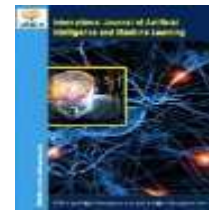




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Research Paper

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Experimental Investigation and ANN-Based Prediction of Dynamic Slope Responses: Crest Settlement, Toe Displacement and Response Time

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ABSTRACT

Dynamic behavior of soil slopes is controlled by the complex interaction of geometric conditions, characteristics of external loads, and reinforcement interventions. In most cases, the nonlinear interactions between the response variables and the effect of the multiple parameters including slope height, inclination, excitation frequency, amplitude and reinforcement condition, cannot be captured by the conventional empirical methods. In the present study an experimental database of 159 observations was consolidated to examine the dynamic stability behavior of reinforced and unreinforced slopes. The experimental program consisted of the slope heights of 300, 400 and 500 mm, slope inclinations of 30° to 40°, excitation frequencies of 1.0–2.0 Hz, amplitudes of 15–30 mm and reinforced and unreinforced conditions. The primary output responses considered were crest settlement, toe displacement, and response time. INDIVIDUAL Artificial Neural Network (ANN) models were developed for crest settlement, toe displacement and response time prediction. The model development was done with five different input parameters i.e., slope height, slope inclination, reinforcement condition, excitation frequency and loading amplitude, whereas the oscillation cycles were not considered as they were kept constant at 10 throughout the experimental program. The dataset was divided into 127 development observations and 32 independent test observations and five-fold cross-validation was carried out during model development to minimize potential information leakage between related experimental conditions. The ANN model had the best prediction performance for crest settlement with the coefficient of determination of independent-test $R^2=0.943$, $RMSE=16.55\text{mm}$ and $MAE=11.35\text{mm}$. Also, good predictions were found for toe displacement ($R^2 = 0.866$, $RMSE = 35.63\text{ mm}$, $MAE = 30.11\text{ mm}$), while response time showed moderate predictability ($R^2 = 0.708$, $RMSE = 0.419\text{ s}$, $MAE = 0.342\text{ s}$). The results show that the response-specific ANN framework is capable of reproducing important non-linear trends in the experimental dataset, with varying predictive performance across the three response variables. Response surface analysis based on ANN was used to further illustrate the combined effect of excitation frequency and amplitude, and reinforcement-effect surfaces were interpreted strictly within the domain of observations made experimentally. The study thus provides a framework for data-driven prediction and interpretation of dynamic slope responses informed by experiments, while acknowledging the limitations of dataset size, experimental domain and response-specific uncertainty.

Keywords: Artificial neural network; dynamic slope stability; reinforced slope; crest settlement; toe displacement; machine learning; response surface; explainable artificial intelligence.

INTRODUCTION

The increasing utilization of artificial intelligence and machine-learning techniques in geotechnical engineering is attributed to their ability to characterize nonlinear relationships that are difficult to model with simple empirical formulations [5,7,8]. ANNs have been used for geotechnical prediction problems because multilayer networks can approximate complex nonlinear input-output relationships [5,6,12,13]. Experiment modeling is a significant tool to study slope behavior under controlled conditions. Physical model experiments may offer direct observation of crest settlement, toe displacement and response time under different loading configurations. However, the interpretation of large experimental datasets can become difficult when the responses are governed by nonlinear and interacting variables. Artificial neural networks

have become increasingly useful for modeling nonlinear engineering systems, as they can approximate complex input-output relationships without requiring an explicit analytical formulation of the governing physical relationship. Unlike conventional linear regression models, ANNs are capable of capturing nonlinear interactions between multiple experimental variables. Behavior of slopes under seismic and vibration loading is often evaluated using deformation-based response measures, as dynamic loading can induce nonlinear deformation and displacement in slopes [1,2]. In this way, the present study develops an ANN-based predictive framework using a consolidated experimental database of reinforced and unreinforced slope observations under dynamic loading. Physically meaningful responses considered are: Geosynthetic reinforcement can change the deformation mechanisms due to the tensile restraint, confinement, and interaction with the surrounding soil [3,4].

1. Crest settlement
2. Toe displacement and
3. Response time. Top of Form

The principal contribution of the study is the development of an experimentally grounded ANN framework capable of integrating multiple geometric, loading, and reinforcement variables for predicting dynamic slope deformation responses. Bottom of Form

2. EXPERIMENTAL DATABASE AND DATA ACQUISITION

2.1 Experimental database

The experimental database was consolidated from multiple observation sheets into a unified ANN-compatible dataset containing 159 observations. The dataset includes reinforced and unreinforced slope conditions and represents combinations of slope geometry and dynamic loading parameters. The database was retained in its experimental form, with slope inclination for the first 40 observations incorporated according to the verified experimental sequence: observations 1–13 corresponded to 30°, observations 14–26 to 35°, and observations 27–40 to 40°.

The consolidated dataset contains the following variables:

Input variables

- Slope height, mm
- Slope inclination, degree
- Reinforcement condition
- Frequency, Hz
- Amplitude, mm
- Oscillation cycles

Output variables

- Crest settlement, mm
- Toe displacement, mm
- Response time, s



Figure 1. Experimental setup, investigated parameters, data acquisition procedure, and overall workflow adopted for ANN-based prediction of dynamic slope responses.

The investigated slope heights were 300, 400, and 500 mm.

$$H = 300, 400, 500 \text{ mm}$$

The investigated slope inclinations ranged from 30° to 40°, including 30°, 35°, and 40° conditions.

$$\theta = 30^\circ, 35^\circ, 40^\circ$$

The reinforcement condition was encoded as a binary experimental input (0 = unreinforced; 1 = reinforced).

$$R = \begin{cases} 0, & \text{Unreinforced slope} \\ 1, & \text{Reinforced slope} \end{cases}$$

The excitation frequency ranged from 1.0 to 2.0 Hz.

$$1.0 \leq f \leq 2.0 \text{ Hz}$$

The loading amplitude ranged from 15 to 30 mm.

$$15 \leq A \leq 30 \text{ mm}$$

The number of oscillation cycles was constant at 10 for all observations and was therefore excluded from the

ANN predictor matrix.

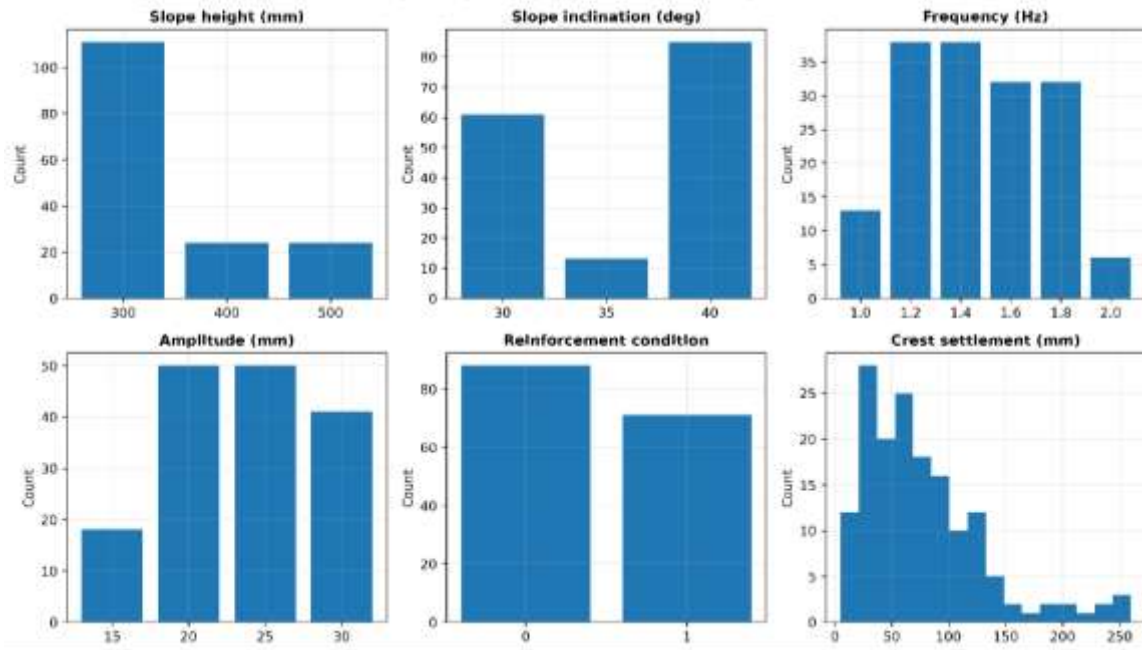


Figure 2. Distribution of experimental input and response variables used for ANN modeling (i.e. slope height, slope inclination, excitation frequency, loading amplitude, reinforcement condition, crest settlement, toe displacement and response time). The distributions illustrate the coverage and variability of the consolidated experimental dataset of reinforced and unreinforced slope conditions.

Table 1. Experimental variables used for ANN development

Variable	Symbol	Unit	Role
Slope height	H	mm	Input
Slope inclination	θ	Degree	Input
Reinforcement condition	R	Binary	Input
Frequency	f	Hz	Input
Amplitude	A	mm	Input
Oscillation cycles	N	–	Constant
Crest settlement	Sc	mm	Output
Toe displacement	Dt	mm	Output
Response time	T	s	Output

3. The ANN framework was selected because the experimental responses were expected to depend on nonlinear interactions among geometric, reinforcement, and loading variables [5,7,8,12,13].

3.1 ANN modelling framework

Artificial neural networks were employed to establish nonlinear relationships between the experimental input parameters and the measured slope responses.

The general ANN relationship can be expressed as:

$$Y = f(X, W, B)$$

where:

- X represents the vector of input variables;
- W represents the network weights;
- b represents the bias parameters;
- $f(\cdot)$ represents the nonlinear mapping defined by the network architecture and activation functions; and
- $\hat{y}$ represents the predicted response.

Three response-specific ANN models were developed for: (i) crest settlement, (ii) toe displacement, and (iii) response time.

The use of independent models was preferred because crest settlement, toe displacement, and response time represent physically different response mechanisms and exhibited different levels of predictability.

3.2 Selection of ANN input variables

Five varying predictors were selected:

$$X = H, \theta, R, f, A$$

where:

- H= slope height;
- θ = slope inclination;
- R= reinforcement condition;
- f= excitation frequency;
- A= excitation amplitude.

Oscillation cycles were excluded from the predictive input matrix because the value was constant at 10 for all observations. A constant variable contains no statistical variation and therefore cannot provide meaningful predictive information to the ANN.

3.3 Dataset division and validation strategy

The dataset was divided into:

- 127 development observations
- 32 independent test observations

The ANN was developed using a grouped validation strategy. Similar conditions were clustered together for experimental observations to prevent information leakage between the development and test data. For model selection and validation, five-fold grouped cross-validation was used. This strategy is more scientifically rigorous than a simple random split, as experimental observations generated under closely related loading conditions might otherwise end up in both training and testing data sets and lead to artificially optimistic performance estimates.

3.4 ANN architecture

The final ANN architectures were selected separately for the three responses.

Crest settlement ANN

$$5 - 8 - 1$$

This architecture contains:

- 5 input neurons;
- 8 hidden neurons; and
- To reduce optimistic bias during model development, validation procedures and data partitioning were treated as essential components of model assessment [16–18].

A ReLU activation function was used.

Toe displacement ANN

$$5 - 12 - 6 - 1$$

This architecture contains:

5 input neurons;
first hidden layer with 12 neurons;
second hidden layer with 6 neurons; and
1 output neuron.

A tanh activation function was used.

Response time ANN

$$5 - 8 - 1$$

The response-time model employed a single hidden layer with 8 neurons and a ReLU activation function.

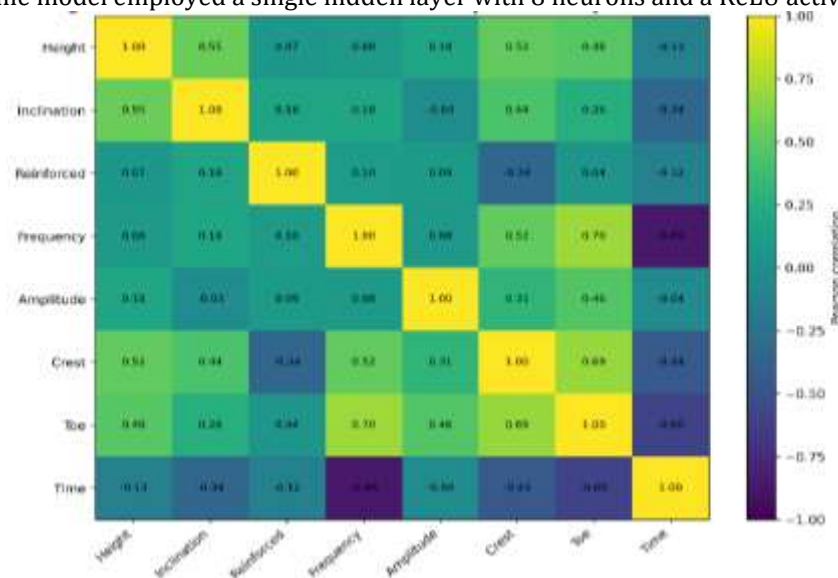


Figure 3. Heatmap of Pearson correlations for the experimental input variables and slope response parameters (slope height, slope inclination, reinforcement condition, excitation frequency, loading amplitude, oscillation cycles, crest settlement, toe displacement, and response time).

The positive and negative correlation coefficients show the direction and relative strength of the linear relationships between the variables examined.

4. ANN MODEL DEVELOPMENT AND PERFORMANCE EVALUATION

4.1 The performance of the ANN models was evaluated using the coefficient of determination, root mean square error, and mean absolute error.

Model performance was evaluated using complementary goodness-of-fit and error metrics [19,20], because no single metric fully characterises predictive accuracy.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where:

- y_i = experimental value;
- $\hat{y}_i$ = ANN prediction;
- $\bar{y}$ = mean experimental value.

4.2 Root mean square error

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

4.3 Mean absolute error

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$



Figure 4. Architecture of the response-specific artificial neural network (ANN) models developed to predict crest settlement, toe displacement, and response time. The networks were constructed using slope height, slope inclination, reinforcement condition, excitation frequency and loading amplitude as input variables. Individual optimized hidden-layer configurations were used for each response parameter.

5. RESULTS AND DISCUSSION

5.1 ANN prediction performance

The predictive performance of the three response-specific ANN models was assessed using grouped cross-validation during development and a 32-observation independent test set for final evaluation. The results should be interpreted response-wise because the three target variables represent different deformation and temporal mechanisms.

Table 2. Performance of the final ANN models

Response	ANN architecture	Activation	CV R^2	Test R^2	Test RMSE	Test MAE
Crest settlement	5-8-1	ReLU	0.892	0.943	16.55 mm	11.35 mm
Toe displacement	5-12-6-1	Tanh	0.773	0.866	35.63 mm	30.11 mm
Response time	5-8-1	ReLU	0.726	0.708	0.419 s	0.342 s

The reported performance metrics were obtained using the 127-observation development dataset and the 32-observation independent test dataset.

5.2 Crest settlement prediction

The ANN model developed for crest settlement achieved the strongest predictive performance among the three investigated responses. On the independent test dataset, the model achieved: -

$$R^2 = 0.943$$

With:

RMSE = 16.55 mm And: MAE = 11.35 mm

The crest settlement model was the best for predictive accuracy among the ANN models studied with an independent-test R^2 value of 0.943. The results indicate that the ANN framework was able to capture the nonlinear relationship between the experimental input parameters and crest deformation. The relatively low prediction errors indicate that the selected geometric, loading and reinforcement variables provide a significant amount of explanatory information for the crest settlement behavior.

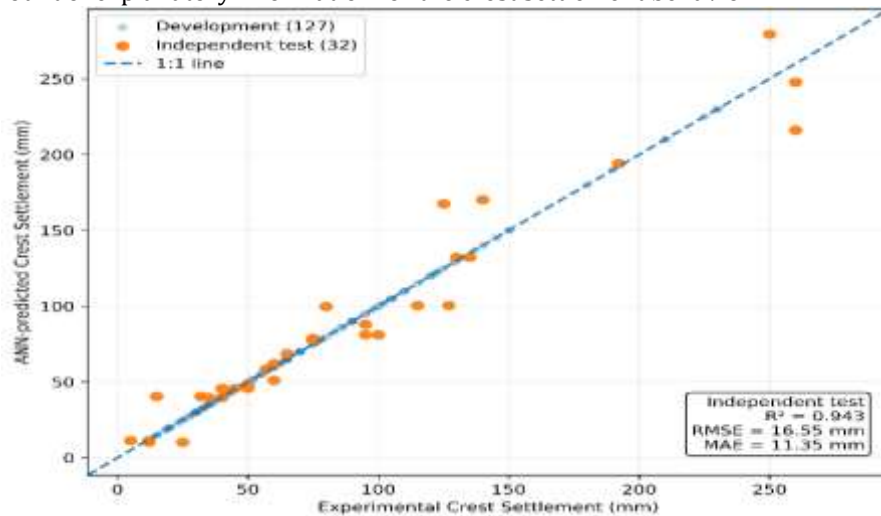


Figure 5. Comparison of experimental and predicted crest settlement with ANN for development and independent test data sets. The 1:1 line of equality shows perfect agreement between experimental measurements and ANN predictions.

The good agreement between experimental and ANN predicted crest settlement is also reflected in the clustering of observations around the equality line. The relatively low scatter of most independent-test observations supports the high predictive capability of the developed ANN model.

5.3 Prediction of toe motion

The proposed model was validated by the independent test dataset with a good predictive performance ($R^2 = 0.866$, RMSE = 35.63 mm, and MAE = 30.11 s).

$R^2=0.866$

MAE=30.11mm

RMSE=35.63mm

The ANN model developed for toe displacement prediction showed good performance with a R^2 value of 0.866 in the independent-test. However, the prediction error was larger compared to the one obtained for the crest settlement. This indicates a larger variability of the toe response. This behavior could be attributed to a complex interaction between dynamic loading and local deformation mechanisms taking place near the slope toe.

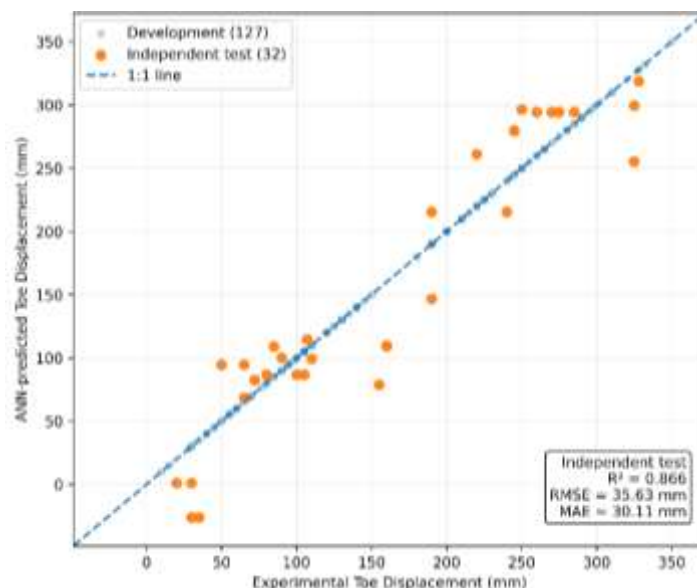


Figure 6. Comparison between experimental and ANN-predicted toe displacement for the development and independent test datasets.

The ANN predictions reproduce the general trend of increasing toe displacements. The toe deformation exhibits a relatively more complex nonlinear response than the crest settlement, as indicated by a higher scatter.

5.4 Response time prediction

The response-time ANN showed moderate predictive performance, with an independent-test $R^2 = 0.708$, RMSE = 0.419 s, and MAE = 0.342 s.

$$\begin{aligned} R^2 &= 0.708 \\ \text{RMSE} &= 0.419 \text{ s} \\ \text{MAE} &= 0.342 \text{ s} \end{aligned}$$

The ANN model predicted response time with moderate accuracy, R^2 of 0.708 on an independent-test set. The lower predictive performance compared to the deformation models suggests that response time might be influenced by other physical processes not entirely captured by the available experimental input parameters.

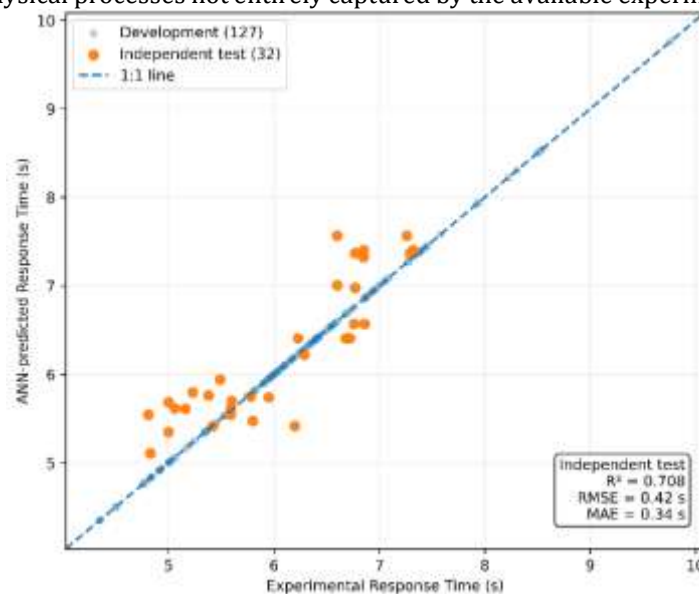


Figure 7. Comparison between experimental and ANN-predicted response time for the development and independent test datasets.

The ANN is able to capture the overall decreasing trend of response time with increasing dynamic loading intensity. However, a higher degree of scatter is observed compared to crest settlement and toe displacement.

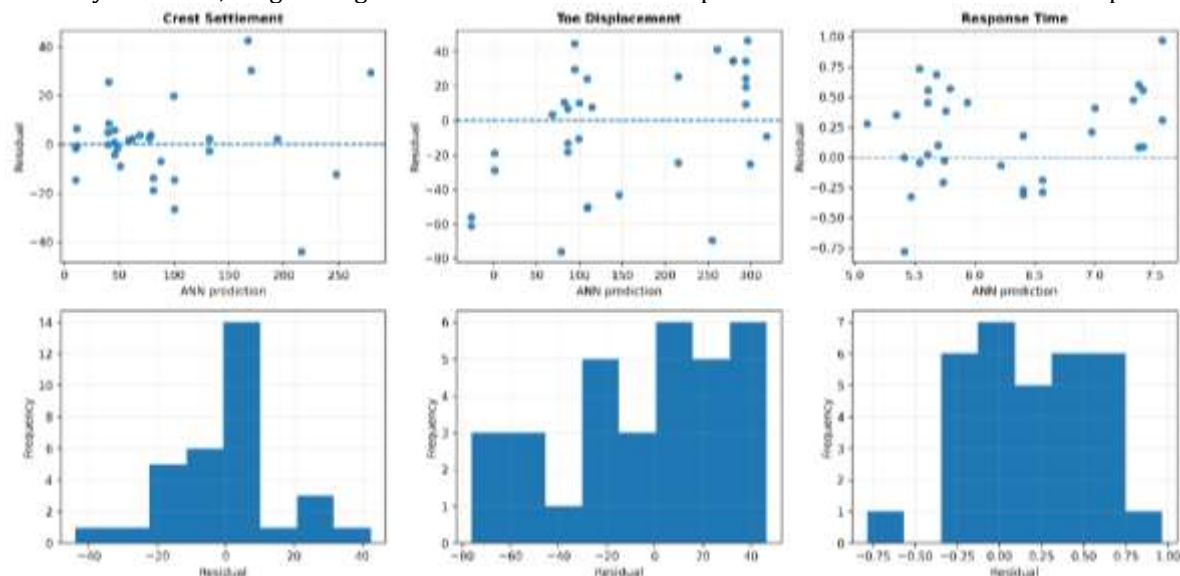


Figure 8. Residual diagnostics for the independent test for the developed ANN models for predicting crest settlement, toe displacement and response time. Figure shows the distribution and variation of residuals (i.e. difference of experimental and ANN predicted values) to assess the prediction

errors and to estimate the possible systematic bias in the models.

6. COMPARATIVE PREDICTIVE ASSESSMENT

The comparative assessment is interpreted as response-dependent rather than as evidence that a single algorithm is universally superior. The comparison should be considered scientifically valid only when all candidate models are trained and evaluated using the same development and independent-test partitions [17,18].

Within the available comparative results, ANN produced the strongest predictive performance for crest settlement, whereas alternative nonlinear models remained competitive for toe displacement and response time. Accordingly, the principal contribution of the comparison is to demonstrate response-specific model behaviour rather than to claim universal superiority of ANN.

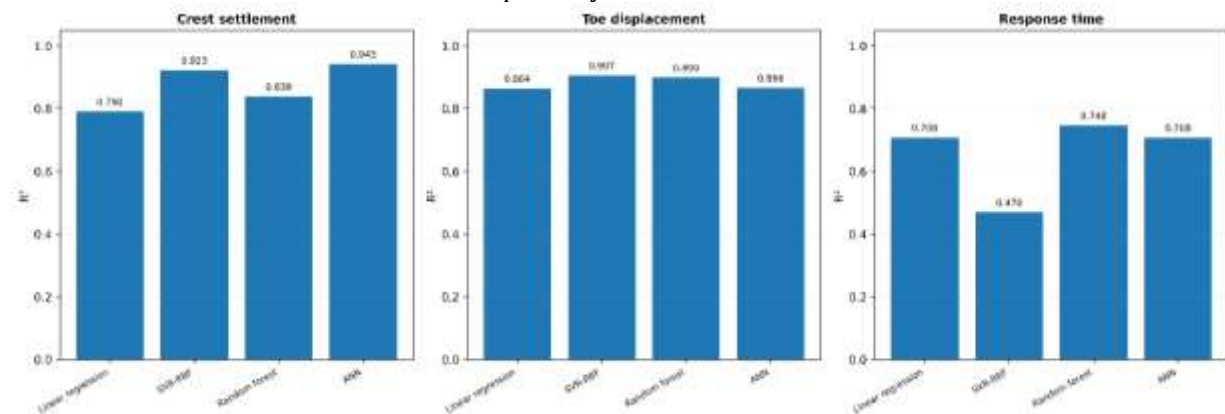


Figure 9. comparison of predictive performance of developed artificial neural network (ANN) and other candidate models for prediction of crest settlement, toe displacement and response time. the performance of the model was evaluated using the independent test dataset based on the coefficient of determination (r^2), which gives a comparative assessment of the predictive capability of the investigated modeling approaches.

7. MODEL INTERPRETATION AND ANN-BASED PARAMETRIC ANALYSIS

The trained ANN models were further interrogated to examine the relative influence of the input variables and the model-predicted response behaviour within the experimental domain. These analyses are interpretive outputs of the validated models and do not represent additional experimental measurements.

7.1 Global feature importance

Permutation-based feature importance was used to evaluate the relative contribution of the five varying input variables to each response-specific ANN model [23–27]. The importance values should be interpreted as model-based sensitivity indicators and not as direct measures of physical causality.

$$15 \leq A \leq 30$$

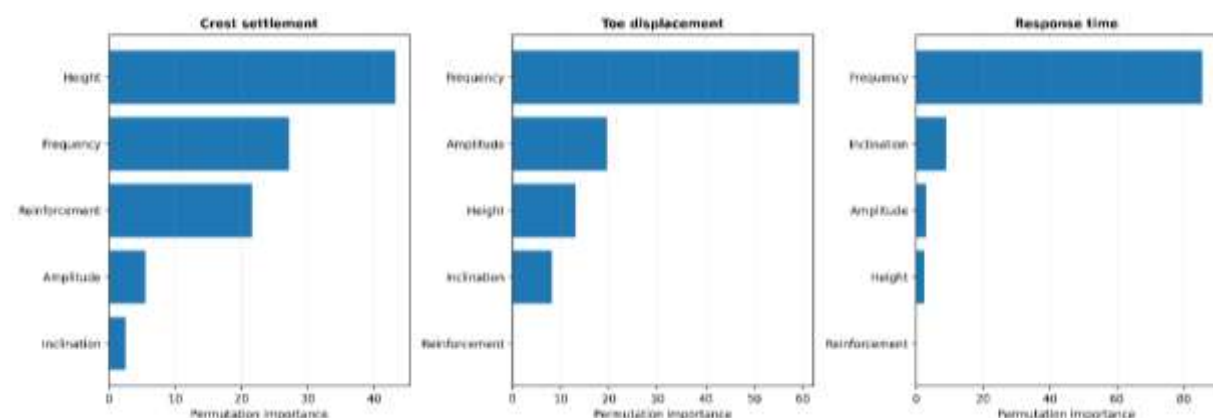


Figure 10. Global importance of experimental input variables for developed ANN models to predict crest settlement, toe displacement and response time. Permutation importance analysis was applied to quantify the relative contribution of slope height, slope inclination, reinforcement condition, excitation frequency and loading amplitude to the predictive performance of each response-specific ANN model.

7.2 Response trends obtained from ANN surfaces

The response trend obtained from ANN for crest settlement shows a progressive increase with increase in excitation frequency and amplitude in the domain investigated. The nonlinearity of the surface means that the effect of frequency is a function of the applied amplitude. The greatest predicted deformation is concentrated toward the more severe combinations of the two loading variables.

7.3 Trend of Toe-displacement response

The toe-displacement response derived from the ANN shows a more complex nonlinear behavior compared to crest settlement. In general, deformation increases with loading intensity but local curvature indicates enhanced interaction effects between governing variables. This is consistent with the independent-test prediction error for toe displacement being relatively larger.

7.4 Trend in response-time

The response-time surface obtained from the ANN shows a general decrease of the predicted response time with increasing excitation intensity, in particular with increasing frequency. Local variations however show that response time is controlled by a relatively complex relationship between geometry, loading and reinforcement conditions.

8. THREE-DIMENSIONAL ANN RESPONSE SURFACE VISUALIZATION

The three-dimensional ANN surfaces represent a visual depiction of the model-predicted nonlinear response over the investigated frequency-amplitude domain. Overlay of measured data for qualitative comparison with the modeled response surface.

The response surfaces are only valid within the range of conditions represented by the experimental dataset and should not be used to support extrapolation beyond the investigated domain [14,17,18].

- Frequency axis;
- Amplitude axis;
- Response axis;
- Experimental observations overlaid on the surface.

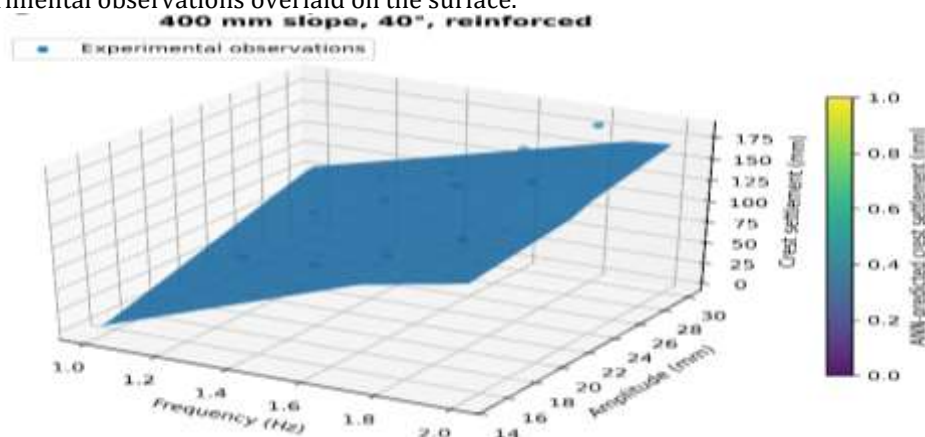


Figure 11 Three dimensional ANN predicted surface for crest settlement versus excitation frequency and amplitude with experimental data overlaid for comparison.

The good agreement between the experimental points and the surface generated by the ANN visually demonstrates the ability of the model to reproduce the main deformation trend.

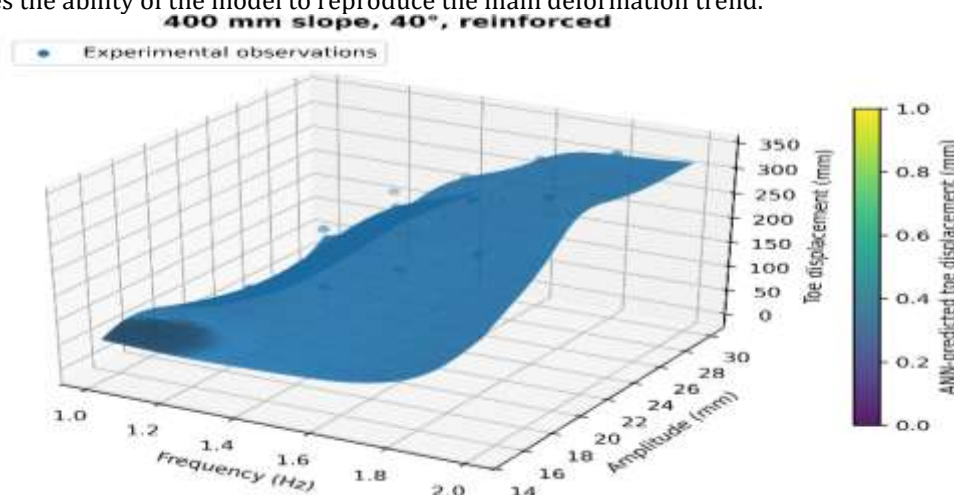


Figure 12. 3D ANN predicted surface for toe displacement versus excitation frequency and amplitude with experimental observations superimposed.

The three-dimensional visualization highlights the nonlinear and spatial complex variation of toe displacement in the investigated loading domain.

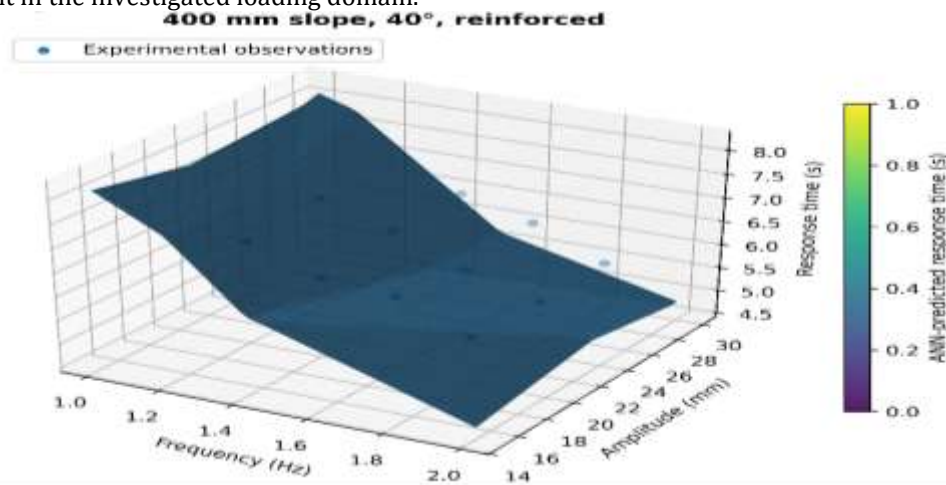


Figure 13. Three-dimensional ANN-predicted surface for slope response time as a function of excitation frequency and amplitude, with experimental observations overlaid.

The surface demonstrates the overall reduction in predicted response time with increasing excitation intensity while also illustrating the nonlinear nature of the response.

9. REINFORCEMENT EFFECT ANALYSIS

$$\Delta S_c = S_{c, \text{unreinforced}} - S_{c, \text{reinforced}}$$

Where:

ΔS_c - Represents the ANN-predicted change in crest settlement between corresponding unreinforced and reinforced conditions.

$$\Delta D_t = D_{t, \text{unreinforced}} - D_{t, \text{reinforced}}$$

Positive values of ΔS_c or ΔD_t indicate a model-predicted reduction in deformation under reinforced conditions, for otherwise comparable input conditions. Represents the predicted reduction in crest settlement due to reinforcement.

Similarly, the toe displacement reduction can be expressed as:

$$\Delta D_t = D_{t, \text{unreinforced}} - D_{t, \text{reinforced}}$$

Positive values indicate a predicted beneficial reinforcement effect.

9.1 Reinforcement effect on crest settlement

The reinforcement-effect surface shows a decrease in the crest settlement predicted by the model for a large part of the studied loading domain. The magnitude of the predicted reduction depends on the excitation frequency and amplitude which indicates that the effectiveness of the reinforcement depends on the interactions. These results are to be interpreted as ANN-based engineering scenarios in the experimental domain.

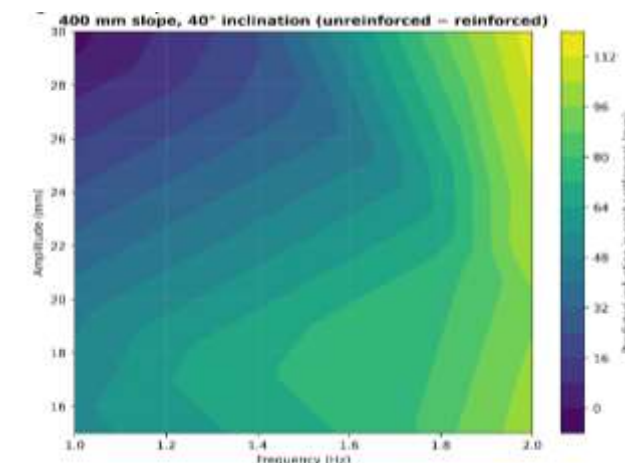


Figure 14. ANN-predicted reduction in crest settlement due to reinforcement as a function of excitation frequency and loading amplitude. Positive values indicate improved deformation control

under reinforced conditions.

9.2 Reinforcement effect on toe displacement

The model does not provide a single factor of deformation reduction for all loading conditions, as the predicted reinforcement effect on toe displacement is not uniform over the frequency-amplitude domain. The observed variation should therefore be interpreted in light of the underlying experimental coverage and response-specific prediction uncertainty.

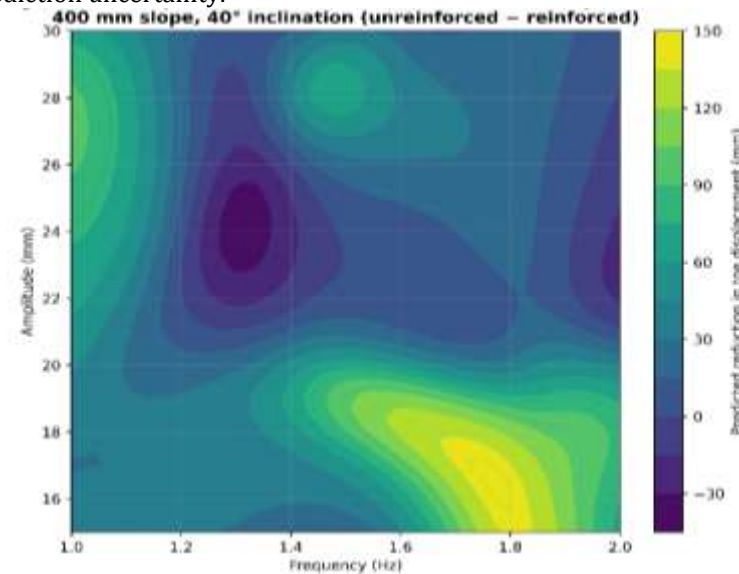


Figure 15. ANN-predicted reduction in toe displacement resulting from reinforcement under different combinations of excitation frequency and amplitude.

10. STUDY LIMITATIONS AND APPLICABILITY DOMAIN

The present study is based on an experimental data set comprising 159 observations. Although grouped cross-validation and an independent test set were used to strengthen the model validation, the data set is still small for neural network modeling [8,16–18]. Therefore, the performance reported should be considered indicative of predictive ability within the experimental domain investigated and not as a universal generalization to field-scale slopes or loading conditions not tested.

Five different predictors were modeled: slope height, slope inclination, reinforcement condition, excitation frequency and loading amplitude. The response times were less predictable than the deformation responses, indicating that additional unmeasured factors may influence the temporal response. Future work should include larger datasets, more experimental campaigns, quantification of uncertainties, and external validation [8,17,18,21,22]. Permutation-based global feature importance remains the main model-interpretation technique in the present manuscript. The revised core manuscript does not include SHAP-based local explanation, as the uploaded source document does not contain a fully documented SHAP workflow and corresponding validated figures. SHAP analysis can be added in a future revision when the computational procedure and outputs are fully reproducible.

11. ENGINEERING SIGNIFICANCE

The main contribution of the study is to predict multiple dynamic slope responses using response-specific ANN models based on the experimental outcome rather than a single aggregated output framework. Such a response-specific approach is in line with the general trend of data-driven models for nonlinear geotechnical response prediction [5,7,8,22].

The comparative deformation results and the surfaces as derived via the ANN show that the excitation frequency and amplitude should be interpreted in a joint manner as the combined effect is nonlinear. The reinforcement-effect analysis also indicates that deformation control is loading dependent and cannot be described by a single uniform improvement factor.

From an engineering point of view, the framework provides a data-driven supplement to experimental interpretation, by providing interpolation of the response behavior within the explored domain [1,2,21,22]. It is not intended as a substitute for physical understanding, traditional stability analysis or site-specific investigation.

The study thus highlights the value of combining controlled physical experimentation with transparent machine learning validation and judicious engineering interpretation.

12. CONCLUSIONS

For ANN-based prediction of dynamic slope responses, a combined experimental data base of 159 observations was formed. The database consisted of slope height, slope inclination, reinforcement condition, excitation frequency, loading amplitude, crest settlement, toe displacement and response time. The first 40 observations were assigned slope inclination according to the verified sequence of experiments, i.e. observations 1-13 = 30°, observations 14-26 = 35° and observations 27-40 = 40°.

Five varying predictors were used for model development. Oscillation cycles were omitted as the value was same at 10 for all observations.

The response-specific ANN models had different performance on the independent test. The prediction was strongest with the Crest settlement ($R^2 = 0.943$; RMSE = 16.55 mm; MAE = 11.35 mm) followed by toe displacement ($R^2 = 0.866$; RMSE = 35.63 mm; MAE = 30.11 mm). The predictability of the response time was moderate ($R^2=0.708$; RMSE=0.419 s; MAE=0.342 s).

To reduce optimistic evaluation caused by closely related experimental conditions, the grouped development strategy and independent test set were adopted. However, the results are still specific to the experimental domain and dataset of the present study.

The ANN response surfaces showed a nonlinear interaction between excitation frequency and amplitude. The surfaces of the reinforcement effect suggested that the predicted deformation reduction is dependent on the loading condition. These surfaces should be regarded as model-based interpolation in the range of the observed experiments.

To summarize, the study reveals that response-specific ANN models can be applied as a nonlinear predictive framework for the experimentally observed dynamic slope behavior. The best utilization of the developed models is as an engineering decision support and interpretation tool within the domain of the parameters explored. Larger datasets, uncertainty analysis and external validation are yet to be tackled in future work.

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