Spatio-Temporal Surface Displacement Prediction in Urban Underground Excavation: A Case Study in Seville

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ABSTRACT

One of the primary challenges in excavating underground in urban areas is controlling and mitigating ground surface displacement caused by Earth Pressure Balance (EPB) tunneling. It is crucial to avoid damaging historical monuments and buildings in these areas. This paper presents a new method for predicting the surface displacement caused by EPB in Seville. A spatiotemporal dataset was generated for this study using numerical simulation in FLAC3D. The simulation replicates the excavation process of the Seville metro line in real-time, and records the surface displacements at selected points in the dataset. The last 20-time steps of excavation are predicted, and the first 80-time steps are chosen for training and tuning hyperparameters, as the dataset is spatiotemporal. A recurrent neural network (RNN) is used to detect and predict patterns between surface displacement and input features at different time steps and locations of the excavation. After fine-tuning the RNN, the model achieved an accuracy of 0.91 for the evaluated R-squared (R2), indicating its practicality for real-time prediction of surface displacement in underground excavations in Seville. The model's performance can be further improved with a larger data range. By deploying it as a hazard detector, the model can issue a warning if the ground displacement exceeds the limit, thereby preventing potential hazards. This approach can help control and mitigate potential hazards in underground excavations in historical cities.

Keywords: surface displacement; EPB; FLAC3D; hazard detection; RNN.

1. Introduction

The construction of tunnels is a complex process that presents various challenges, including the possibility of surface displacement due to excavation activities. As urban populations continue to grow, there is an increasing demand for underground excavation, resulting in controlled ground movements. Accurate prediction of ground movements and identification of danger zones in previous excavation steps are crucial for safe and effective tunnel excavation. Any potential risks should be reported, as tunnel excavation can have a major impact on neighboring surface buildings and infrastructure. To minimize potential hazards, it is important to reduce uncertainties, ensure safety, and mitigate risks. Empirical, numerical methods, and artificial intelligence have been developed to predict the surface displacement induced by underground excavation.

1.1. Empirical and Numerical Methods

Extensive research has been conducted on ground displacement caused by tunnel excavation using empirical methods based on experimental results (Chakeri and Ünver 2014; Cui et al. 2016; Franza and Marshall 2019; Lin et al. 2021; Lu et al. 2020). The empirical technique for predicting ground displacement may not always be reliable due to the challenges in measuring important factors in underground excavation such as geological conditions, excavation procedures, support methods and other uncertainties. Additionally, this methodology is inadequate for providing a precise analysis due tunnel excavation. On the other hand, numerical models offer several advantages over empirical models. They can enhance the accuracy of estimating ground displacement resulting from tunnel excavation. By studying of the correlation between different parameters and ground displacement, numerical models provide a better understanding of the excavation process. Furthermore, they allow for analysis and monitoring of ground displacement throughout the excavation process (Oraee, Zandi, and Oraee 2013; Rahmani et al. 2012; Zhou et al. 2020).

Several academic studies have used numerical modeling techniques to simulate underground excavation with mechanized methods (Alsahly, Stascheit, and Meschke 2016; Mollon, Dias, and Soubra 2013; Z. X. Zhang et al. 2016; Nematollahi and Dias 2022; Oreste et al. 2021; Kavvadas et al. 2017). These researchers thoroughly addressed real-world aspects such as excavation face pressure, burden load, and tunnel lining implementation at their actual locations. These studies aimed to improve the accuracy of the numerical models in simulating the excavation process by incorporating realistic properties.

1.2. Machine learning

In the field of geotechnics, machine learning and deep learning models offer several advantages over numerical modeling. These models can efficiently process large datasets, enabling them to make accurate predictions. They are also cost and time-efficient, capable of learning over time and identifying patterns and relationships that numerical modeling may overlook (Morgenroth, Khan, and Perras 2019; Baghbani et al. 2022; Phoon and Zhang 2023; Durgapal, Bawa, and Sharma 2021). As a result, predictive processes in geotechnical engineering have become more accurate and efficient than ever before thanks to the use of artificial intelligence (AI) The use of AI in this field is a growing area of study. It is noteworthy that the artificial method has the highest value for predicting surface displacement and identifying excavation hazards and risks. Consequently, researchers attempted to predict the maximum surface displacement induced by the underground excavation. The researchers used geotechnical properties, tunnel geometry, excavation boundaries, and excavator parameters to mitigate errors and uncertainties in their excavation process (Santos and Celestino 2008; Suwansawat and Einstein 2006; Moeinossadat, Ahangari, and Shahriar 2017; Chen et al. 2019; Lu et al. 2022). Some other researchers predict ground displacement by EPB in the urban area (Bouayad, D. Bouayad, and Emeriault 2017; Hasanipanah et al. 2016; Shuangshuang Ge et al. 2022).

1.3. Integrating numerical modeling and machine learning

The use of machine learning and deep learning in the field of excavation is challenging due to the limited availability of data and the difficulty in recording all important features in real-world situations. Furthermore, the integration of numerical modeling with artificial intelligence enables the creation of a dataset that includes all variables that are impractical to directly monitor them in real time excavation (Fu and Reiner 2023; Marcher et al. 2021; D. Zhang et al. 2022).

Yong et al (2022) conducted a study on the analysis and prediction of diaphragm wall deflection induced by deep braced excavations. The study utilized the finite element method (FEM) in combination with artificial neural networks (ANN) optimized by metaheuristic algorithms. The aim of the study was to accurately predict of diaphragm wall deflection (DWD) to ensure the safety of surrounding structures in construction projects. The study investigated the behaviors of DWD through the analysis of 1120 finite elements. The authors propose two intelligent models: MLP-HHO (MLP optimized by Harris hawk's optimization) and MLP-WO (MLP optimized by whale optimization). Both models demonstrate high accuracy in predicting DWD.

Oh et al (2021) utilized machine learning techniques, specifically the Gradient Boost (XGB) and Multilayer Perceptron (MLP) algorithms, to predict the rate of settlement change for a piled raft caused by nearby tunneling. The research aimed to comprehend the interaction between tunnels and the foundations of structures in urban areas. The settlements of both the raft and piles were determined by conducting 3D numerical analysis and the change rate of settlement along the pile length was also calculated. A machine learning model was developed to predict the pile and construction displacement as well as the rate of settlement.

Raja and Shukla (2021) utilized PLAXIS 3D, athree-dimensional finite element simulation software to conduct numerical simulations, collecting a total of 475 data points from which they derived a model, the ANN-GWO, which predicts the settlement of geosynthetic-reinforced soil foundations (GRSF) using a combination of the gray-wolf optimization (GWO) algorithm and an ANN. The model was then statistically tested and verified.

D. Zhang et al (2022) present an auto machine learning (AutoML) approach for predicting the maximum surface displacement caused by underground excavation. The study utilizes a dataset generated from 183 numerical models.

1.4. Novelty and limitation

This research aims to predict ground displacement during underground excavation in Seville using the FLAC3D numerical model. This study analyses the ground displacement values throughout the excavation process and determines the optimized conditions of the EPB (Earth Pressure Balance) for tunnel excavation. Additionally, the research aims to predict surface displacement by considering the spatiotemporal aspects of underground excavation. Recurrent neural networks (RNNs) are used in this research because of their ability to capture patterns in sequential data. This algorithm is appropriate for spatiotemporal datasets of surface displacement in this context (Seng et al. 2021). Although this study is limited to specific excavation and geotechnical properties in Seville, efforts have been made to improve its comprehensiveness and applicability to more general excavation conditions for future projects.

2. Case study and dataset

The main goal of this study is to predict surface displacement during the underground excavation for metro lines in Seville, the capital of Andalusia, in southern Spain. Line 1 of the Seville metro line was completed in 2009, and future excavations are planned for other lines (Cagigal 2012; Mazo et al. 2009). During the excavation of Line 1 of the Seville metro line, the city was faced with some uncontrolled ground surface displacement in some neighborhoods and damaged construction buildings. Two notable incidents took place 2005 in the Los Remedios neighborhood and in 2008 in the Puerta de Jerez area of Seville. These incidents posed a hazard to residents and traffic in the affected areas. Recognizing the value of surface displacement during the underground excavation and the location of the high amount of surface displacement is crucial in Seville (José Antonio Sánchez, n.d.).

The Seville metro line's first section comprises twin tunnels excavated 6 meters apart, each with a diameter of 6.3 meters. The first tunnel was excavated entirely before work began on the second tunnel in the opposite direction(Bahri et al. 2022; Soriano-Cuesta et al. 2023).

Furthermore, in this study a dataset from the previous metro tunnel excavation was collected and used to simulate the underground excavation with EPB in Seville using FLAC3D.A total of 244 simulations were developed with different excavation parameter and geotechnical properties. Fig. 1 displays the twin tunnels in FLAC3D.

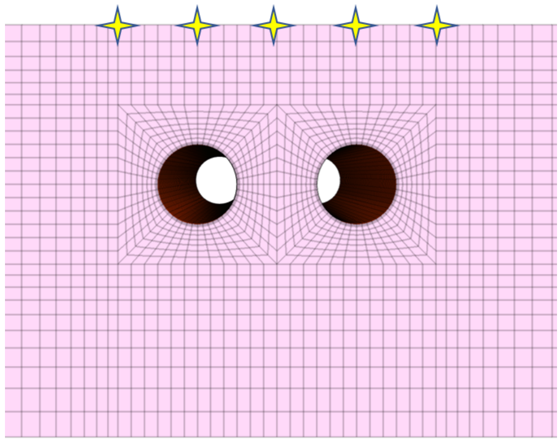

Figure 1. Geometry of a twin tunnel in FLAC3D and selected point on the surface

To simulate the underground excavation in FLAC3D for this study, various parameters are changed in different excavation simulations. These parameters include soil layer configuration, soil properties, burden load, the depth of the tunnel, the face pressure of the EPB, grout pressure, and the depth of the water table are parameters that are changing in different excavation simulations. Each model is excavated in 100-time step of excavation, with 50-time steps taken to excavate the second tunnel. The purpose of this excavation is to simulate the temporal aspect of underground excavation in the models. Figure 1 shows that the surface of each FLAC3D model contains 3,567 nodes. To simplify the analysis and avoid dealing with a large dataset in this study, we recorded the ground displacement for each time step of excavation at nodes X (-18, -12, -6, 0, 6) (Fig. 1). This resulted in the recording of ground displacement in 205 nodes across 100 excavation steps for the 244 underground simulation. The dataset consists of excavation steps as the temporal component and nodal locations as the spatial component, resulting in a spatiotemporal dataset of the tunnel excavation.

Table 1 illustrates the range of face pressure, grout pressure, burden load, and tunnel depth that were used in the simulations to predict surface displacement. Additionally, the table reports the output of surface displacement from the underground simulation, which ranges from 23.8 cm to 0.18 cm. Table 2 is generated to illustrate the varying physical and mechanical properties of the soil layers in these underground simulations.

Table 1. Ranges of varying parameters in simulation models

	Continuous data				**Categorical data**		
	Face Pressure (kPa)	**Grout Pressure (kPa)**	**Burden Load (kPa)**	**Surface displacement (cm)**		**Water depth (m)**	**Tunnel depth (m)**
max	310.0	360.0	12.0	23.8	Max	14	5
mean	185.1	231.3	72.8	3.62	Min	10	3
min	50.0	100.0	133.0	0.18			

Table 2. Ranges of soil physical and mechanical properties in simulation models

Soil Unit	**Density (Kg/m^3)**		**Young module (MPa)**		**Poisson's ratio**		**Cohesion (kPa)**		**Friction angle (degrees)**		**Permeability (cm/s)**	
	Min.	Max	Min.	Max	Min.	Max.	Min.	Max	Min.	Max.	Min	Max
Layer 1	2.10	1.80	7.0	12.6	0.2	0.6	2.0	6.0	24.0	26.0	-	
Layer 2	2.20	2.00	29.0	45.0	0.2	0.4	4.0	10.0	30.0	40.0	$2e^{-8}$	$2e^{-6}$
Layer 3	2.20	1.80	20.0	29.0	0.2	0.4	17.0	50.0	26.0	29.0	$2e^{-5}$	$2e^{-2}$
Layer 4	2.20	2.00	40.0	70.0	0.2	0.4	0.0	0.0	35.0	39.0	$5e^{-6}$	$5e^{-2}$
Layer 5	2.2	1.90	70.0	100.0	0.2	0.4	32.0	44.0	26.0	28.0	$2e^{-9}$	$3e^{-9}$

The numerical model in FLAC3D was validated based on real-time monitor data to simulate real-time excavation in Seville. The model accurately follows all trends of dispersion, as demonstrated in the publication by Bahri et al. (2022), indicating its reliability and high accuracy.

3. Methodology of AI

3.1. Spatiotemporal dataset

After generating a dataset in FLAC3D that is validated using real monitoring data, a prediction model should be developed to predict the surface displacement at selected points in different time steps of excavation. Since this generated dataset is based on spatial and temporal components, it is referred to as a spatio-temporal dataset. Spatial components refer to details about physical locations or geographic areas, such as GPS coordinates or street addresses. Temporal data, on the other hand, refers to time-related information such as dates, times, and time intervals. Spatiotemporal data combines spatial and temporal components to provide information on how phenomena change and evolve over time and space. For instance, spatiotemporal data can contain measurements of air quality at different locations within a city over time or satellite imagery indicating changes in vegetation cover across a region over a year (Zhu et al. 2021; Amato et al. 2020; Rozemberczki et al. 2021).

3.2. Recurrent neural networks

Because of the complex pattern between the geographical and temporal components of the spatiotemporal dataset, it would be challenging to detect and evaluate this pattern. Moreover, deep learning architectures show great potential to analyze and predict targets in timeseries and spatiotemporal datasets (LeCun, Bengio, and Hinton 2015; Goodfellow, Bengio, and Courville 2016).

RNNs are highly suitable models for predicting sequential and time-dependent datasets. RNN are particularly effective in detecting and capturing time sequence data, making them unique for spatiotemporal datasets. They can successfully capture the underlying patterns and dynamics of this type of data (Seng et al. 2021).

Fig. 2 displays a basic structure of RNN. In this structure, x_t represents the input vector at time step t, while h_t indicates the hidden state of the RNN cell at the same time step. The computation of h_t depends on both the hidden state ($h_t -1$) from the previous time step (t–1) and the current input vector (x_t) at the present time step (t). The output of the hidden units in the simple RNN is expressed in Eq. (1).

$$h_t = \tanh(W_x \cdot x_t + W_h \cdot h_{t-1} + b) \qquad (1)$$

Equation (1) shows that the hidden state at time step (t) is determined by applying the activation function of tanh to the sum of the input weight ($W_x \cdot x_t$) and hidden state weight of the previous time step ($W_h \cdot h_{t-1}$) and a bias term (b). It is important to note that the output of the RNN is dependent on both the current and previous time steps, allowing it to utilize all sequence-based information. Furthermore, In the context of RNNs, the optimization and updating of weights and biases in the RNN architecture are achieved by minimizing the loss function through gradient-based optimization. However, the use of RNNS introduces the challenge of vanishing gradients. This phenomenon occurs when gradients become extremely small during training, which can impact the RNN´s ability to effectively capture long-term dependencies (Pascanu, Mikolov, and Bengio 2013).

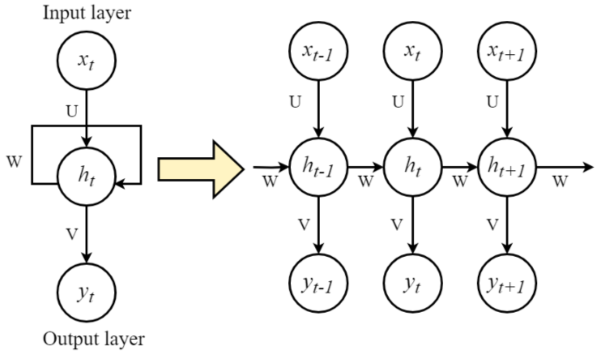

Figure 2. The structure of RNN

3.3. Preprocessing dataset to train RNN architecture.

After collecting the dataset from the FLAC3D model, some crucial steps should be taken. In order to predict the surface displacement in the following excavation, the dataset should be split into two sets: training and testing. The RNN model is then trained on the training dataset, and after tuning the RNN and finding the optimal model, the final model would predict the test dataset. For this study, we will use the first 80-time steps of excavation for training, and the last 20-time steps as a test dataset.

Afterwards, the dataset was normalized using the min-max normalization approach (Eq. (2)), which rescaled all values to a range of 0 to 1. This method is commonly used to standardize input data and improve the effectiveness of artificial intelligence algorithms.

$$\text{Min-Max Normalization:} \quad X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (2)$$

3.4. Tuning of RNN hyperparameters

The hyperparameters of RNN were tuned using K-cross validation and using the Keras tuner in TensorFlow that is developed by Google AI. Since Keras Tuner is a user-friendly and efficient method for dealing with large datasets, it was chosen for this study(Banna et al. 2021; O'Malley et al. 2019).

To train these architectures and achieve optimal performances, it is necessary to evaluate the best hyperparameters such as the number of nodes, number of hidden layers, dropout rate, learning rate, batch size, number of epochs, and activation function. Table 3 provides definitions for these hyperparameters (LeCun, Bengio, and Hinton 2015; Goodfellow, Bengio, and Courville 2016). Additionally, Table 4 presents the range and values of RNN hyperparameters used in this study.

Table 3. Definitions of hyperparameter for RNN architecture

Hyperparameter	Definitions
Epoch	One complete pass through the entire training dataset.
Dropout rate	A technique in neural network architecture where neurons are randomly ignored during the training dataset, which helps prevent overfitting.
Learning rate	The hyperparameter controlling the step size for weight updates during training
Batch size	The number of training examples used in each iteration of gradient descent.
Activation function	A function that determines the output of a neural network node, introducing non-linearity to the model.

Table 4. Ranges of hyperparameter for deep learning architecture

Hyperparameters	Min	Max	Step	Choices	Default
Number of Nodes	16	256	16		
Number of Hidden Layers	1	3	1		
Drop out				0-0.1-0.5	
Regularization				0.01-0.1	l2
Activation function				tanh-linear-sigmoid	
Batch size					128
Learning rate					
Number of epoch					60

3.5. Evaluation metrics methods

In this research, we evaluated the accuracy of the RNN structure using the coefficient of determination (R2), root mean square error (RMSE), and mean square error (MSE). The R2 value ranges from 0 to 1, indicating the correlation between observed and simulated values. Optimal performance is achieved when RMSE and MSE values approach 0 since surface displacement is a continuous value.

4. Result and discussion

4.1. Final prediction of surface displacement

The final architecture of the RNN model is detailed in Table 4, after identifying the optimal hyperparameters and training the model for 41 epochs until convergence. Additionally, using the metric methods outlined in Section 3.6, the R2, RMSE, and MSE of the final model are reported as 0.91, $5.97e^{-3}$, and $3.57e^{-5}$, respectively. It's important to note that this model was trained on the first 80-time steps of excavation and evaluated on the last 20-time steps.

Table 5. Hyperparameter of final RNN architecture

Parameters	Values
Units Layer 1	128
Units Layer 2	64
Units Layer 3	32
Units Layer 4	16
L2 Regularization	0.001
Activation Function	tanh
Optimizer	Stochastic Gradient Descent (SGD)

4.2. Visualization of surface displacement

In urban underground excavation using EPB, the relationship between face pressure and grout pressure exhibit with surface displacement is indirect, while the relationship between burden load is direct, as highlighted in (Bahri et al. 2022), with the support of this study. The focus of this analisys is to predict surface displacement based on the location and time step of excavation. To visualize surface displacement during different excavation steps, we generated 3D scatter plots that display surface displacement at specific study locations.

As stated in Section 3.2, we selected five points (-18, -12, -6, and 0) on the X-axis to analyze surface displacement across all Y-axis points that corresponds to twin tunnel excavations. Fig. 3 displays surface displacement for selected points located on the X-axis (-6), providing an interactive view of surface displacement during various excavation time steps.

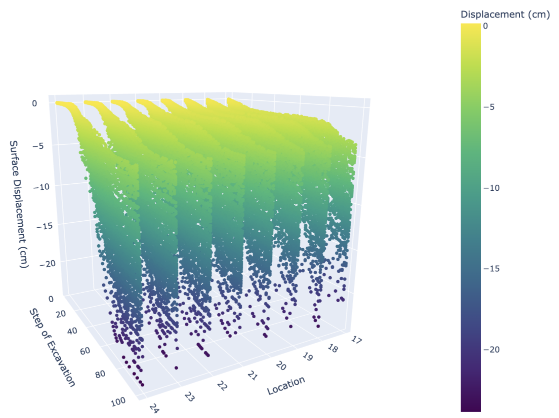

Figure 3. Surface displacement at point X= -6

4.3. Visualization of surface displacement prediction

Figure 4 provides a visual representation to enhance our understanding of the surface displacement prediction model across various underground simulations. This figure provides a detailed comparison between the real and predicted surface displacement for selected points located in the last 20 steps of the excavation process. The data presented in Figure 4 suggests that the RNN-based prediction model has good accuracy at certain points but deviates significantly at others with high and peak distances.

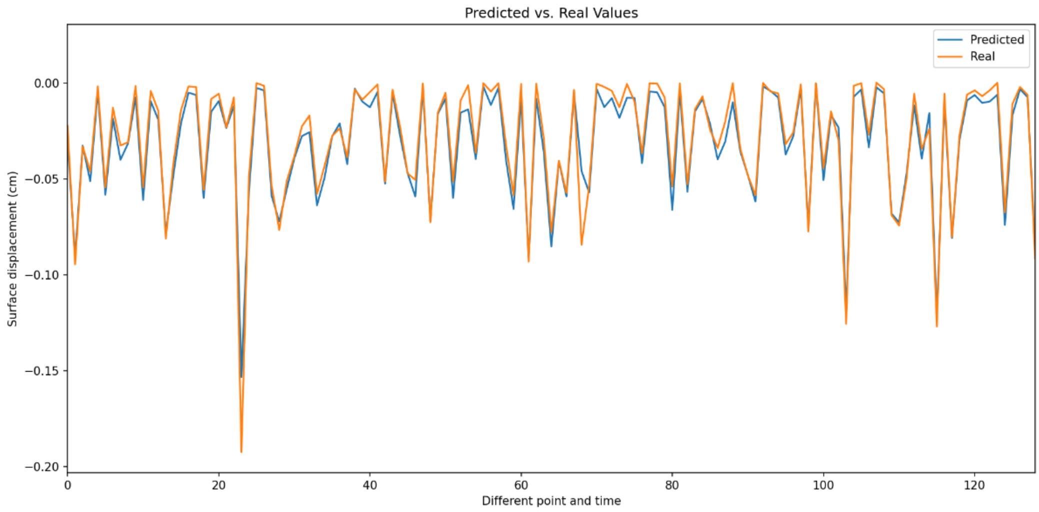

Figure 4. Prediction and real value of surface displacement in last 20 step of excavation for some selected points

To address the relative error between the real and predicted values for surface displacement in underground excavation, a percentage error was introduced Eq. (3).

$$Percentage\ Error = \frac{Real\ value - Predicted\ value}{Real\ value} \times 100 \quad (3)$$

Figure 5 presents the percentage error value, highlighting the model's performance. The majority of predictions fall within the -20% to 20% range of percentage error. In the future, it would be practical to increase the model's accuracy and reduce the percentage of error.

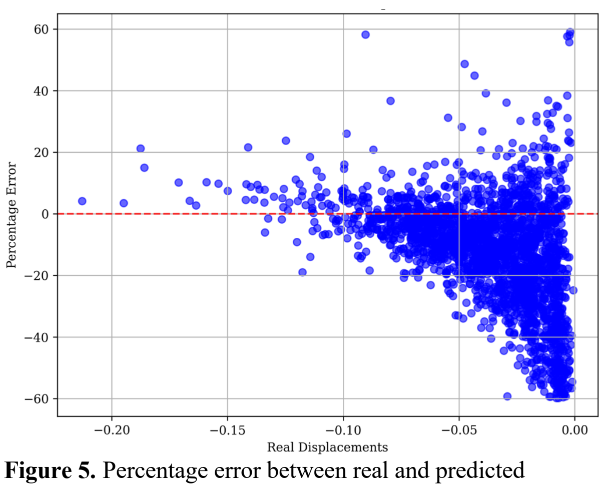

Figure 5. Percentage error between real and predicted displacements

5. Conclusion

This study presents a dataset of underground excavation simulations in Seville generated by FLAC3D. The numerical model´s accuracy is validated by comparing it with real monitoring data. The dataset is structured based on excavation time steps and locations. The research employs an optimized recurrent neural network (RNN) as a predictive model fine-tuned during the first 80-time steps and evaluated against a test dataset representing the last 20 steps of excavation. Impressively the RNN model demonstrates high accuracy, with an R2 value of 0.91 and an RMSE of $5.97e^{-3}$.

It is important to note that this study considers excavation properties and geotechnical parameters at selected points based on the step of excavation and location. By incorporating these parameters into the predictive model, our study successfully forecasts future excavation endeavors in Seville, particularly the expansion of the metro line. Furthermore, it provides insights into the expected surface displacement at specific points during the next excavation phases. However, this research has some limitations because this study used the Seville database, so it would only be applicable to Seville, Spain. Additionally, due to limited computational resources, the study only examines surface displacement at selected points and not at other locations. Therefore, the model's accuracy is limited outside of the excavation area. Additionally, it is important to mention that this study utilizes the RNN model to forecast surface displacement. In future research, other deep learning architectures suitable for predicting spatiotemporal datasets could be included to compare different models, improve prediction accuracy, and minimize the loss function.

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