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Prediction of seismic displacements in tailings dam decommissioning using artificial neural networks

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ABSTRACT: This study investigates the application of artificial neural networks to predict seismically induced permanent displacements in tailings dams during the decommissioning process. Training was conducted using finite element analyses with constitutive models specifically designed for cyclic loading (PM4Sand and PM4Silt), combined with 14 seismic records corresponding to a 10.000-year return period. The dam foundation was characterized as soft rock (Class B, VS30 = 800 m/s). Input variables included peak ground acceleration, Arias Intensity, Cumulative Absolute Velocity, fundamental vibration period, and the ratio between excavated height and initial dam height. Results confirm the potential of neural networks to anticipate permanent displacements in complex dynamic scenarios, supporting more effective safety and risk management strategies in mining structures.

KEYWORDS: Artificial neural networks; tailings dam; seismic behavior; permanent displacements.

1 INTRODUCTION

Tailings dams are critical structures in mining, whose stability must be ensured even in regions of low seismicity. Predicting permanent displacements induced by seismic loading becomes essential for risk management and operational safety. Traditional analysis methods, although robust, have limitations when faced with the complexity of the dynamic behavior of geotechnical materials.

In this context, the use of artificial neural networks emerges as a promising alternative, capable of learning patterns from numerical analyses and representative seismic records. This approach offers greater precision in anticipating structural responses and contributes to more effective risk mitigation strategies in mining structures.

2 ANALYSIS OF DYNAMIC RESPONSE

Four geotechnical units were defined to characterize the structure of the dam under study, as shown in Figures 1 and 2: a) Tailings (R), subdivided into R11, R12, R21, R22, R31 and R32; b) Starter Dike (DP), consisting of compacted alluvial soil embankments at the base of the structure; c) Subsequent Perimeter Dikes (DA), formed by alluvial soil and/or coarse tailings embankments that increase the dam height, which may or may not be compacted; d) Rock Foundation (FR), composed of rock and highly weathered soils.

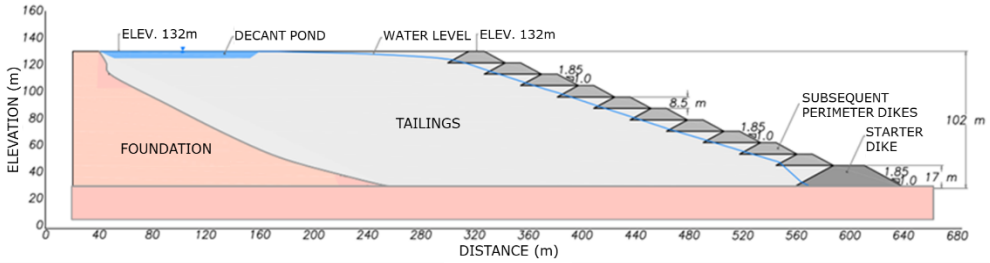


Figure 1. Geometry of the cross-section of the analyzed tailings dam.

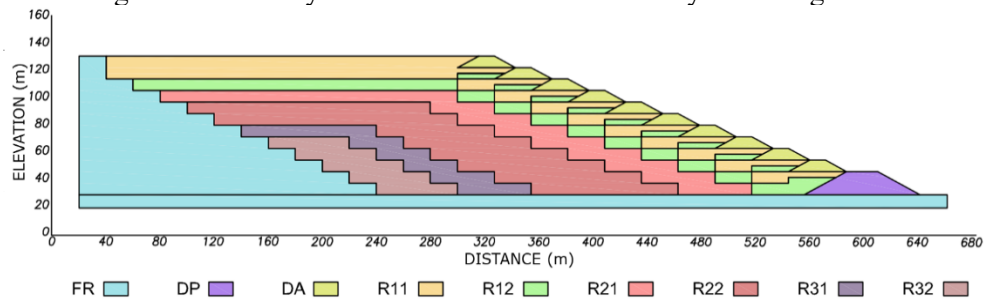


Figure 2. Distribution of constituent materials in the dam cross-section.

2.1 Parameters of cyclic constitutive models

In the numerical modeling of the dam behavior, the following constitutive models were employed: a) Linear Elastic Model for the foundation in both static and cyclic simulations; b) Hardening Soil Small (HSS) Elastoplastic Model for the tailings, starter dam, and raise dams in the static loading simulation; c) Hardening Soil Small (HSS) Elastoplastic Model with Rayleigh damping addition for the starter dam and raise dams in the cyclic loading simulation; d) PM4Sand and PM4Silt Models for the tailings in the cyclic loading simulation, whose parameters are listed in Tables 1 and 2. Tailings R11, R12, R21, and R22 were classified as silty sand (SM), while tailings R31 and R32 were classified as low plasticity clayey silt (ML).

Table 1. Parameters of the PM4Sand model used in the cyclic simulation of tailings classified as silty sand (SM)

Material	Description	Dr	G_0	hpo	e_{max}	e_{min}
			(-)	(-)	(-)	(-)
R11	R Dr:30 hp0:0,02 Sand	0,3	430,3	0,02	1,25	0,49
R12	R Dr:30 hp0:0,40 Sand	0,3	430,3	0,40	1,25	0,49
R21	R Dr:50 hp0:0,40 Sand	0,5	624,9	0,40	1,25	0,49
R22	R Dr:50 hp0:0,85 Sand	0,5	624,9	0,85	1,25	0,49

Note: Values calibrated according to recommendations by Boulanger & Ziotopoulou (2023), considering different relative density (Dr) and plasticity parameters.

Table 2. Parameters of the PM4Silt model used in the cyclic simulation of tailings classified as low plasticity clayey silt (ML)

Material	Description	γ_{unsat}	γ_{sat}	$S_{u,ratio}$	G_0	hpo
		(kN/m^3)	(kN/m^3)	(-)	(-)	(-)
R31	R Su:0,2 Silt	19	20	0,2	350	20
R32	R Su:0,4 Silt	19	20	0,4	400	30

Nota: Parâmetros ajustados com base em ensaios laboratoriais e recomendações de Boulanger & Ziotopoulou (2023), incluindo densidade aparente, resistência não drenada (Su,ratio) e módulo inicial de cisalhamento (G0).

2.2 Seismic Records

The selection of seismic records (Table 3) was carried out to adequately represent the local site effects, considering Brazil's classification as a Stable Continental Region (SCR). Records obtained from seismographic

stations with shear wave velocity (V_{S30}) equal to 800 m/s, compatible with the foundation's geotechnical profile, were employed. The spectral matching of the records was performed to reflect conditions associated with a 10.000-year return period, according to safety criteria applied in seismicity studies for tailings dams. The choice of seismic records for defining the design earthquake considered criteria such as spectral content, magnitude, epicentral distance, and focal mechanism, in agreement with the results of the previously conducted seismic hazard disaggregation. The Pacific Earthquake Engineering Research Center (PEER, NGA-East) database was used to select real accelerograms meeting these characteristics, which were subsequently adjusted for use in the numerical modeling of the dam.

The generation of the design earthquake adopted the time-domain spectral matching method, based on the algorithm by Al Atik and Abrahamson (2010). This method modifies real seismic records by adding or subtracting wavelets in segments of the acceleration history where discrepancies exist between the record's response spectrum and the target spectrum. This technique is especially recommended in situations with limited availability of representative seismic records for the site under study.

Table 3. Seismic records considered in the spectral matching for rock foundation with V_{S30}= 800 m/s and 10.000-year return period.

#	Earthquake Name	Year	Station Name	Magnitude	R_{jb} (km)	R_{rup} (km)	V_{S30} (m/s)
1 / 2	Saguenay_1988-11-25	1988	US,DCKY	5,85	190,15	192,07	822,1
3 / 4	Saguenay_1988-11-25	1988	US,ISFL	5,85	319,53	320,51	866,7
5 / 6	Mineral_2011-08-23	2011	Standing Stone_ PA	5,74	298,58	298,64	940
7 / 8	Mineral_2011-08-23	2011	Standing Stone_ PA	5,74	298,58	298,64	940
9 / 10	Mineral_2011-08-23	2011	Blacksburg_ VA	5,74	227,25	227,33	789
11 / 12	Sparks_2011-11-06	2011	Salina_ OK	5,68	175,43	175,53	799,4

In the characterization of artificial earthquakes, seismic intensity measures (IMs) were considered, selected based on their relevance to different response mechanisms. Arias Intensity (AI) is recognized as a robust parameter for evaluating seismic slope displacements, as it reflects the energy accumulated during ground motion (Bray and Travasarou, 2007). Cumulative Absolute Velocity (CAV), especially in its modified version CAV5, has been used as a reliable indicator for the triggering of soil liquefaction, as it captures the contribution of repeated amplitudes throughout the seismic record (Kramer and Mitchell, 2006). The choice of these IMs is justified by their ability to directly relate motion intensity to potential geotechnical and structural effects, differing from other measures limited to spectral parameters or isolated peaks. AI and CAV values were determined for each seismic record, forming the methodological basis for evaluating performance and structural response under the different simulated seismic loading conditions.

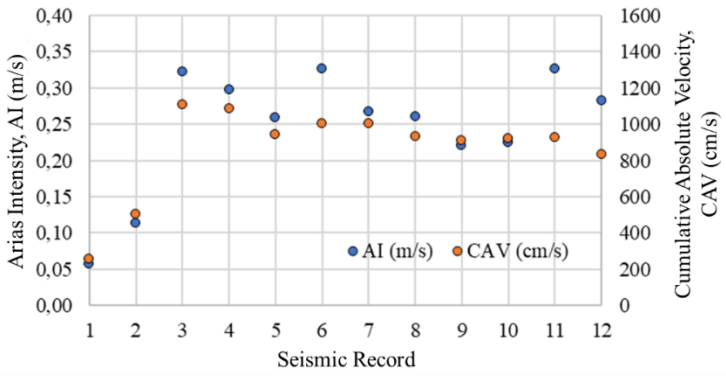


Figure 3. Seismic intensity measures (Arias Intensity and CAV) of the records matched for a 10.000-year return period.

2.3 Dynamic Response

The analysis of the seismic behavior of the tailings dam was conducted using a performance-based approach, aligned with guidelines proposed in seismic and geotechnical engineering studies (e.g., Kramer, 1996; Bray & Travasarou, 2007). This methodology allows evaluating not only the immediate structural response to seismic loading but also the accumulated effects that compromise the global stability of the structure. Unlike traditional approaches based on strength criteria, performance-based assessment seeks to identify acceptable response levels in terms of permanent displacements, plastic deformations, and excess pore pressure generation, providing parameters directly related to the dam's operational safety.

Figure 4 presents the observation points used for predicting permanent displacements in the dam. Points P1 to P5 were strategically positioned along the crest of the raise dams to optimize the monitoring of deformations in critical regions of the structure. This figure shows the temporal evolution of displacements induced by artificial earthquake 1 (Saguenay 1988), applied to the compliant base of the numerical model, corresponding to a 10.000-year return period. This approach allows estimating the dynamic behavior of the dam under extreme seismic events.

In this context, Figure 5(a) presents the field of total permanent displacements, highlighting the zones with the highest concentration of deformations induced by seismic loading. Complementarily, Figure 5(b) illustrates the final distribution of the excess pore pressure ratio (r_u), allowing the identification of regions with greater susceptibility to liquefaction and, consequently, higher structural vulnerability. The integration of these results enables a comprehensive assessment of the dam's response, reinforcing the importance of the performance-based approach as a tool for reliability studies and risk mitigation in large-scale geotechnical works.

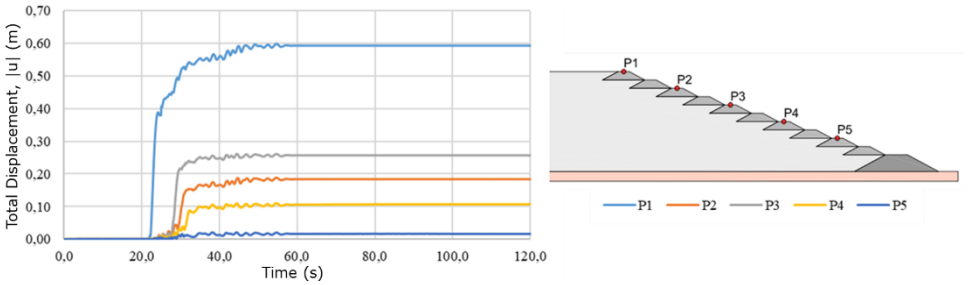


Figure 4. Temporal evolution of permanent displacements at points P1 to P5, obtained for the Saguenay (1988) seismic record, matched for a 10.000-year return period, considering a compliant base.

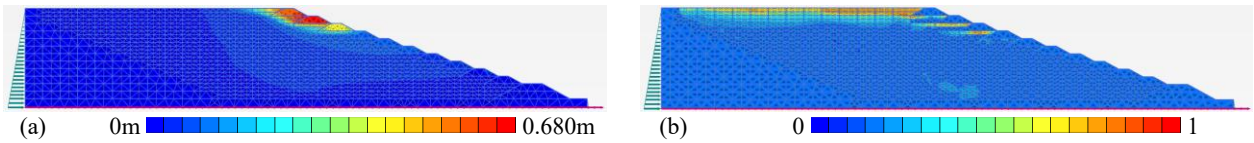


Figure 5. (a) Field of accumulated permanent displacements and (b) final distribution of the excess pore pressure ratio (r_u) after application of the Saguenay (1988) seismic record.

3 PERFORMANCE PREDICTION USING NEURAL NETWORKS

3.1 Multilayer Perceptron neural network

The use of artificial neural networks, especially the Multilayer Perceptron (MLP) architecture, proves highly effective in predicting nonlinear systems, such as the dynamic performance of geotechnical structures. The MLP consists of input, hidden, and output layers, connected by neurons with nonlinear activation functions, trained by backpropagation algorithms and adjusted by the conjugate gradient method. This structure allows the approximation of complex functions through training and validation samples with strong robustness against uncertain or noisy data. Even with a single hidden layer, the MLP can represent nonlinear behaviors with high precision, being recommended for small datasets to avoid overfitting and maintain generalization capability. The appropriate selection of the number of layers and neurons is essential to achieve good predictive results.

The artificial neural network can approximate any nonlinear mapping through learning and has broad application prospects in predicting nonlinear systems. The operating principle of artificial neural network

prediction is mainly divided into two stages: first, using training samples to design and train the network to obtain prediction rules; then, validating the test samples according to the rules obtained to verify its reliability with the accuracy of the test results (LIU B. et al., 2021).

The main advantage of artificial neural network algorithms is their strong adaptability to training samples. They have a strong capacity to process uncertain information. They can still function normally in the presence of noisy or nonlinear data. The artificial neural network possesses strong robustness, memory capacity, nonlinear mapping capacity, and strong self-learning capacity during training (Voukantsis D. et al., 2011; Chaudhuri B. & Bhattacharya U., 2000).

The Multilayer Perceptron (MLP) neural network is a unidirectional propagation multilayer feedforward network structure based on the error backpropagation algorithm. As shown in Figure 6, its structure can be divided into three layers, namely the input layer, the hidden layer, and the output layer. Each layer consists of several nodes, and each layer can be passed to the next layer until the output layer. Except for the input nodes, each node is a neuron with a nonlinear activation function. Equation (1) is its output, ωnj is the node weight, and bjk is the bias.

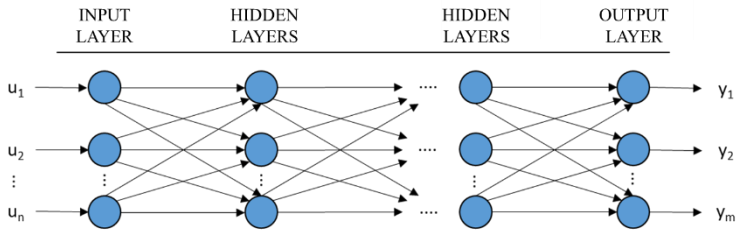


Figure 6. General structure of the multilayer perceptron (MLP) neural network, composed of input, hidden, and output layers.

$$o_k = \sum_j w_{nj} x_n + b_{jk} \tag{1}$$

MLP is a typical supervised learning algorithm, and its loss function is defined as Eq. (2), where $o_{\omega,b(x)}$ is the MLP output value and y is the actual value

$$J(w, b, x, y) = \frac{1}{2} \left\| o_{w,b(x)} - y \right\|^2 \tag{2}$$

Parameters are adjusted by the conjugate gradient method to minimize the loss function. The calculation formulas for the conjugate gradient method are Eqs. (3) and (4).

$$S(n+1) = -g(n+1) + \beta(n+1)\, x\, S(n) \tag{3}$$

$$\beta(n) = \frac{(-g(n+1))^T x (g(n) - g(n+1))}{g(n)^T x g(n)} \tag{4}$$

The hidden layer in the MLP neural network model can be single or multiple. However, provided the number of neuron nodes in the hidden layer is appropriately adjusted, a single hidden layer neural network can approximate any nonlinear function. Therefore, a single hidden layer can meet most engineering needs.

With the application of Multilayer Perceptron (MLP) neural networks, it is possible to approximate a nonlinear function, verified by the training and validation loss values, as well as the prediction and observation outputs.

In the MLP neural network, choosing the number of hidden layers and the number of neurons in each layer is particularly important. In a small dataset, many hidden layers will not only make the model more complicated but also lead to overfitting of the model and low generalization capability. Therefore, in small datasets, one or two hidden layers of the MLP neural network are generally used for modeling.

3.1.1 Error assessment

After model development, the accuracy of the model depends on the error, which can be calculated with the aid of statistics. Each error has different criteria for checking model accuracy.

In this model, the first error evaluation method used was the coefficient of determination R^2 (Eq. 5); its value typically ranges between 0 and 1, and a value close to 1 indicates a smaller error. 'y' represents the observed or actual value, while 'w' represents the predicted value.

The mean absolute percentage error (Eq. 6), mean absolute error (Eq7), mean squared error (Eq. 8), and root mean squared error (Eq. 9) were also used to determine the final number of the hidden layer.

The error valuation criterion used in this research was the root mean square deviation (RMSE) (Eq. 9). In the case of RMSE, a value closer to 0 is good compared to a value further from 0, therefore 0 is considered the benchmark. In the RMSE equation, the actual value is represented by 'y' and the predicted value by 'w'. The mean absolute error (MAE) (Eq. 7) was also used in this research; the closer the value is to zero, the better the predicted results.

$$R^2 = \frac{\sum_{t=1}^{n}(y_t - \bar{y})\,(w_t - \bar{w})}{\sqrt{\sum_{t=1}^{n}(y_t - \bar{y})^2 \sum_{t=1}^{n}(w_t - \bar{w})^2}} \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - w_t}{y_t}\right| \tag{6}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - w_t| \tag{7}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - w_t)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - w_t)^2} \tag{9}$$

To predict seismic-induced displacements in tailings dams, a Multilayer Perceptron (MLP) neural network model was developed. The model architecture comprises seven input neurons, two hidden layers, and one output neuron, as illustrated in Figure 7.

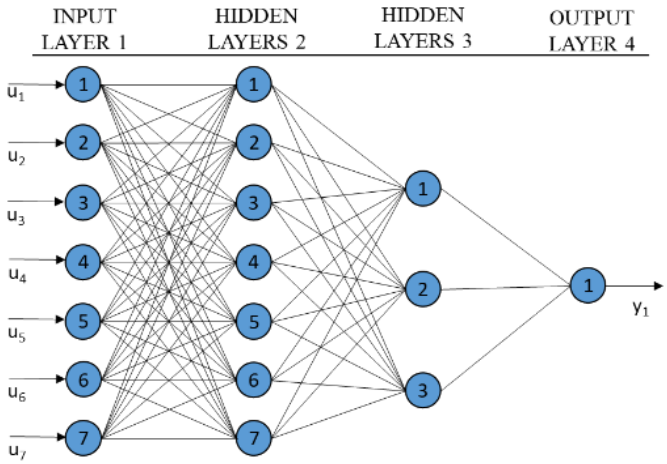


Figure 7. Architecture of the MLP Neural Network for Seismic Displacement Prediction.

Input Variables Description – The seven input parameters were selected based on their relevance to seismic response and geotechnical behavior:

- x_1 – Peak Ground Acceleration (PGA): Maximum acceleration during the seismic event, expressed in g.
- x_2 – Arias Intensity (AI): A measure of seismic energy, expressed in m/s.
- x_3 – Cumulative Absolute Velocity (CAV): Represents the total absolute velocity over time, expressed in cm/s.
- x_4 – Fundamental Vibration Period (Ts): Calculated using the expression Ts = 4H/Vs, where H is the dam height and Vs is the shear-wave velocity.
- x_5 – Relative Observation Height (y/H): Ratio between the elevation of the observation point and the initial dam height. Values considered: P1= 5/5, P2= 4/5, P3= 3/5, P4= 2/5 e P5= 1/5
- x_6, x_7 – Material Strength Scenarios: Binary indicators representing different geotechnical conditions:
    - Standard scenario: [0, 1]

- Safety scenario: [1, 0]
- Maximum performance scenario: [0, 0]

Output Variable

- y – Displacement (D): Predicted permanent displacement at the observation point, expressed in meters.

During model calibration, the input variables were manipulated to improve correlation and predictive accuracy. The use of neural networks proved advantageous for capturing the nonlinear relationships inherent in seismic response analysis. The MLP architecture was selected for its robustness and adaptability in modeling complex geotechnical phenomena. The methodology and training process of the neural network are detailed in the following section.

3.2 Evaluation of the neural network architecture

Networks with a larger number of layers were tested, where 80% of the data were chosen for network training and 20% of the data were chosen for network validation. The attempts with different neural network architectures are presented below (Table 4) for Tr = 10.000 years. It shows the errors in the training data and validation data, obtaining low error values, indicating good predictive capability.

Table 4. Training and validation errors for the MLP neural network architecture applied to seismic displacement prediction (Tr = 10.000 years).

	Model (7-7-3-1)	
	Training	**Validation**
R^2	0,9440	1,0771
MAPE	0,0151	0,5617
MAE	0,0639	0,0999
MSE	0,0041	0,0100
RMSE	0,0639	0,0999
Epochs	5000	

In the figures presented below, the prediction results obtained from the training and validation datasets are illustrated. In Figure 8, the consistency between the training and validation results is evident, demonstrating good predictive capability in both sets. This behavior indicates that the model presents high stability and robustness, being suitable for application in the proposed predictions. A decreasing trend and convergence of the losses of the training and validation data can be seen, discarding overfitting.

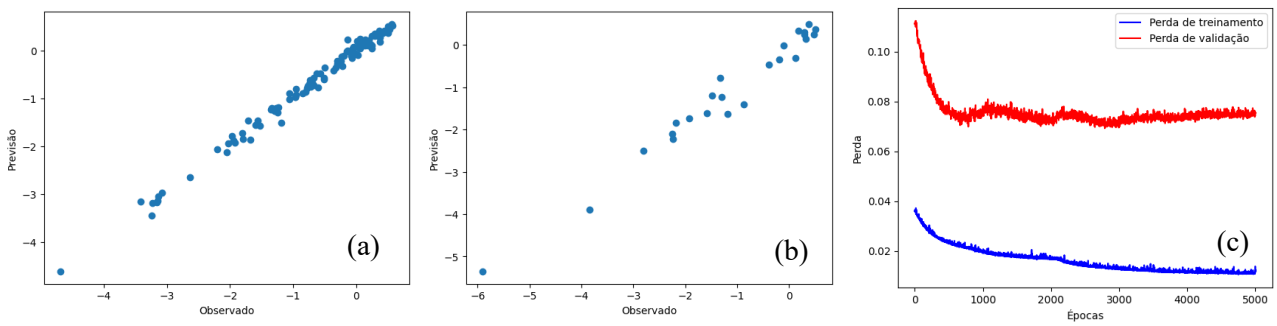


Figure 8. Prediction results for (a) training set, (b) validation set and (c) Evolution of losses.

3.3 Forecast for Tailing Dam

For this study, an upstream-raised tailings dam with representative geotechnical and hydraulic characteristics was adopted as a reference case (Figure 9). This configuration was used to evaluate the predictive capacity of neural network models in estimating seismic-induced displacements. Based on numerical modeling, the displacement at the dam crest (P1) immediately after the seismic event was 0.83 m, corresponding to a percentage variation of approximately 13.70% when compared with the prediction obtained from the neural network model.

Input Variables of the Neural Network Model

- x_1 – Peak Ground Acceleration (PGA): 0,25 g.
- x_2 – Arias Intensity (AI): 1,59 m/s.
- x_3 – Cumulative Absolute Velocity (CAV): 1765 cm/s.
- x_4 – Fundamental Vibration Period (Ts): 0,25s.
- x_5 – Relative Observation Height (y/H): P1= 1,0
- x_6, x_7 – Material Strength Scenarios: [0, 0]

Output Variable of the Neural Network Model

- y – Displacement (D): 0,73 m.

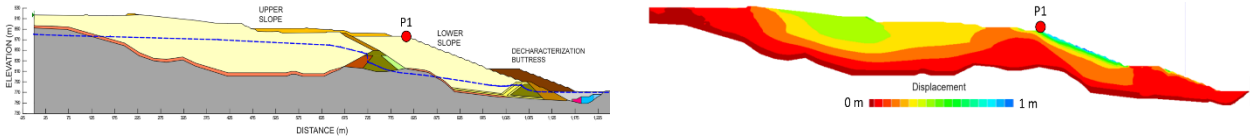


Figure 9. Application of the Neural Network Model to a Tailings Dam Compared with Numerical Modeling Results.

4 CONCLUSION

The findings highlight the effectiveness of artificial neural networks, particularly the Multilayer Perceptron (MLP) architecture, in predicting permanent displacements in tailings dams subjected to extreme seismic loading. The proposed model exhibited strong performance, with high generalization capability and consistent stability across both training and validation datasets.

The inclusion of dynamic behavior variables—such as peak ground acceleration, Arias Intensity, Cumulative Absolute Velocity, fundamental vibration period, geometric ratios, and material strength scenarios—proved effective in capturing the primary structural response mechanisms.

Overall, the neural network approach complements traditional numerical methods, enhancing safety strategies and risk management in tailings dam decommissioning, especially under stringent regulatory and environmental protection requirements.

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