Diyala Journal of Engineering Sciences

Journal homepage: https://djes.info/index.php/djes

ISSN: 1999-8716 (Print); 2616-6909 (Online)

Predict settlement of soft clay soil treated with temperature using Deep Neural Network

Qasim A. Aljanabi[1], Saad Sh. Sammen[2*],, Ozgur Kisi[3,4,5]

[1]Department of Highway and Airport Engineering, College of Engineering, University of Diyala, 32001 Diyala, Iraq
[2] Department of Civil Engineering, College of Engineering, University of Diyala, 32001 Diyala
[3] Department of Civil Engineering, Lubeck University of Applied Science, 23562, Lubeck, Germany
[4] Department of Civil Engineering, Lia State University, 0179, Tbilisi, Georgia
[5] School of Civil, Environmental and Architectural Engineering, Korea University, Seoul 02841, South Korea

ARTICLE INFO

Article history:
Received April 04, 2025
Revised July 06, 2025
Accepted July 16, 2025
Available online September 01,2025

Keywords:

Settlement
Soft clay soil
Treated Clay Soil
Deep Neural Network

ABSTRACT

Many The treatment of soft clay soil at different temperatures substantially influences its settlement properties. Increased temperatures can accelerate the consolidation of soft clay, resulting in alterations in settlement behavior. Estimating the settlement of soft clay soil beneath building foundations is a fundamental aspect of geotechnical engineering design. Traditionally, engineers rely on empirical formulas and classical consolidation theories, such as Terzaghi's one-dimensional consolidation model, to predict settlement behavior. While these conventional methods provide useful approximations, they often struggle to capture the highly nonlinear and site-specific characteristics of soft clay soils. Recently, artificial intelligence (AI) models, particularly Deep Neural Networks (DNN) and other machine learning algorithms, have emerged as powerful tools for forecasting settlement more accurately. This study applied one of intelligent technique by using deep learning artificial Settlement model (S_{DNN}) model to forecast underground settlement of soft clay soil treated with temperature. DNN model adopted 365 data set, input data parameters such as time period, various of distance between the heaters, temperature and load applied. The outcomes indicate that the S_{DNN} model effectively forecasted ground settlement, showing similar results between actual and predicted values. The performance of the S_{DNN} network model was notably impressive, achieving a mean absolute error (MAE) of 4.3356 % and a mean squared error (MSE) of 0.4494%. The artificial model also demonstrated strong efficiency and a favorable variance calculation coefficient.

1. Introduction

Soft clay is one of the hardest things for a geotechnical engineer to work with when designing and building. This is because soft clay has a low resistance to deformation and compaction and low shear strength. Because of these things about soft soil, many problems can happen during building projects or the structure's planned life [1]. Clayey soils that have cohesion parameter (Cu) less than 40 kPa are what we mean when we talk about soft soil. There are many techniques to treat soft soil under footing illustrated and categorized in literature. [2, 3]. The settlement behavior of soft clay soil is a critical factor in geotechnical engineering, especially for structures built on compressible subsoils. Experimental studies have shown the effect of thermal treatment on the settlement properties of soft clay soil under varying temperature conditions. The results indicate that increasing the soil temperature accelerates the consolidation process, which in

* Corresponding author.
E-mail address: Saad123engineer@yahoo.com
DOI: 10.24237/djes.2025.18303

turn influences the overall settlement magnitude and rate [4].

Heat transfer in clay soils plays a significant role in both natural environmental processes and various geotechnical and geochemical applications [5, 6]. Accurately predicting heat transfer in unsaturated clay is important for addressing soil-atmosphere interactions, climate change, land management, and other applications. Concerningcesses of long-term repositories for high-level radioactive waste, concerning heat-generating waste, the reversibility and high mobility of unsaturated bentonite need to be accounted for, considering temperature-induced cation exchanges, swelling, and stress. Generally, heat transfer across heavy argillaceous formations, sometimes over hundreds of thousands of years, plays a major role in defining the geochemical response in the engineered barrier system in high-level radioactive waste disposals [7]. In geotechnical applications, the rising temperature around deep-buried nuclear waste storage facilities may affect the mechanical behavior of soil. The literature surrounding the prediction of heat transfer in unsaturated clay soil has evolved significantly over the past decade, particularly with the advent of advanced computational techniques. Artificial neural networks (ANN) and hybrid methodologies highlight the potential of ANN. In geotechnical engineering applications, settlement under footing, predict maximum lateral displacement of retaining wall and specifically addressing the challenges associated with predicting heat transfer in unsaturated clay soils [8-9]. Their work lays the groundwork for understanding how deep ANN can be employed to model complex thermal dynamics in soil, emphasizing the need for innovative approaches in geotechnical modeling. Deep neural network (DNN) is a useful technique and may be suitable for this purpose. These methods are being applied successfully in Geotechnical engineering [10]. DNNs, such as those using deep learning-based artificial neural network architectures, have demonstrated improved accuracy in predicting soil consolidation characteristics, such as the compression index (Cc), by analyzing variables like natural water content and plasticity index [11]. The research by [12] use of hierarchical models, like the Gated Recurrent Unit (GRU) network, allows for the analysis of preloading patterns and settlement changes, which enhances prediction accuracy by considering the specific characteristics of soft soil layers. Physics-informed neural networks (PINNs) utilize short-term excess pore water pressure data to predict long-term consolidation processes, effectively reducing the need for extensive datasets while maintaining accuracy [13]. Techniques like the CEEMDAN-LSTM model decompose univariate data into multidimensional components, allowing for accurate predictions even with limited training data, which is particularly beneficial in scenarios with small sample sizes [14]. By incorporating short-term predicted values that meet statistical criteria, neural network models can iteratively improve their predictions, adapting to new data and reducing uncertainty in settlement predictions [15] .The adaptability of DNNs to different soil characteristics and conditions, as demonstrated in various case studies, underscores their potential for widespread application in geotechnical engineering [12] .While DNNs offer significant improvements in prediction accuracy and efficiency, challenges remain, such as the need for large datasets and computational resources. Additionally, the complexity of these models requires careful design and tuning to ensure optimal performance. Despite these challenges, the integration of DNNs in geotechnical engineering continues to evolve, promising further advancements in the field.

In this study contributes to the broader understanding of soil improvement techniques and showcases how combining experimental thermal treatment with advanced predictive models can enhance settlement forecasts, mitigate structural risks, and promote more sustainable geotechnical solutions. Deep Neural Networks (DNN) model adopted to predict settlement behavior of soft clay soil under loading with treated by temperature. DNN model includes input features such as, time period, various of distance between the heaters, temperature and load applied to predict output feature settlement behaviour. The model has proven its intelligence and strength in predicting settlement values for soft soil. Future work may focus on hybrid models that integrate physical laws with AI algorithms to further refine prediction reliability for diverse soil conditions.

2. Methodology

2.1 Prepare Data study

In this study, features data are prepare to used it in S_{DNN} model where collect it from experience previous tests. Soft soil treated by various temperatures with foundations information to measured settlement under loading [16].

The analysis included multiple cases which varied in their parameters. The analysis included 365 data sets that were observed. The review included consideration of every individual case. The model underwent both training and testing procedures.

2.2 Features S_{DNN} Model

In this study, a complete comprehension of factors influenced to get predictions with more accurate results that includes traditional precipitation, for Time (hr.), Distance (cm). Temperature (degree C^o), Applied load to forecast surface Settlement (S) of the soft soil under the foundation [17]. Statistics analyzed for All data (input and output data) make as shown in Table 1. Coefficient Variation (CV) is useful for measuring distribution statistical data.

$$CV = \frac{SD}{Mean} \times 100 \quad (1)$$

Where: *SD* is standard deviation. All the parameters recorded the Coefficient of Variation between 29.471 and 99.953%. The properties of soft clay soil and the static load applied to it vary among the parameters. Therefore, this causes the settlement of soft soil due to the load. Subsequently, when utilizing S_{DNN} Model, the data is split into two groups: the training group and the testing group. One group is dedicated to training the Artificial Intelligent model while another group handles evaluation which results in prediction outcomes. The researchers implemented a stopping rule which led to random division of the data into two distinct groups. The dataset split allocated seventy percent for training purposes and thirty percent for testing purposes [18]. Many studies have found that the way data is divided can significantly affect the results obtained.

Success of automatic algorithms depends on the quality of the model data. In order for artificial intelligence operating networks to function correctly, data processing is done. It was certain during training stage that knowledge was passed on to build the model." The process is followed by scaling known, logarithmic form and scaling exponential, standardization and transmitting of data processing [18]. Input and Output data have been treated for expansion. This was done after splitting the data into subgroup to eliminate their size and making sure all the variables were similar. The variables of entry the scale are still advised. Min-max scaling is used in this study by considering the feature's minimum value which results in a feature range between 0 and 1, which rescales each feature x [19,20] according to the following formula:

x' = (x - x_min) / (x_max - x_min) (2)

Where:

x: is the original value of a feature.

x_min: is the minimum value of that feature in the dataset.

x_max: is the maximum value of that feature in the dataset.

x': is the normalized value

2.3 Structure of Deep Neural Network (DNN)

Deep neural networks are strong neural networks inspired by how the human brain works. They are created to learn and handle complex data representations. These networks consist of multiple layers of linked nodes, called neurons, which change the data to find patterns and characteristics [21, 22].

2.4 Performance Evaluation of DNN Model

After the model's training stage is completed successfully, its performance is checked with validation data that did not play a role in building the model. The purpose of this validation phase is to ensure that the model can apply what it has learned beyond the specific examples it was trained on, instead of just remembering the connections between inputs and outputs from the training data [21].

The evaluation of ANN model performance can be undertaken by.

- The R^2 coefficient was employed to quantify the correlation between observed data and the values predicted by calculations.

$$R^2 = \frac{\sum_{k=1}^{n}(d_k - \bar{D})^2}{\sum_{k=1}^{n}(y_k - \bar{D})^2} \quad (3)$$

Where: The desired output value (d_k) is compared to the predicted output (y_k), with $\bar{D}$ representing the difference between the two. The desired output's mean is calculated from the number of data points, denoted as n.

- Standard Error: The measure of the variability or precision of a sample statistic (such as the sample mean) as an estimate of the population parameter. The formula for the standard error depends on the statistic being calculated. Below are some common formulas:

$$SE = \frac{\sigma}{\sqrt{n}} \quad (4)$$

Where σ: population standard deviation, n : sample size

- The Mean Absolute Percentage Error (MAPE): MAPE is commonly employed in trend analysis to assess how accurately time series data has been fitted. A perfect fit occurs when the MAPE equals zero. In this calculation, the absolute values for each forecasted or fitted point are added together and then divided by the total number of fitted points, denoted as n. Typically, the MAPE is presented as a percentage, as shown in the formula of Eq. 5

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{d_k - y_k}{y_k}\right| \quad (5)$$

- The mean absolute error (MAE).

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|y_k - d_k| \quad (6)$$

All of these statistical analyses are employed to assess the validity and examine the strength of the Deep learning machine models.

Table 1: An analysis of the measured settlement parameters

Metric	Time (hr.)	Distance (cm)	Temperature (degree C°)	Applied load (kN/m²)	Settlement (mm)
Mean	8	15	350	89.324	4.844
Min	4	10	200	0	0
Max	12	20	500	353.7	18.71
SD	3.241	4.420	115.891	71.955	4.842
CV	40.518	29.471	33.111	80.555	99.953

3. Results and discussion

This study explored geotechnical structure foundations using artificial neural networks to predict the settlement (SDNN mode) of weak clay enhanced by temperature in experimental setups. A deep neural network (DNN) system utilizing the multilayer perceptron (MLP) algorithm was employed to create the SDNN model presented in this paper.

The model that showed the best results was MLP-NN, which applied a sigmoid transfer function for the link between the input layer and hidden layers, and a different transfer function for the hidden to output layers. The number of neurons ranged from 1 to 20. According to the training data set's lowest MSE value, the optimal number of neurons for the hidden layer turned out to be 10, as shown in Figure 1.

Correlation matrix: The correlation analysis of the input variables with precipitation outputs helps to understand the factors most influencing the prediction. If there is a strong correlation between a particular variable as shown in Figure 2 the applied load (P) and precipitation settlement soil under load "S", it means that this variable plays an important role in prediction. If there are weakly correlated variables, they may not have a significant impact, and some can be excluded to reduce complexity.

Figure 3 Histogram of Errors this chart shows the distribution of errors. If the distribution is close to the Gaussian distribution, this indicates that the errors are distributed normally, and the model is working in balance. Errors seem to be acceptably distributed, but there may be some minor deviations that need to be adjusted.

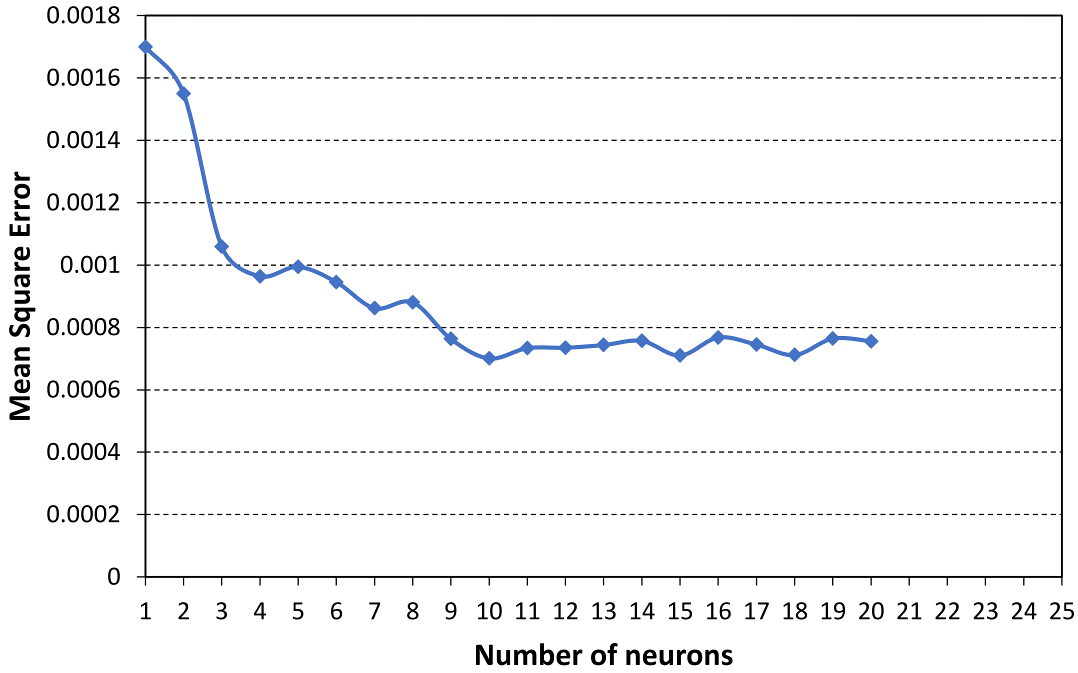

Figure 1. Connection between the count of neurons and MSE.

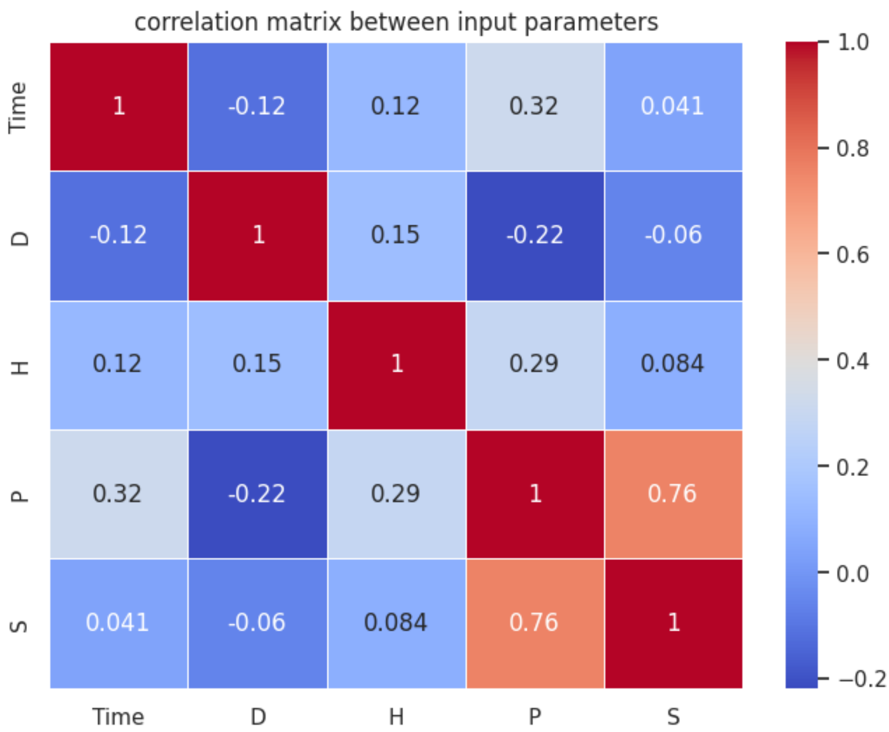

Figure 2. Correlation heat map matrix between Input and output

The analysis of sensitivity shows that the forecast of the settlement (S_{DNN}) model matches the fundamental physical measure of settlement, as well as the technique used for treating weak clay soil at different temperatures (H). The level of significance for input variable i can be calculated using this formula:

$$I_j = \frac{\sum_{m=1}^{m=N_k}\left(\left(|W_{jm}^{ih}|/\sum_{k=1}^{N_i}|W_{km}^{ih}|\right)\times|W_{mn}^{ho}|\right)}{\sum_{k=1}^{k=N_i}\left\{\sum_{m=1}^{m=N_k}\left(\left(|W_{km}^{ih}|/\sum_{k=1}^{N_i}|W_{km}^{ih}|\right)\times|W_{mn}^{ho}|\right)\right\}} \quad (7)$$

In this context, Ij represents how important the jth input parameter is for the output parameter. The variables Ni and Nh indicate the sum of input neurons and hidden neurons is indicated, where W represents the strength of the links. The letters “i,” “h,” and “o” refer to the input, hidden, and output layers, in that order. The smaller letters “k,” “m,” and “n” denote the input, hidden, and output neurons, accordingly. In this scenario, the parameters hold significant relative importance at 61.43% in comparison to the other parameters, and they also result in a lower error rate, as illustrated in Figure 4 below.

The development settlement of soil (S_{DNN}) model relies on specified input features. These features include distances among the heaters, temperature settings, and applied loads. A notable enhancement was seen when results from the models were compared, taking into account the coefficient of determination, mean squared error, and settlement. Additionally, the suggested S_{DNN} model proved to be more precise in predicting settlements and reacted suitably to a range of input features, aligning well with the expected behavior of soft clay soil subjected to temperatures.

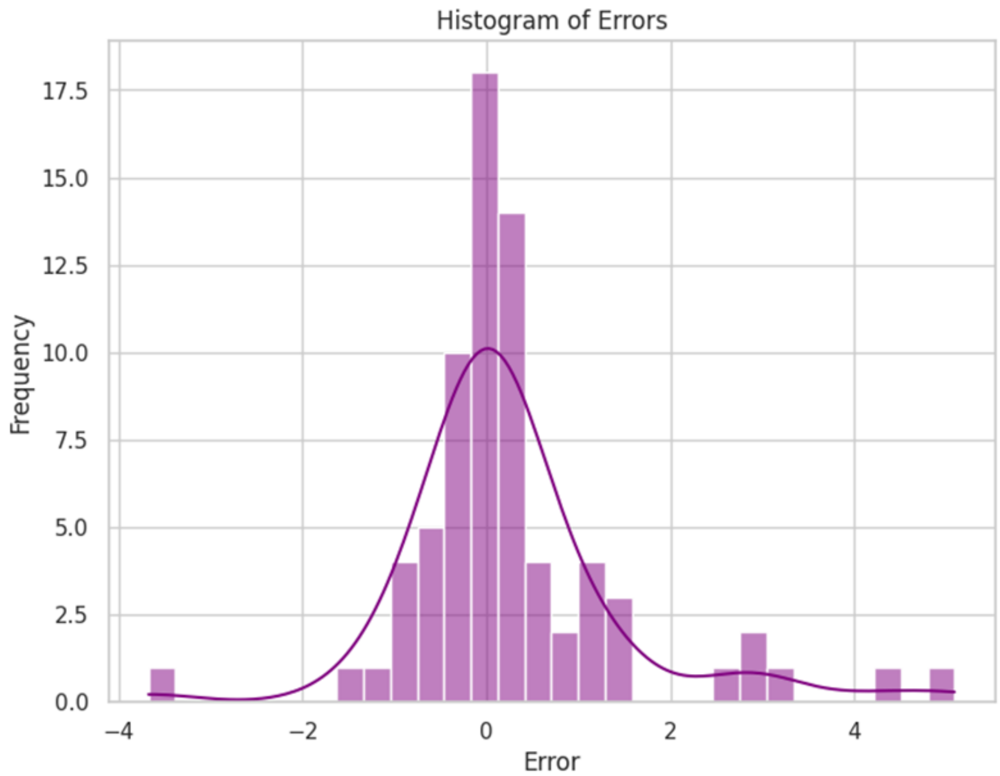

Figure 3. Histograms of Settlement value (S) with normal distribution

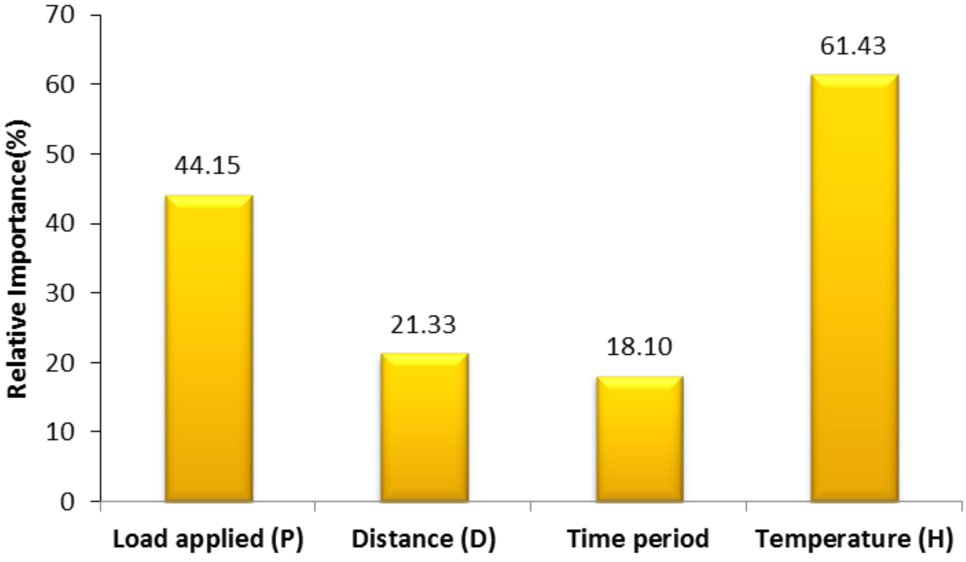

Figure 4. Importance comparison of the input variables for the DNN by using Equation

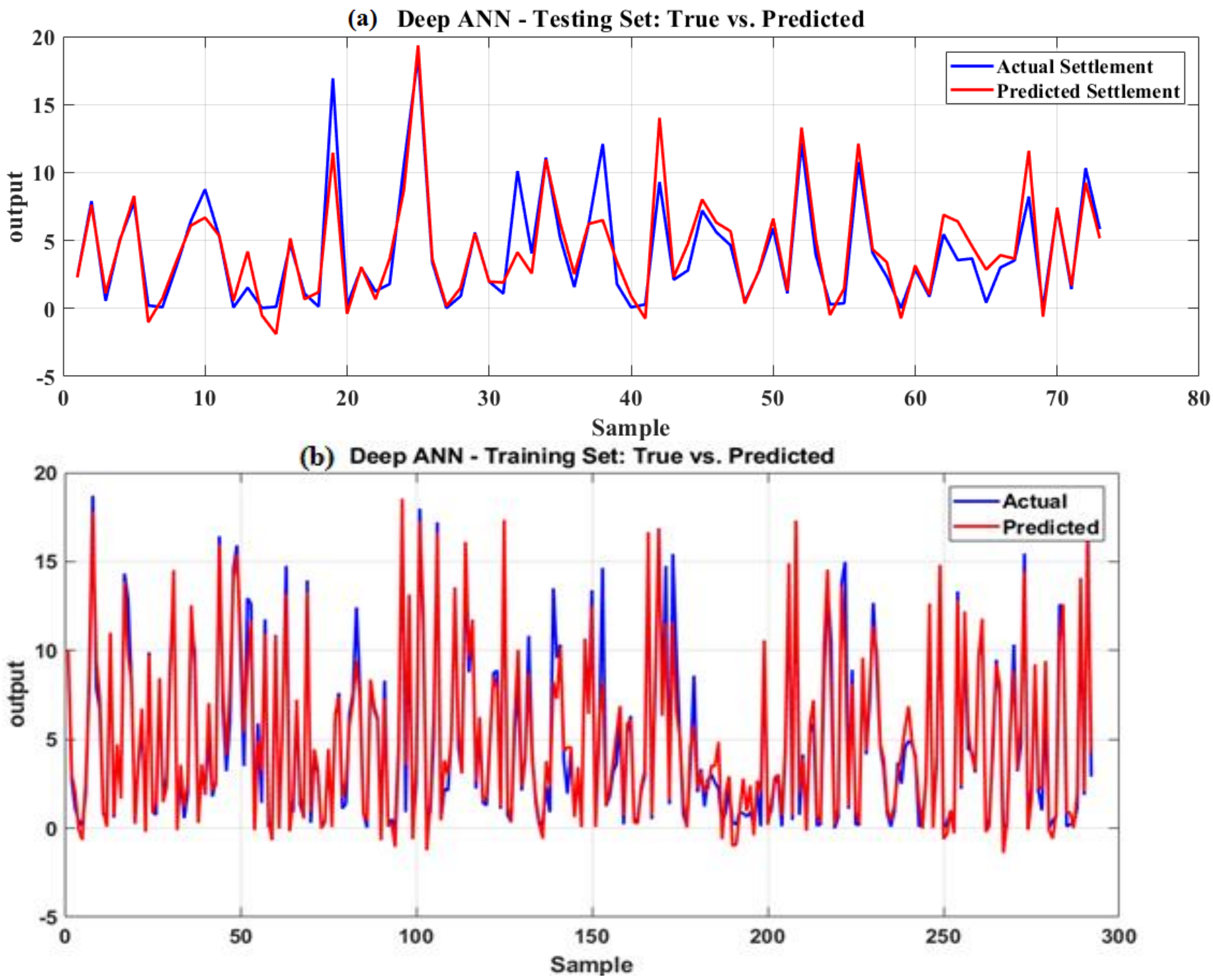

Figure 5. Predicted settlement for: a) testing model, b) training model

The ability of the DNN model to adapt to learning is based on how acceptable training and testing of the model are the alignment of the testing data with prediction data serves as a standard for assessing the quality and strength of the model. In Figures 5a–b, the training data from the back-propagation network is illustrated, showcasing the application of a training algorithm for settlement model S_{DNN}. Initially, data points were scattered and did not correspond with the field data. However, after the training phase, the model was able to align all the data points more closely to the target values which showed a better correlation and performed better against the training data. The S_{DNN} model achieves a high efficiency rating of 0.9490during training and 0.8336 during testing, as demonstrated in Table 2.

Throughout this research, the residual errors of each model have been tracked and analyzed. The predicted errors for the S_{DNN} model remained closer to the zero line, illustrated in Figure 6. This indicates that the model demonstrates superior learning capabilities and higher prediction quality. This finding correlates with the results in Figure 5.

From Figure 5, Figure 6 The leftover error of the settlement weak clay soil model S_{DNN} is displayed. It can be determined that there is a significant match between the predicted values and the actual values, as this model provided greater consistency and precision and the measured values, as this model gave more agreement and accuracy, where this model can be relied on to predict the settlement of footing above soft clay soil.

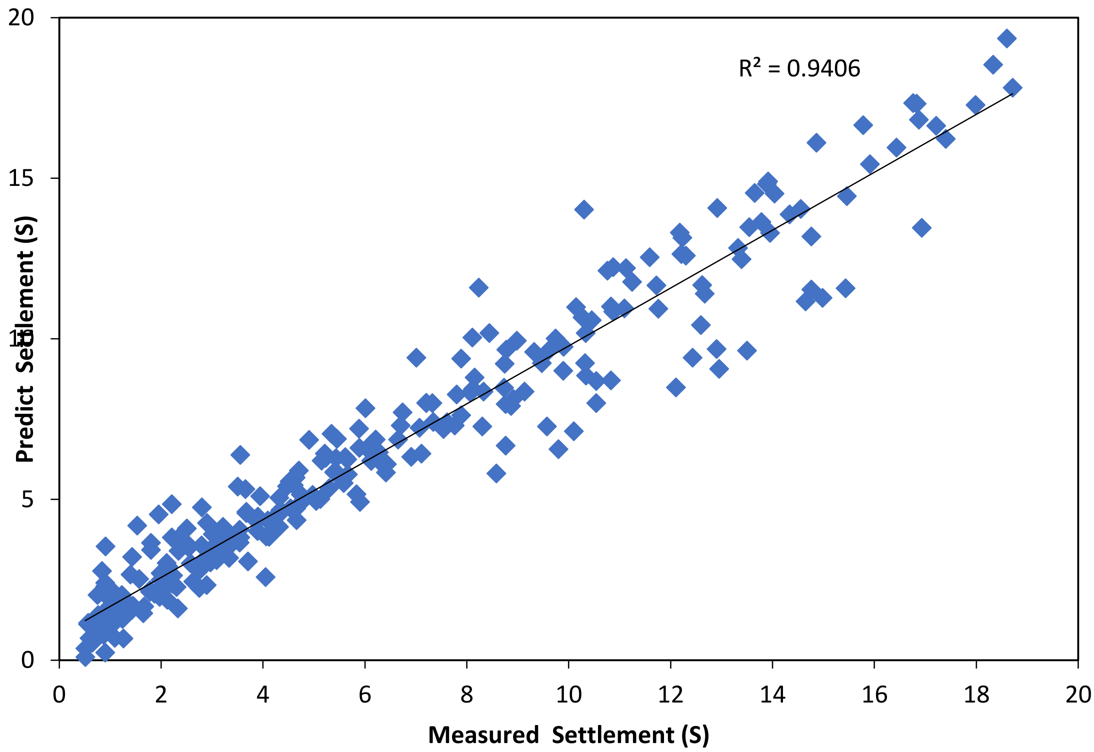

Figure 6. The measured and predicted settlement using SDNN model for all data

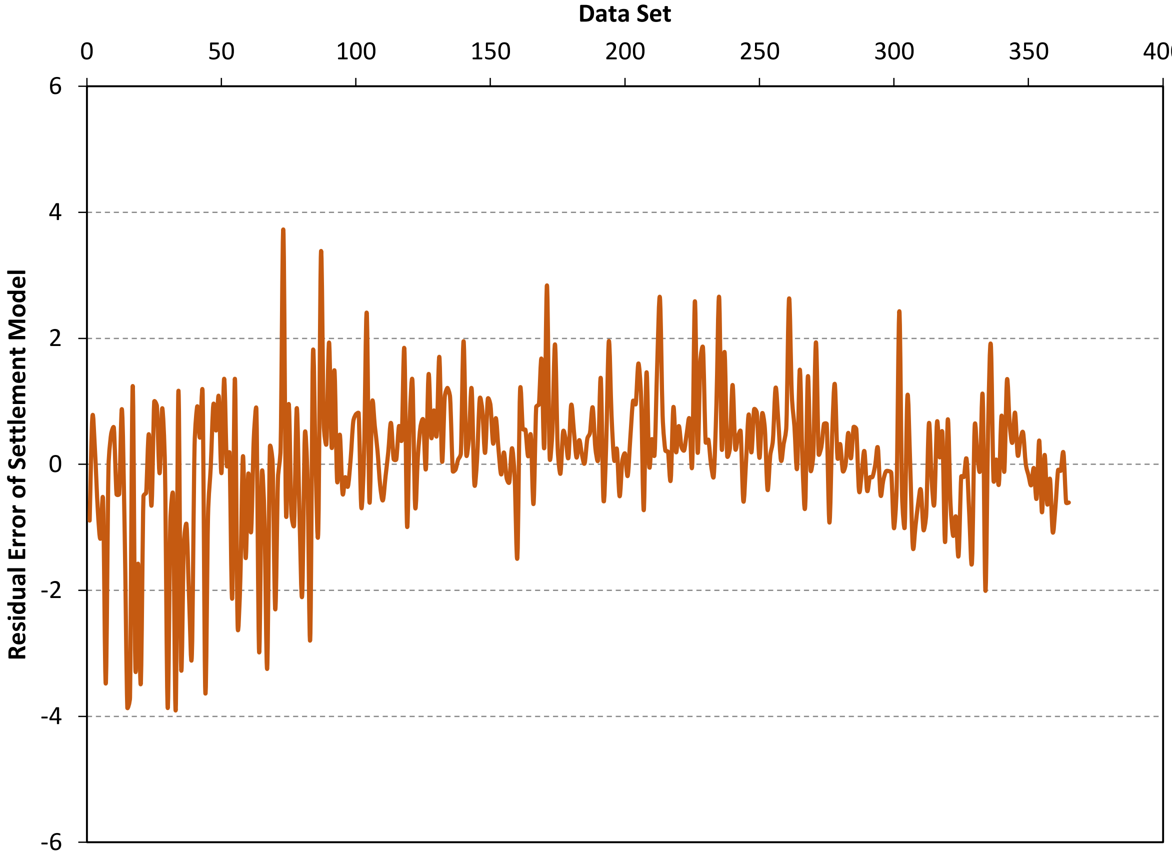

Figure 7. Residual error for settlement using SDNN model

Table 2: Summary results from both training and testing of the S_{DNN} model

Metric	Training Set	Testing Set	All Data Set
Mean Absolute Error (MAE)	3.9765	5.8061	4.3356
Mean Squared Error (MSE)	0.3627	0.8057	0.4494
Root Mean Squared Error (RMSE)	6.0223	8.9762	6.7037
Standard Error (SE)	1.5639	2.5930	1.3548
R-squared (R^2)	0.9490	0.8336	0.9327

4. Conclusions

This research explored how effective Intelligent settlement model (S_{DNN}) able to be forecasting settlement of footing placed on soft clay soil. The DNN models have proven to be superior to commonly used traditional techniques and have been optimized for regular applications in the field. From the results of this study, we arrived at these conclusions:

- The DNN model (S_{DNN}) can accurately predict how much footings will settle on weak soft soil.
- Key factors influencing settlement include the time period, various distance between the heaters, temperature and load applied.
- Compared to experimental model, the DNN model demonstrated exceptional performance, achieving the highest accuracy along with the mean absolute error (MAE)

which reached its lowest point at 4.3356, while the mean squared error (MSE) was at 0. 4494. The coefficient of efficiency and variance accounted for reached impressive levels of more than 0.9 and, showing that DNN can effectively predict foundation settlement in soft clay soil.

References

[1] Kempfert H. G. and Gebreselassie B. Excavations and foundations in soft soils.Springer Science and Business Media, 2006.

[2] Brand E. W. and Breuner R. P. .Soft clay engineering. Elsever scientific published company Amsterdam, 1981.

[3] Qasim A. Aljanabi, Z Chik, A Kasa . "Construction of a new highway embankment on the soft clay soil treatment by stone columns in Malaysia". Journal of *Engineering Science and Technology*, vol. 8 (4), pp. 448-456.2013.

[4] Das, B.M. . Principles of Geotechnical Engineering. Cengage Learning. Boston, MA, USA, 2019.

[5] Yiyi Wang, Yong Liu , "Research on Thermal Characterization of Soil Heat Transfer in Cross-Seasonal Borehole Thermal Storage Systems", Environmental science and engineering, vol. 1, pp. 321-338, 2024.

[6] D Bennaceur, N Laredj, M Maliki, H Missoum, "Numerical investigation of heat and moisture migration in clayey and sandy soils, exploring seasonal fluctuations", *Studies in Engineering and Exact Sciences* , vol.5 (2), pp.e8061-e8061, 2024.

[7] Zdankus, T., & Vaiciunas, J., "Experimental Research of the Heat Transfer into the Ground at Relatively High and Low Water Table Levels", *Buildings*, vol. 13(5), pp.1272, 2023.

[8] QA Aljanabi, Z Chik, MF Allawi, AH El-Shafie, AN Ahmed, A El-Shafie, 'Support vector regression-based model for prediction of behavior stone column parameters in soft clay under highway embankment", *Neural Computing and Applications*. Vol. 30, pp. 2459-246938, 2018.

[9] Johari A, Javadi AA, Najafi H. A genetic-based model to predict maximum lateral displacement of retaining wall in granular soil. Sci Iran. 2016;23:54–65. https:// doi. org/ 10. 24200/ sci. 2016. 2097.

[10] Shahin MA, Jaska MB, Maier HR 'Predicting settlement of shallow foundation using neural networks', *J Geotech Geoenviron Eng (ASCE)* , vol.128(9), pp.785–793, 2002.

[11] Kim, M., Senturk, M. A., Tan, R. K., Ordu, E., & Ko, J. . Deep Learning Approach on Prediction of Soil Consolidation Characteristics. Buildings. 2024. https://doi.org/10.3390/buildings14020450

[12] Kim, S., Kim, J. W., Kim, T., & Jung, J.-H. . A Hierarchical Gated Recurrent Unit Network Model for Settlement Prediction. 2023. https://doi.org/10.1145/3599957.3606246

[13] Gong, W., Zuo, L., Li, L., & Wang, H. . Prediction of stratified ground consolidation via a physics-informed neural network utilizing short-term excess pore water pressure monitoring data. Computer-Aided Civil and Infrastructure Engineering. 2024. https://doi.org/10.1111/mice.13326

[14] Cao, Y., Zhou, X., Yan, K., & Yan, K. . Deep Learning Neural Network Model for Tunnel Ground Surface Settlement Prediction Based on Sensor Data. Mathematical Problems in Engineering, 2021, 1–14. 2021. https://doi.org/10.1155/2021/9488892

[15] Kanayama, M., Rohe, A., & van Paassen, L. A. . Using and Improving Neural Network Models for Ground Settlement Prediction. Geotechnical and Geological Engineering, 32(3), 687–697. 2014. https://doi.org/10.1007/S10706-014-9745-8

[16] Naeini, S.A., Moayed, R.Z., Kordnaeij, A., Mola-Abasi, H. "Elasticity modulus of clayey deposits estimation using group method of data handling type neural network", *Measurement*, vol.121, pp.335–343, 2018.

[17] DM Hanoon, QA Aljanabi, "Experimental study on soft clay soils to improve settlement and ultimate stress using thermos mechanical loads". *Proceedings on Engineering* vol.5 (3), pp. 525-538,2024.

[18] QA Aljanabi , "SOFT Ground subsidence prediction of highway based on the BP neural network" *Diyala Journal Of Engineering Sciences*, vol. 8 (4) pp 183-188, 2015

[19] Géron, A. . Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (3rd ed.). O'Reilly,2022.

[20] Kelleher, J.D., Mac Namee, B., & D'Arcy, A.. Fundamentals of Machine Learning for Predictive Data Analytics (2nd ed.). MIT Press. 2020.

[21] Z Chik, QA Aljanabi, A Kasa, MR Taha ,"Tenfold cross validation artificial neural network modeling of the settlement behavior of a stone column under a highway embankment". *Arabian Journal of Geosciences*, vol. 7, 4877-4887, 2014.

[22] Sohail, A., Watanabe, K. and Takeuchi, S. , "Runoff analysis for a small watershed of Tono area Japan by back propagation Artificial Neural Network with seasonal data", *Water Resour Manage*, pp.1–22. 2008.