the distribution of each variable affecting the differential settlement of the ground. This demonstrates that the Young's modulus has the greatest influence on ground differential settlement. The effect of the variable on the wall was established by converting the SHAP value of each case into the root mean square.

The results of the sensitivity analysis for loose, compact, and dense soils are shown in Figs. 7(a)-7(c), Figs. 7(d)-7(f),

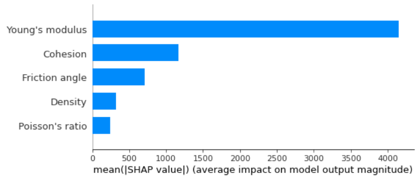
Fig. 6 SHAP values of the variables for all samples



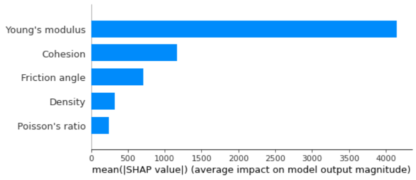
(a) wall displacement (Loose)



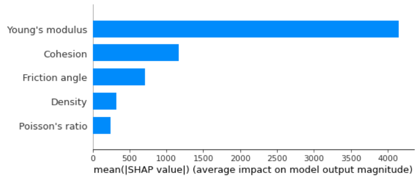
(b) anchor axial force (Loose)



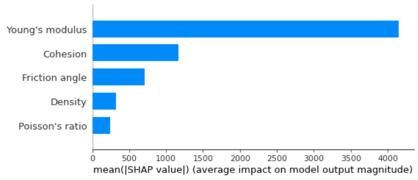
(c) Differential settlement (Loose)



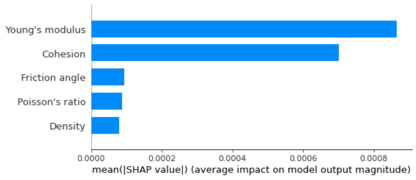
(d) wall displacement (Compact)



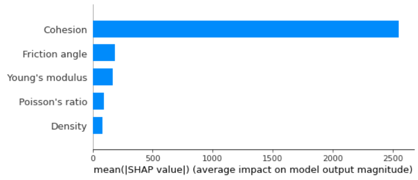
(e) anchor axial force (Compact)



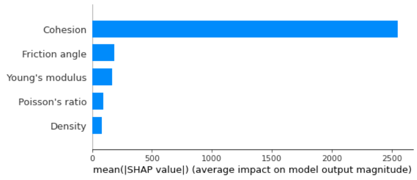
(f) Differential settlement (Compact)



(g) wall displacement (Dense)



(h) anchor axial force (Dense)



(i) Differential settlement (Dense)

Fig. 7 Wall stability evaluation systems

and Figs. 7(g)-7(i), respectively. These figures show that except for the axial force in the dense soil case, the Young's modulus has the greatest effect in all situations. A back analysis was performed on the retaining walls in this study, with the Young's modulus and cohesion as variables.

4. Back analysis using the DEA

4.1 Differential Evolution Algorithm(DEA)

The differential evolution algorithm proceeds through the following operations: initialization, mutation, crossover, and selection, which are used to generate a randomly initialized population, perform mutation operations, perform crossover operations, and select population, respectively(An *et al*. 2019).

Fig. 8 illustrates the process of generating mutation vectors in the differential evolution algorithm. The following equations represent the computational steps of the differential evolution algorithm(An *et al.* 2020): Random vectors are chosen from the previous generation's population, and using the selected vectors, mating vectors

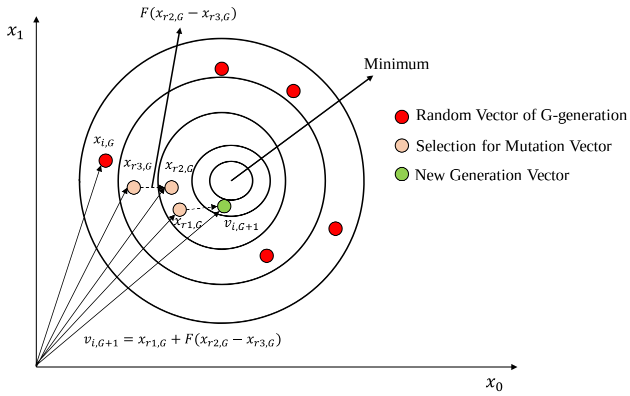


Fig. 8 The procedure of DEA in 2D space (Storn and Price 1997)

($v_{i,G+1}$) are generated as described in Eq. (5). N represents the number of populations, and F is a mutation factor that ranges from 0 to 2.

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \tag{5}$$

To generate a trial vector ($u_{ji,G+1}$), the parent vector is combined with the mutant vector through crossover. The crossover rate (CR) is a constant value between 0 and 1.

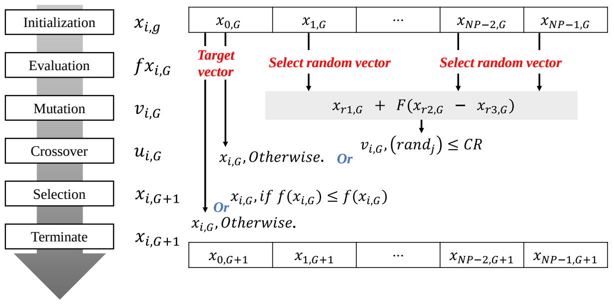


Fig. 9 Calculation process of differential evolution algorithm using DE (Shon *et al*. 2013)

Here, "rand" signifies that the vector used for variation is randomly selected, represented by the integer I_{rand}. Eq. (6) describes the crossover step.

$$u_{ji,G+1} = \begin{cases} u_{ji,G+1} & if\ rand_j < CR\ or\ j = I_{rand} \\ u_{ji,G} & if\ rand_j > CR\ or\ j \neq I_{rand} \end{cases} \quad (6)$$

The target vector $(x_{i,G+1})$ is compared with the trial vector based on their fitness. Subsequently, individuals with superior fitness are selected for the next generation. This process allows each trial vector to transmit favorable genetic traits to the parent individuals, enabling the transfer of superior genetic characteristics to the next generation. Eq. (7) describes the target vector step.

$$x_{i,G+1} = \begin{cases} x_{i,G+1} & if\ f(u_{i,G+1}) \leq f(x_{i,G}) \\ x_{i,G} & otherwise \end{cases} \quad (7)$$

Through these steps, the best population in the population are maintained in the next generation, corresponding to the parameters specified in the differential evolution algorithm. The iterations continue until reaching the designated number of generations or until population satisfy the optimal criteria. Fig. 9 represents the general flow of the differential evolution algorithm, illustrating the overall procedure.

4.2 Back analysis case

The numerical analysis model used for the back analysis consisted of two strata located 6 m below the ground surface (Fig. 5). A back analysis was performed using the DEA for the Cohesion and Young's modulus for each stratum. The population number of 10, mutation constant of 0.5, recombination factor of 0.7, and maximum number of evolution iterations of 1,000 were applied in the algorithm. The analysis could be completed inconsistently when the tolerance was less than 0.01; the convergence condition was satisfied when the tolerance became 0.01 or less. The parameters of the actual ground, which is the target for the back analysis, are listed in Table 2.

4.3 Back analysis condition

The objective of back analysis in geotechnical engineering is to minimize the difference between the measured values of structures during construction and the values obtained through the back analysis. A back analysis is typically performed based on displacement; however,

Table 2 Unit and range of input parameters in the back analysis

Layer	Parameters	Unit	Symbol	Value
Layer1	Young's modulus	MPa	E_{s1}	20
	Cohesion	kPa	c_1	21
Layer2	Young's modulus	MPa	E_{s2}	40
	Cohesion	kPa	c_2	25

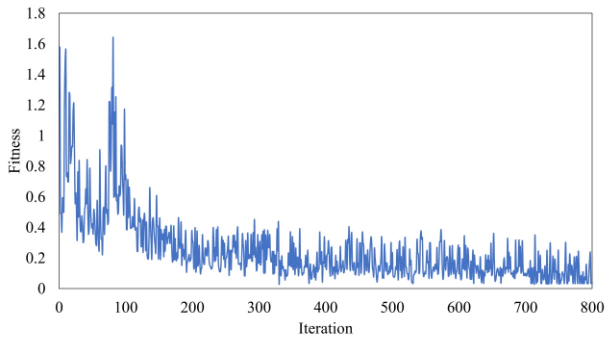


Fig. 10 Back analysis fitness by iteration

when the displacement is small, as the effect of the parameters on displacement is minor, the method can converge to a local solution. Therefore, if the displacement and stress are made dimensionless, they can be considered in the back analysis with fitness (proposed by An *et al.* (2016), Eq. (8)). dx_i and dy_i are the displacement and stress estimated using back analysis, respectively, and Dx_i and Dy_i are the displacement and stress measured in the construction field, respectively.

$$f = \sum_{i=1}^{n} \sqrt{\left(\frac{dx_i - Dx_i}{dx_i}\right)^2} + \sqrt{\left(\frac{dy_i - Dy_i}{dy_i}\right)^2} \quad (8)$$

To examine the fit of the displacement–stress basis, a back analysis was performed for the retaining wall model, considering the displacement of the wall, ground differential settlement, and the axial force of the anchor.

4.4 Back analysis result

The back analysis of multistrata using the DEA was performed for 1,000 iterations, but the convergence condition was achieved in 800 generations to produce a ground parameter. The degree of fitness was calculated to be 0.034, with a tendency to converge gradually with each generation (Fig. 10). The accuracy of the parameters acquired through the back analysis was confirmed to be higher than 95% for the four variables in the two strata (Table 3).

5. Artificial neural network for wall stability

5.1 Training dataset

The actual ground parameters were evaluated through a back analysis, and the stability of the wall was investigated

Table 3 Accuracy of the back analysis

Target			DEA result	
			Result	Accuracy (%)
Layer$_1$	Young's modulus	Model	20.00 MPa	98.20
		Estimated with DEA	20.36 MPa	
	Cohesion	Model	21.00 kPa	97.57
		Estimated with DEA	20.49 kPa	
Layer$_2$	Young's modulus	Model	40.00 MPa	95.53
		Estimated with DEA	41.79 MPa	
	Cohesion	Model	25.00 kPa	94.88
		Estimated with DEA	23.72 kPa	
Accuracy (%)			96.54	

Table 4 Ground cases used in the training data

Composition of the ground	Layer$_1$	Layer$_2$
Case$_1$	Loose	Loose
Case$_2$	Loose	Compact
Case$_3$	Loose	Dense
Case$_4$	Compact	Compact
Case$_5$	Compact	Dense
Case$_6$	Dense	Dense

using the ANN. The groundwater level and the state of the complicated ground were utilized to build the training data Fig. 5, and six types of ground conditions that may exist in the actual ground were analyzed Table 4.

FLAC3D was used to compose the ground parameters by varying 15 variables, such as excavation depth, Young's modulus, friction angle, and cohesion. The variables (ground parameters) were distributed with a uniform probability in the specified range. A total of 30,000 cases of retaining walls were used as the training data in the numerical analysis. In addition, the data for each stage of excavation were acquired to analyze the stability during excavation. Table 5 shows the variables used for training.

5.2 Preprocessing of training data

5.2.1 Tendency of FOS with loamy sand

The activation function in an artificial neural network plays a critical role in transmitting signals from the preceding layer to neurons in subsequent layers. Within the realm of artificial neural networks, the activation function is divided into two categories: linear and nonlinear functions. Nonlinear functions are predominantly employed as activation functions in order to introduce complexity and enable the network to capture nonlinear relationships within the data.

For the stability analysis conducted in this study, the Rectified Linear Unit (ReLU) function in Fig. 11, proposed by Nair and Hinton in 2010, was chosen as the activation function for the artificial neural network. The ReLU

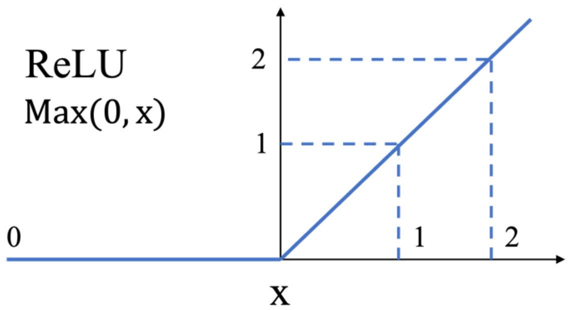


Fig. 11 ReLU activation function

function exhibits a simple yet effective behavior: when the input value is positive, it is preserved unaltered, whereas for negative values, it is replaced with zero. By incorporating the ReLU activation function, the network becomes capable of handling both positive and negative signals in an efficient manner, enabling effective learning and representation of complex patterns.

In order to ensure the suitability of the data for the chosen activation function, a preprocessing step was performed. The input data was designed to consist of positive values, as the ReLU function is inherently well-suited for such data. To further enhance the compatibility with the ReLU function, the input data underwent normalization using the MinMaxScaler from the sklearn library in Python. This normalization process rescaled the input data to a range between 0 and 1, facilitating stable and effective learning within the ReLU-based artificial neural network.

Output data were prepared by using the training data collected with FLAC3D for the ANN. The structural stability of the wall, which is a numerical variable in the training data, was divided into sections through binning and replaced with categorical data. For ground differential settlement, categorical data were substituted based on the limits of angular displacement for the structures proposed by Bjerrum (1967). The binning procedure was performed using a 1/500 stability limit, which prohibits cracks in the building, and a 1/300 limit, which predicts the first crack in the partition wall or floor. According to the Korea Expressway Corporation's measurement and inspection standards for temporary retaining facilities (2010), preprocessing was performed on the displacement of the wall and the axial force of the anchor while selecting the first, second, and third management standards for binning. The following are the standards and results for preprocessing Tables 6-8.

5.3 Artificial neural network structure used in machine learning

According to Gordan *et al.* (2018), an ANN has a high predictive capacity for determining a safety factor with a low level of error. And it is a powerful computational tool for discovering hidden and intricate correlations between sets of data (Salehi and Erduran 2022). Thus, in this study, artificial intelligence learning was performed by using an

Table 5 Parameters used in the training data

‘	Value	Unit	Symbol	Range
Friction angle$_1$	Input	degree	ϕ_1	25.4–29.0
Cohesion$_1$	Input	kPa	c_1	7–37
Young's modulus$_1$	Input	MPa	E_1	4.12–51.5
Unit weight$_1$	Input	kN/m^3	γ_{d_1}	17–20
Layer depth$_1$	Input	M	L_{d_1}	0-10
Friction angle$_2$	Input	Degree	ϕ_2	25.4–29.0
Cohesion$_2$	Input	kPa	c_2	7–37
Young's modulus$_2$	Input	MPa	E_2	4.12–51.5
Unit weight$_2$	Input	N	γ_{d_2}	17–20
Layer depth$_2$	Input	m	L_{d_2}	0-10
Wall displacement	Input	m	$W.D$	0-0.84
Anchor force	Input	kN	$A.F$	28-96
Differential settlement	Input	-	S	0-0.045
Excavation depth	Input	m	H_L	0–10
Groundwater level	Input	m	W_L	0–10
Wall structural safety rank	Output	-	$S.F_W$	0,1,2,3,4,5
Differential Settlement rank	Output	-	$S.F_S$	0,1,2
Wall displacement rank	Output	-	$S.F_D$	0,1,2,3
Anchor force rank	Output	-	$S.F_F$	0,1,2,3

Table 6 Binning of wall stability parameters

Wall structural safety factor binning	Category	Rank
[3.0, 10)	A	0
[2.5, 3.0)	B	1
[2.0, 2.5)	C	2
[1.5, 2.0)	D	3
[1.0, 1.5)	E	4
[0, 1.0)	F	5

Table 7 Binning of differential settlement

Differential settlement binning	Category	Rank
[0, 1/500)	A	0
[1/500, 1/300)	B	1
[1/300, 1)	C	2

Table 8 Binning of wall displacement and anchor force (I.F. = initial axial force)

Wall displacement binning	Anchor force binning	Category	Rank
[0, 0.20%H)	[I.F., I.F. + 5ton)	A	0
[0.20%H, 0.29%H)	[I.F. + 5ton, I.F. + 10ton)	B	1
[0.29%H, 0.35%H)	[I.F. + 10ton, I.F. + 15ton)	C	2
[0.35%H, 1%H)	[I.F. + 15ton, I.F. + 30ton)	D	3

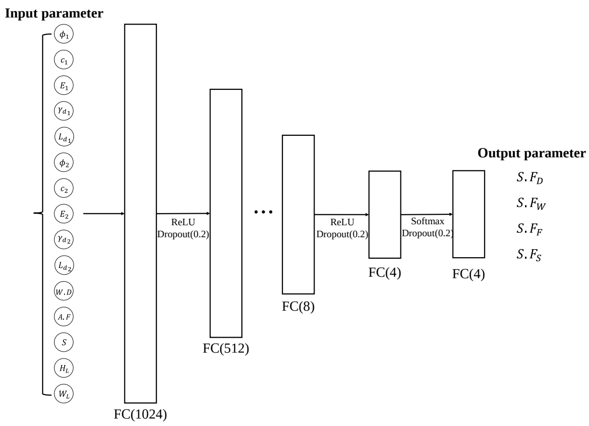
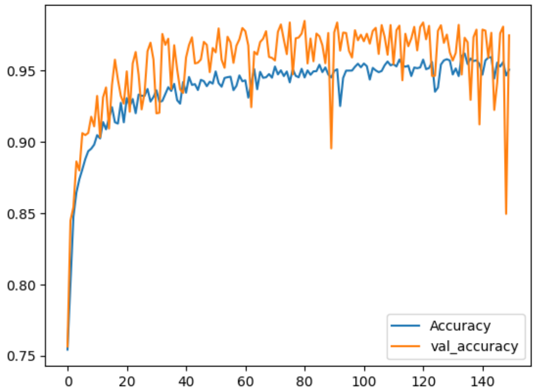


Fig. 12 ANN structure used for wall stability analysis

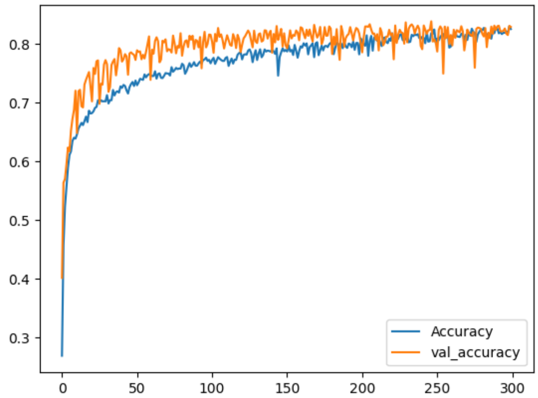
ANN to analyze the stability of the retaining wall. The ANN is composed of an input layer with 15 nodes; a hidden layer with 1024, 512, 256, 128, 64, 32, 16, 8 and 4 nodes; and an output layer Fig. 12. The analysis of the ANN was conducted using the Python programming language, employing the Keras library, which is a prominent component of the TensorFlow framework. The input data utilized for the learning process of the ANN and the corresponding output data obtained from the learning are presented in Table 5.

5.4 Verification of wall stability and ANN training results

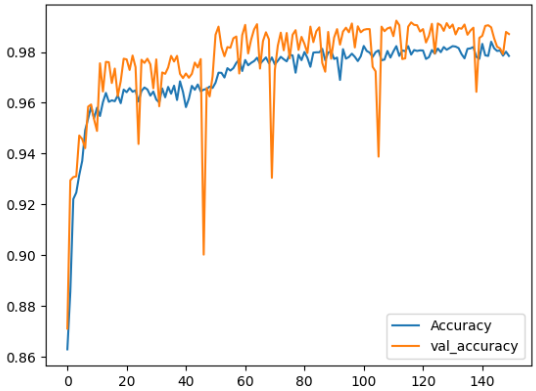
The ANN was applied to perform artificial intelligence learning using 30,000 datasets. The training model was evaluated by using 20% of the total training data as test data and 30% of the training data as validation data. The average training accuracy for the four factors was 93.33% (See Table 9), and the training validation accuracy was 94.32%. In addition, the accuracy showed upward trends as the number of epochs increased (see Figs. 13(a)-13(d)). This indicates that the results of learning for the ground differential settlement, anchor axial force, and wall



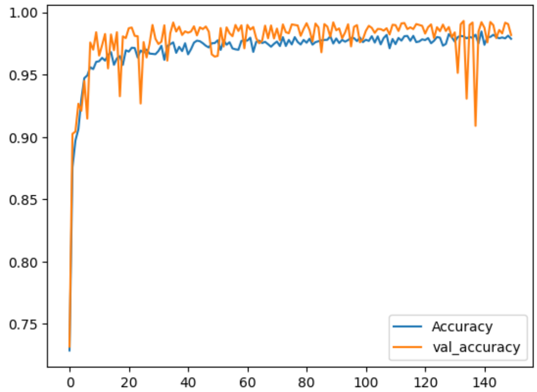
(a) Wall displacement



(b) Wall structure safety factor



(c) Anchor force



(d) Differential settlement

Fig. 13 ANN learning results

Table 9 ANN learning accuracy for retaining walls

ANN learning results	Training accuracy (%)	Training validation accuracy (%)
Wall displacement	95.07	97.47
Wall structure safety factor	82.54	82.90
Anchor force	97.85	98.71
Differential settlement	97.87	98.18

Table 10 Evaluation metrics for wall displacement

Rank	Precision	Recall	F1-score
0	0.90	1.00	0.95
1	0.95	0.85	0.90
2	0.92	0.90	0.91
3	1.00	1.00	1.00
Test accuracy (%)		97.87	

Table 11 Evaluation metrics for wall structure safety factor

Rank	Precision	Recall	F1-score
0	0.90	0.82	0.86
1	0.81	0.78	0.79
2	0.73	0.72	0.73
3	0.76	0.81	0.79
4	0.78	0.88	0.83
5	0.96	0.95	0.96
Test accuracy (%)		83.88	

displacement are relatively accurate compared with those of the structural stability of the wall. The precision, F1-score, and recall evaluation metrics for each training iteration are presented in Tables 10-13, as follows.

These tables provide a comprehensive evaluation of the precision, F1-score, and recall metrics for each training iteration. These metrics are crucial for assessing the performance and effectiveness of the developed Stability Evaluation System in predicting the stability of retaining walls.

Table 12 Evaluation metrics for anchor force

Rank	Precision	Recall	F1-score
0	0.98	0.67	0.80
1	0.92	0.94	0.93
2	0.93	0.87	0.90
3	0.99	1.00	1.00
Test accuracy (%)		98.42	

Table 13 Evaluation metrics for differential settlement

Rank	Precision	Recall	F1-score
0	1.00	0.98	0.99
1	0.88	0.93	0.90
2	0.97	1.00	0.98
Test accuracy (%)		98.13	

Table 14 ANN validation parameters

Layer	Young's Modulus (MPa)	Friction angle (Degree)	Cohesion (kPa)	Density (kN/m^3)
Layer$_1$	20.36	26.68	20.49	18.64
Layer$_2$	41.79	28.14	23.72	19.74
Wall height (m)	Strata boundary(m)	Displace-ment (m)	Axial force (kN)	Differential settlement
10	6	0.026	176.35	0.0009

The stability of the wall was assessed by inputting the properties obtained via the back analysis using the DEA into the ANN model. The fifth case is the ground condition used for the back analysis, as indicated in Table 4. The first stratum is compact, and the second stratum is dense. The boundary of the layer is located 6 m below the ground surface, and no groundwater level is present. The properties used to validate the trained model are listed in Table 14.

The results of the analysis revealed grade B for wall displacement, grade C for wall structural stability with a safety factor of 2.0 to 2.5, grade D for anchor axial force, and grade A for ground differential settlement. The analysis was performed with the initially specified ground parameters to verify the analysis results by inputting the ground properties obtained in the back analysis to the ANN Table 3. The analysis was performed using the initial numerical analysis model, the model based on the ground properties obtained from the back analysis, and the model combining the back analysis and ANN. The two numerical analysis models and the ANN model produced the same results.

6. Conclusions

The risk associated with retaining walls and accident instances involving such walls were examined in this study. Sensitivity analysis was used to evaluate the importance of the ground parameters for investigating the behavior of the walls. Back analysis using the DEA was utilized to acquire the ground properties on the back side of the walls to examine the condition of the ground during excavation works. The back analysis can be used to monitor the stability of walls and ground via integration into a safety management system using an ANN. As the ground parameters were categorized by using the N value acquired from the SPT, the results of this study can be applied to specific types of ground. Furthermore, in future research, the types of ground to which the wall safety management system can be applied can be expanded by specifying the range of ground properties that can represent the entire ground. Furthermore, if a back analysis is performed using real-time measurement data during excavation and is utilized for the ANN learning, the learning accuracy can be enhanced, and the safety of temporary structures can be determined in real time. Additionally, the groundwork for digital twin technology in excavation construction can be built if a solution is suggested when the stability of temporary structures begins to decline and technology that can be implemented in the field after verification by using numerical analysis programs is developed (see Fig. 3). Future studies should be conducted to determine the real-time stability of the wall using a safety management system employing measurement data. Additionally, studies are required to implement digital twins for walls, and a solution suggestion algorithm for walls with reduced stability must be developed and verified.

Acknowledgments

This study was conducted with the support of the National R&D Project for Smart Construction Technology (No. 21SMIP-A158708-02) funded by the Korea Agency for Infrastructure Technology Advancement under the Ministry of Land, Infrastructure, and Transport and managed by the Korea Expressway Corporation.

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