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DESIGN ASSISTANT FOR EXCAVATION SUPPORT SYSTEM IN LARGE CONSTRUCTION PROJECT

Hyunsung Roh[1], Ghang Lee[1,2]
[1]Yonsei University, Seoul, Republic of Korea
[2]Technical University of Munich, Munich, Germany

Abstract

Previous expert systems for excavation support system (ESS) recommendations often overlooked lateral supports and water-barrier methods, limiting their applicability to small projects with a single retaining wall type. These methods were unsuitable for large-scale projects, where varying site conditions require different ESS configurations for each excavation side. This study proposes an ESS design assistant tailored for large construction projects. While LLMs like GPT-4.0 and DeepSeek show promise, they struggle with practical ESS recommendations. To address this, we developed a multi-step machine learning-based ESS recommendation system, achieving weighted F1 scores of 0.951 (retaining walls), 0.981 (water-barrier applications), and 0.831 (lateral supports).

Introduction

Research background

The excavation support system (ESS) consists of three components: a retaining wall, a water barrier, and lateral support. Each component protects the site by preventing soil and groundwater inflow and resisting overturning forces on the ESS. Therefore, in the early stages of design, information on surrounding buildings and site conditions must be collected to design an appropriate ESS. However, since ESS is classified as a temporary structure in construction programs, it does not receive the same amount of design time as the main building or structure (European Committee for Standardization, 2004). This limitation can lead to a chain reaction of issues, including insufficient site data, inappropriate selection of ESS components, and incomplete designs (Boone & Westland, 2004).

To overcome these challenges, systems leveraging machine learning (ML) have been proposed to automate the ESS design process. ML algorithms that perform classification and clustering tasks—such as case-based reasoning (Yang, 2004), decision tree (Choi & Lee, 2010), and AdaBoost (Shin et al., 2009)—have been applied to develop recommendation systems for ESS components. However, prior studies have primarily focused on recommending retaining walls, while relatively scarce research has been conducted on recommending water barrier treatment or lateral support methods by considering their interrelationships. Furthermore, existing studies have proposed recommendation models trained on between 100 to 300 site-level datasets, based on the assumption of "A single ESS for an entire site." However, this approach requires improvement in the following three aspects:

First, training with a small dataset may lead to overfitting and limit the model's ability to generalize to cases outside of the trained dataset (Charilaou & Battat, 2022). Second, even within a single site, excavation conditions may vary for each side. In urban areas, different buildings may be adjacent to each excavation side, and in large-scale sites, variations in rock layers and groundwater conditions can exist, so that appropriate ESS components should be designed on every excavation side. Finally, existing recommendation models do not consider the interrelationship between retaining walls, water barriers, and lateral supports, requiring designers to select additional ESS components manually.

Preliminary study

Unlike traditional machine learning method, which requires training on large-scale datasets, recent advancements in large-scale multimodal models (LMMs) that have been pre-trained on vast amounts of data have led to an increasing number of studies exploring their application in design automation tasks through prompt-based methods (Jang et al., 2023; Qin et al., 2024; Saka et al., 2024).

In this study, we conducted a preliminary test to investigate whether LMMs can serve as a design assistant for ESS. We prompted LMMs to recommend appropriate ESS components based on selection factors extracted from existing ESS design cases (e.g., excavation depth, rock layer, groundwater). The results generated were then compared with actual ESS cases to assess the potential of LMMs in ESS component recommendation (Figure 1). The prompt provided to the LMM is as follows:

- Prompt 1: The following are the conditions for the excavation side of my project. Could you recommend the most suitable retaining wall method from the following options: Cast-in-Place Pile (CIP), Soil

Cement Wall (SCW), Slurry Wall (Diaphragm Wall), Soldier Piles and Lagging Wall, or Shotcrete?

- Prompt 2: Based on the given conditions and the recommended retaining wall method, is an additional water-barrier treatment necessary? If so, which method would be most effective?
- Prompt 3: Based on the recommended retaining wall method and the water-barrier treatment, which lateral support system would be appropriate? Please choose from the following options: Earth Anchor, Slab, Strut, Soil Nail, Rock Bolt, Raker, or No Support.

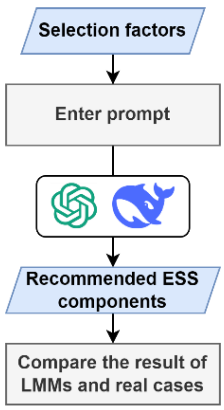

Figure 1: The flow of the preliminary test

LMMs provide recommendations for appropriate ESS components along with justifications in a manner that is sufficiently convincing for designers. However, discrepancies were observed between the responses generated by the LMMs and the actual design outcomes (Figure 2). As noted by Sahoo et al. (2024), LMM responses are highly dependent on the quality of the prompts.

The LLMs may have generated incorrect answers due to the absence of constructability-related factors such as budget, labor, and time, which were not included as initial selection factors. Additionally, rather than referencing actual ESS design cases, the LMM appears to rely on generalized construction knowledge, which could further contribute to the observed differences in results.

Given these limitations, developing an effective design assistant for ESS would require the advancement of machine learning models trained on case-specific data in addition to LMM-based approaches.

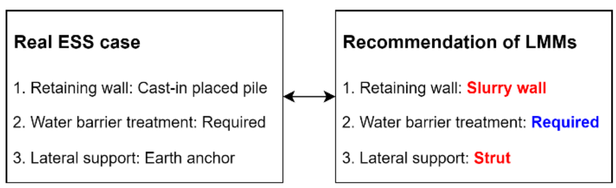

Figure 2: ESS component in the real ESS case and the result of LLM

Research objectives

To address these issues, the following research objectives have been established to bridge the research gaps in existing studies:

1. Develop a design assistant capable of recommending ESS for each excavation side by applying the "A single ESS for each excavation side" approach to data collection and model training, thereby improving recommendation performance compared to previous methods.
2. Propose a multi-step recommendation process that covers all ESS components (retaining walls, water barriers, and lateral support).

Research Method

The research method for achieving the research objectives is as follows. First, an excavation-side-level ESS dataset is constructed to develop a model for the ESS recommendation task. Next, a prediction process is established by considering the interdependencies among ESS components. In this study, two strategies are adopted for training the recommendation model:

- Dependent process, which accounts for the interdependent relationships between ESS components.
- Independent process, which does not consider these interdependencies.

Simultaneously, hyperparameters within the algorithm are tuned to ensure optimal fitting to the dataset. Finally, the Wilcoxon Signed-Rank Test is conducted to verify that the dependent process is a valid approach for predicting ESS components (Figure 3).

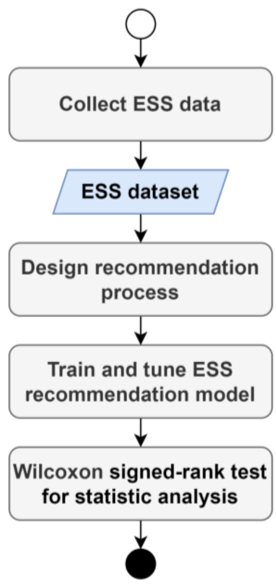

Figure 3: Research method

ESS dataset

In this study, an excavation side-level ESS dataset was constructed, differing from previous datasets that were structured at the site level. The side-level dataset was collected by dividing excavation areas based on changes in excavation conditions or whenever there was a change in the orientation of excavation sides. For example, if a project site has a rectangular shape, it will have four excavation sides: top, bottom, left, and right.

Following this approach, data were collected from 124 construction projects, resulting in a dataset containing 1,880 excavation sides. The ESS dataset consists of three key components: ESS components, ESS selection factors, and associated values (Figure 4).

The ESS components were categorized into three groups: retaining walls, water barrier applications, and lateral support methods.

- Retaining walls include soldier piles and lagging walls, cast-in-place pile walls (CIP), soil cement walls (SCW), shotcrete, and slurry walls.
- Water barriers vary depending on the materials used. Therefore, instead of a detailed classification, the data was structured as a binary classification (applied/not applied).
- Lateral support methods were classified into seven categories: earth anchors, rakers, slabs, struts, open cuts, soil nails, and rock bolts.

Beyond ESS components, construction methods can vary by country, company, or proprietary patents, and some techniques may be classified as innovative. However, gathering detailed information on every individual case poses challenges. Therefore, in this study, ESS components were categorized using generally recognized and widely accepted terminology to ensure consistency and clarity.

The ESS selection factors are the key considerations in selecting ESS components and include project information, adjacent building information, and ground information (Table 1).

Project information consists of factors determined during the design phase based on the scale of underground construction and the shape of the building. The relevant factors include: 'Excavation depth', 'Distance to the opposite side', and 'Length of the excavation side.' These values are typically found in 2D drawings, such as floor plans or section views, and were manually collected for this study. Adjacent building information refers to data regarding buildings that are directly facing each excavation side. The selection factors in this category include: 'Number of adjacent buildings', 'Distance to adjacent buildings.' Since the number and proximity of adjacent buildings affect the lateral earth pressure acting on each excavation side, adjacent building information is an essential consideration when selecting ESS components. To collect this data, buildings near the excavation sides were identified, and their location data from building registration information was used. Finally, ground information contains the most critical selection factors. The relevant factors include: 'Groundwater', 'Thickness of soil', 'Presence of sandy soil', 'Depth to the rock layer', 'Thickness of the rock layer', 'Bottom rock layer', 'Groundwater location', and 'Groundwater impact.' Ground information was collected by analyzing drill logs from the nearest available boreholes to each excavation side, ensuring that all relevant selection factors were accurately recorded.

Table 1: Definitions of selection factors

Category	Selection factor	Definition
Project information	Excavation depth	Vertical depth of the excavation side where the ESS is installed
	Distance to the opposite side	Distance between opposing excavation sides
	Length of the excavation side	Horizontal length of an excavation side where the ESS is installed
Adjacent building information	Number of adjacent buildings	Number of buildings located within a horizontal distance of (excavation depth) × 2 from the excavation side
	Distance to adjacent buildings	Average distance from the excavation side to each adjacent building
Ground information	Groundwater	Initial depth at which groundwater appears during excavation
	Thickness of soil	Thickness of the soil layer within the excavation depth
	Presence of sandy soil	Presence of sandy soil during excavation
	Depth to the rock layer	Depth at which the rock layer (weathered, soft, moderate, hard) first appears during excavation
	Thickness of the rock layer	Thickness of the rock layer (weathered, soft, moderate, hard) within the excavation depth
	The bottom rock layer	The lowest rock layer within the excavation depth
	Groundwater location	The rock layer where groundwater appears within the excavation depth
	Groundwater impact	Presence of groundwater within the excavation depth

Recommendation process and model development

To develop a recommendation model that considers all ESS components (retaining wall, water barrier application, and lateral support) while accounting for the interrelationships among them, two recommendation processes (independent process and dependent process) were implemented and evaluated for recommendation performance.

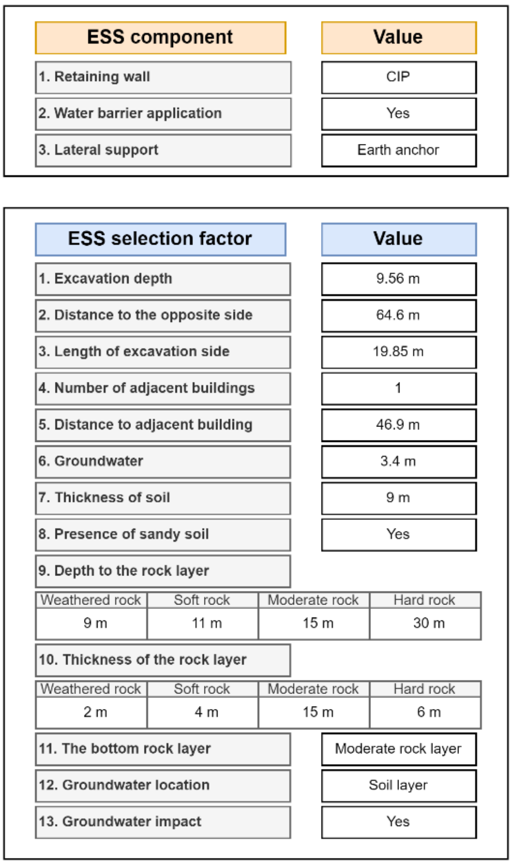

Figure 4: Example of ESS dataset

In the independent process, when selection factors are provided as input, each ESS component is recommended independently. Since the recommendations are treated as independent trials, the suggested ESS components are determined solely based on selection factors without ensuring any interrelationship between components. The dependent process follows the same initial steps as the independent process, where selection factors are input, and the retaining wall is recommended first. However, after recommending the retaining wall, the water barrier application and lateral support are determined by considering the previously recommended components. In the water barrier application recommendation, the selection factor set includes the retaining wall. In the lateral support recommendation, the selection factor set includes both the retaining wall and water barrier application (Figure 5).

By incorporating previously recommended components into the selection process, the dependent process ensures a more cohesive and interrelated recommendation of ESS components compared to the independent process.

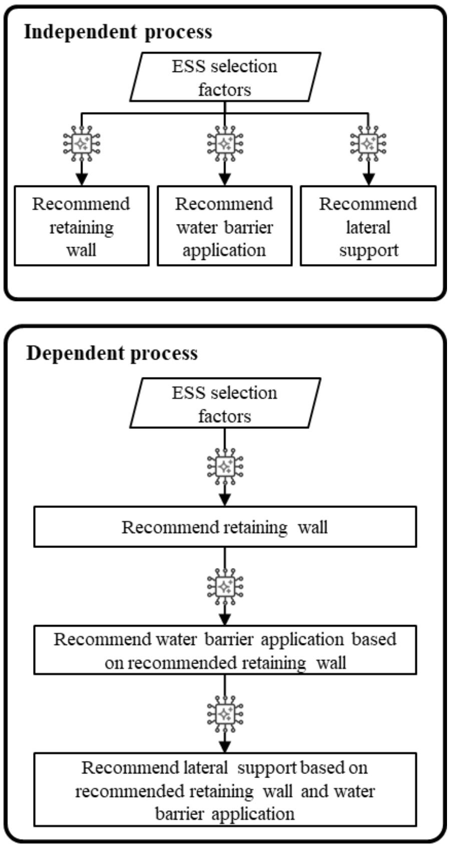

Figure 5: Comparison of recommendation process (Up: independent process, down: dependent process)

Nine algorithms were selected to perform the recommendation task: Decision tree, Naïve bayes, K-nearest neighbor, Support vector machine, AdaBoost, Gradient Boosting Machine (GBM), LightGBM, eXtreme Gradient Boosting (XGBoost), and CatBoost. These boosting-based algorithms use decision trees as base learners and share common characteristics such as error minimization through ensemble learning, handling of missing values, and overfitting prevention (Natekin & Knoll, 2013). Among them, XGBoost achieves a faster training speed compared to GBM due to data parallelization and memory optimization (Chen & Guestrin, 2016). While GBM and XGBoost adopt a level-wise growth strategy, LightGBM employs a leaf-wise growth strategy, enabling relatively faster training (Ke et al., 2017). CatBoost has a similar training speed to XGBoost but is specifically optimized for categorical features, reducing preprocessing time (Prokhorenkova et al., 2018).

The recommendation process was applied to all nine algorithms, and the 1,880-instance ESS dataset was split into a training set (80%) and a test set (20%), resulting in 1,504 training instances and 376 test instances.

Within the 1,880 data samples, the label distribution was not uniform, exhibiting an imbalanced nature. In the retaining wall category, a large proportion of cases consisted of CIP (38.3%, 728 cases) and soldier piles and lagging walls (36.2%, 688 cases). In the lateral support category, earth anchors accounted for the majority (46.3%, 870 cases).

To evaluate the recommendation performance, the weighted F1-score, which reflects imbalanced datasets, was used as the primary metric.

WSRT for recommendation process

In this study, we conducted experiments to examine the performance differences among nine models. Since a sufficiently large sample size (30 or more) was not available, it was more appropriate to compare the results based on ranks rather than means. Additionally, as the results of recommendation performance did not follow a normal distribution, we employed the Wilcoxon Signed-Rank Test (WSRT) instead of the paired t-test to determine whether there were significant differences in performance between recommendation processes (Rey & Neuhäuser, 2011).

The null hypothesis and the alternative hypothesis used in WSRT are as follows:

- The null hypothesis: The recommendation process did not cause the recommendation performance
- The alternative hypothesis: The recommendation process caused the recommendation performance

If the p-value is less than 0.05, the alternative hypothesis is accepted. Conversely, if the p-value is 0.05 or higher, the null hypothesis is accepted.

Experimental Result

ESS component recommendation performance

Nine different machine learning algorithms (decision tree, K-nearest neighbor, Naïve Bayes, support vector machine, AdaBoost, GBM, LightGBM, XGBoost, and CatBoost) were applied to independent and dependent recommendation processes across three ESS components.

For retaining wall recommendation performance, XGBoost achieved the highest performance with a weighted f1-score of 0.951, outperforming other algorithms (Table 2). Additionally, this performance surpasses previous retaining wall prediction models, including AdaBoost by Shin et al., (2009) (Accuracy: 0.884), decision tree by Choi & Lee, (2010) (Accuracy: 0.826), and self-organizing maps by Kim et al., (2021).

Here, no values are provided for the dependent process in retaining wall recommendation because retaining walls are recommended first before other components in the dependent process.

Table 2: Recommendation performance of retaining wall

ML algorithm	Independent process	Dependent process
Decision tree	0.815	-
K-nearest neighbor	0.717	-
Naïve bayes	0.533	-
Support vector machine	0.732	-
AdaBoost	0.465	-
GBM	0.898	-
LightGBM	0.905	-
XGBoost	0.951	-
CatBoost	0.903	-

For water barrier application, the dependent process consistently outperformed the independent process across all ML algorithms. Among them, XGBoost achieved the highest performance with a weighted f1-score of 0.981. KNN and Naïve Bayes demonstrated relatively lower performance compared to other algorithms, with scores in the 0.6 to 0.8 range when adopting independent process. However, both algorithms showed an improvement in performance when the dependent process was applied. The performance increase suggests that considering the interdependence between ESS components has a positive influence on water barrier recommendation (Table 3).

For lateral support, the dependent process slightly improved performance for all nine ML algorithms. CatBoost showed the best performance with a weighted F1-score of 0.831 (Table 4).

Table 3: Difference of recommendation performance between dependent process vs. independent process – water barrier application

ML algorithm	Independent process	Dependent process
Decision tree	0.869	0.933 (↑)
K-nearest neighbor	0.787	0.843 (↑)
Naïve bayes	0.617	0.632 (↑)
Support vector machine	0.856	0.909 (↑)
AdaBoost	0.835	0.920 (↑)
GBM	0.917	0.945 (↑)
LightGBM	0.928	0.968 (↑)
XGBoost	0.925	0.981 (↑)
CatBoost	0.925	0.978 (↑)

When trained using the dependent process, the performance of both water barrier application and lateral support improved. However, the performance improvement for water barrier application (maximum increase of AdaBoost: 0.085) was greater than that for lateral support (maximum increase of SVM: 0.037). This result indicates that water barrier recommendation is more closely related to the retaining wall than lateral support is.

Table 4: Difference of recommendation performance between dependent process vs. independent process – lateral support

ML algorithm	Independent process	Dependent process
Decision tree	0.711	0.704
K-nearest neighbor	0.699	0.734 (↑)
Naïve bayes	0.569	0.592 (↑)
Support vector machine	0.686	0.723 (↑)
AdaBoost	0.563	0.574 (↑)
GBM	0.784	0.792 (↑)
LightGBM	0.794	0.805 (↑)
XGBoost	0.807	0.811 (↑)
CatBoost	0.810	0.831 (↑)

Statistical analysis of Dependent vs. Independent processes

The recommendation performance of the dependent process was consistently higher across all ESS components and ML algorithms. However, to determine whether this improvement was statistically significant or merely due to chance, the Wilcoxon Signed-Rank Test was conducted based on the obtained results.

The results of WSRT that the recommendation performances of water barrier application and lateral support vary depending on the recommendation process (Table 5). Values of positive ranks were larger than values of negative ranks in recommending both water barrier application and lateral support. Furthermore, p-values of water barrier application and lateral support were observed as 0.008 and 0.015, respectively. Based on the WSRF results, recommendation performances were increased when using a dependent process compared to an independent process, it corresponds to (a); if all features are smaller, it corresponds to (b); if they are equal, it corresponds to (c).

Discussion

Through this study, the following key findings and discussions were derived:

- Increase in recommendation performance: The use of boosting algorithms with ensemble learning enabled precise hyperparameter tuning and fast training. Additionally, by utilizing 1,880 excavation side-level data samples, the model was able to recommend ESS components appropriate for more granular excavation units.
- Recommendation order in the dependent process: The dependent process proposed in this study follows the recommendation order of retaining wall → water barrier application → lateral support. While this approach successfully enhances ESS component recommendation performance, the recommendation order may vary depending on the stakeholders involved in the design process.
- Possibility of design parameter recommendation: The dependent process not only considers interrelationships between ESS components but also incorporates the design sequence. Since actual design processes typically follow a work breakdown structure, where tasks are progressively subdivided from larger units to smaller ones, this pattern could be applied to recommend design parameters as well. For example, if the specific type of retaining wall is trained along with its design parameters, the recommendation model could predict dimensional

Table 5: The result of Wilcoxon signed-rank test

ESS component		N	Mean rank	Sums of rank	P-value	Result
Water barrier application	Negative ranks	0^a	0	0	0.008	The recommendation process caused the recommendation performance
	Positive ranks	9^b	5.0	45		
	Ties	0^c	-	-		
	Total	9	-	-		
Lateral support	Negative ranks	1^a	2	2	0.015	The recommendation process caused the recommendation performance
	Positive ranks	8^b	5.38	43		
	Ties	0^c	-	-		
	Total	9	-	-		

information in addition to component selection, based on the given selection factor input data.

Conclusions

This study proposed an excavation support system (ESS) recommendation framework that accounts for the interdependence among ESS components, addressing limitations in prior models that treated components independently. The absence of a structured approach in existing methods led to inconsistencies in selecting water barriers and lateral support methods, ultimately reducing recommendation performance.

With the emergence of LLMs, it has become possible to generate desired results using only prompts, without requiring the large-scale datasets traditionally needed in machine learning. However, since LLMs do not reference actual design cases of ESS from construction sites and instead generate responses based on general construction knowledge, their accuracy is lower than that of machine learning models trained on case-specific data. Therefore, relying solely on LLMs presents inherent limitations.

To overcome these challenges, we proposed a multi-step machine learning-based ESS recommendation system that accounts for the interrelationships among ESS components. The study aimed to: (1) develop a recommendation system at the excavation-side level rather than the site level, and (2) incorporate all ESS components (retaining wall, water barrier application, and lateral support) into a unified recommendation process.

To achieve these objectives, an excavation-side-level dataset was constructed, consisting of 1,880 excavation sides from 124 construction projects. Two recommendation processes — independent and dependent processes — were implemented using machine learning algorithms. The Wilcoxon Signed-Rank Test (WSRT) was conducted to determine the significance of performance differences between the two processes.

The experimental results demonstrated that the dependent process consistently improved recommendation performance, particularly for water barrier application and lateral support. The weighted F1-scores achieved in the dependent process were 0.951 for retaining walls, 0.981 for water barrier applications, and 0.831 for lateral support, outperforming the independent process. The WSRT results confirmed that these improvements were statistically significant.

The key contributions of this study include:

- Enhancing recommendation performance through a dependent process, ensuring better alignment between ESS components.
- Proposing an excavation-side-level recommendation approach, allowing for more granular and precise predictions compared to previous site-level models.
- Demonstrating the potential for design parameter recommendations, as the structured dependent process can be extended beyond ESS components to optimize design dimensions and engineering parameters.

These findings suggest that a dependent recommendation framework improves the accuracy and applicability of ESS selection, ultimately assisting engineers in making more informed and automated decisions in excavation projects.

Acknowledgments

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