Anbar Journal of Engineering Science (AJES) **Vol. 15 , No. 1 (2024) , pp. 17 ~ 24**
P-ISSN: 1997-9428 ; E-ISSN: 2705-7440 DOI: http://doi.org/10.37649/aengs.2024.144108.1064

University of Anbar

Anbar Journal of Engineering Science

journal homepage: https://ajes.uoanbar.edu.iq/

Prediction of Load-Settlement in Bored Piles Using Artificial Neural Networks

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PAPER INFO

Paper history
Received: 29/10/2023
Revised: 19/02/2024
Accepted: 25/03/2024

Keywords:
Piles,
load-settlement,
Modeling,
Artificial Neural Networks (ANN)

ABSTRACT

Pile foundations are typically employed when top-soil layers are unstable and incapable of bearing super-structural pressures. Accurately modeling pile behavior is crucial for ensuring optimal structural and serviceability performance. However, traditional methods such as pregnancy testing, while highly accurate, are expensive and time-consuming. Consequently, various approaches have been developed to predict load settlement behavior, including using artificial neural networks (ANNs). ANNs offer the advantage of accurately replicating substrate behavior's nonlinear and intricate relationship without requiring prior formulation.

This research aims to employ artificial neural network (ANN) modeling techniques to simulate the load-settlement relationship of drilled piles. The primary aims of this study are threefold: firstly, to assess the effectiveness of the generated ANN model by comparing its results with experimental pile load test data; secondly, to establish a validation method for ANN models; and thirdly, to conduct a sensitivity analysis to identify the significant input factors that influence the model outputs. In addition, this study undertakes a comprehensive review of prior research on using artificial neural networks for predicting pile behavior. Evaluating efficiency measurement indicators demonstrates exceptional performance, particularly concerning the agreement between the predicted and measured pile settlement. The correlation coefficient (R) and coefficient of determination (R^2) indicate a strong correlation between the predicted and measured values, with values of 0.965 and 0.938, respectively. The root mean squared error (RMSE) is 0.051, indicating a small deviation between the predicted and actual values. The mean percentage error (MPE) is 11%, and the mean absolute percentage error (MAPE) is 21.83%.

1. Introduction

Piles are a type of deep foundation frequently used in situations where the upper layers of soil are unstable and unable to bear the stresses imposed by the superstructure. Piles serve the purpose of transferring these loads from the superstructure to deeper layers of the soil. Consequently, the

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behavior of piles significantly influences the safety and stability of structures that rely on pile support. Furthermore, accurate prediction of pile behavior is necessary to provide adequate structural and serviceability performance [1][2].

Designing pile foundations calls for careful consideration of both load-bearing capacity and settlement. Traditionally, these two aspects have been addressed separately, with separate designs for bearing capacity and settlement. However, it is important to recognize that soil resistance and settlement are interrelated and can mutually influence each other. As a result, when building pile foundations, the bearing capacity and settlement should be evaluated concurrently. The whole load-settlement solution for the piles must be precisely designated. Regardless, it is well established that precise load-settlement response of pile foundations can only be acquired by expensive and time-consuming in-situ load measurements [3].

Pile loading testing is the most accurate method of determining the serviceability and stability of pile foundations. Apart from highly critical constructions, the cost makes every design stage impractical. Creating a strong link between pile loading tests and in-situ soil testing, such as SPT, would be immensely beneficial to work engineers since it would provide a model based on simple experiments that could be utilized for stability and serviceability assessments [4].

Many theoretical and practical strategies for anticipating pile settlement are available in the geotechnical literature. Because obtaining undisturbed samples is complex, many settlement prediction procedures, such as the cone penetration test (CPT), standard penetration test (SPT), and dilatometer test, have focused on correlations with in situ testing. However, most techniques simplify the problem by making many assumptions about the factors influencing pile settlement. As a result, precisely anticipating settlement is complex, and most systems now fall short of this goal. Alternative methodologies that use artificial neural networks to predict settlement more precisely are thus necessary [5].

The use of ANNs has recently increased, employed with different grades of effectiveness to anticipate the load settlement curve. Artificial neural networks can provide a more accurate solution in certain cases. Furthermore, the capacity of networks to capture the nonlinear and complicated relationship of the substrate behavior without the requirement for an a priori formula is an advantage of modeling artificial neural networks over traditional methods. Recently, artificial neural networks have emerged. Many geotechnical engineering problems have been solved using it [6].

The Aim and Objectives. (i) Use the ANN modelling technique to predict the load-settlement behavior relationship of drilled piles and compare the performance of the created ANN model to the experimental pile load test results. (ii) Conduct a sensitivity analysis to determine which input factors significantly affect the model outputs.

2. Related works

The load-settlement curve can only be obtained through full-scale pile load testing. Additionally, methods such as cone penetration test (CPT), standard penetration test (SPT), and other in-situ testing can be utilized to assess the ultimate pile capacity. However, these procedures can be costly and time-consuming, limiting their practicality. Consequently, various techniques have been developed to predict the load-settlement behavior of piles as alternatives to time-intensive and expensive testing methods.
. [7]

[8]Used the Artificial Neural Network approach to develop a model to anticipate the results of a comprehensive Static Load Pile test. The model could anticipate the full pile load test from start to finish by incorporating the pile configuration, soil parameters, and groundwater table in a single artificial neural network model. The proposed method helps reduce the expense of such costly testing or predicting pile performance in advance.

[1] An artificial neural network (ANN) was utilized to forecast the behavior of pile foundations under axial loads in sand or mixed soils regarding load settlement. The findings demonstrate that the developed ANN models can accurately replicate the nonlinear behavior of soil under stress, including strain-hardening effects. Comparisons between the ANN models and other methodologies, both graphically and numerically, indicate that the ANN models outperform load-transfer methods in describing load settlement behavior. Therefore, in summary, artificial neural network (ANN) models exhibit dependability and

present a viable substitute for forecasting load settlement behavior.

[9] Created a feed-forward artificial neural network to predict driven concrete pile settling. The error estimation showed that, compared to conventional techniques, the ANN trained using the error propagation method can forecast pile settling more accurately. According to a comparison of the acquired data with previous methodologies, acquiring a substantial amount of data for each pile type is required to produce the best outcomes. However, because of their high accuracy and learnability, neural networks appear to be a practical and user-friendly method for calculating pile settlement.

[3] A prediction model was developed using recurrent neural networks (RNNs) to simulate the load-settlement behavior of steel-driven piles under axial loading. Cone penetration tests and in-situ full-scale pile load testing data were used to calibrate and validate the model (CPT). The results indicate that the proposed RNN model can accurately predict the load-settlement response of axially loaded steel-driven piles. This suggests that the RNN model can be a valuable tool for geotechnical engineers in standard design practices when dealing with such piles.

In addition to analyzing pile load-settlement behavior [4], a high-order neural network (HON) was created with inputs from pile characteristics and SPT data throughout the pile embedment depth to model the pile load-settlement curve. According to the results, the quality of HON forecasts has improved. Compared to elastic and hyperbolic model predictions, the proposed HON model surpasses existing theoretical models.

Previous research in geotechnical engineering [10] has extensively explored the modeling of pile-bearing capacity and settling. As methodologies for forecasting pile behavior, analytical models, numerical simulations, and experimental testing have all been examined. However, there has recently been a surge of interest in predicting pile behavior using (ANNs).

3. Development of Neural Network Model

All the information utilized for calibrating and validating artificial neural network models was obtained from various sources to achieve a comprehensive and scientifically sound integration of work. These sources encompassed 12 projects, and their data consisted of practical experimental results. These tests were conducted in different sites and for different soil types and geotechnical conditions. These tests include laboratory measurements of piles and correspond to all stages of our work. This predictive model was created with SPSS V23 software and a software package (excel).

3.1 Model inputs and outputs.

To effectively develop a reliable model, it is critical to identify the factors that have the greatest impact on pile-bearing capacity and settling. [11]. When additional input parameters are added to an ANN model, the data required to estimate the connection weights are produced accurately, and the connection speed decreases [12]. These parameters consist of as shown in Figure (1)

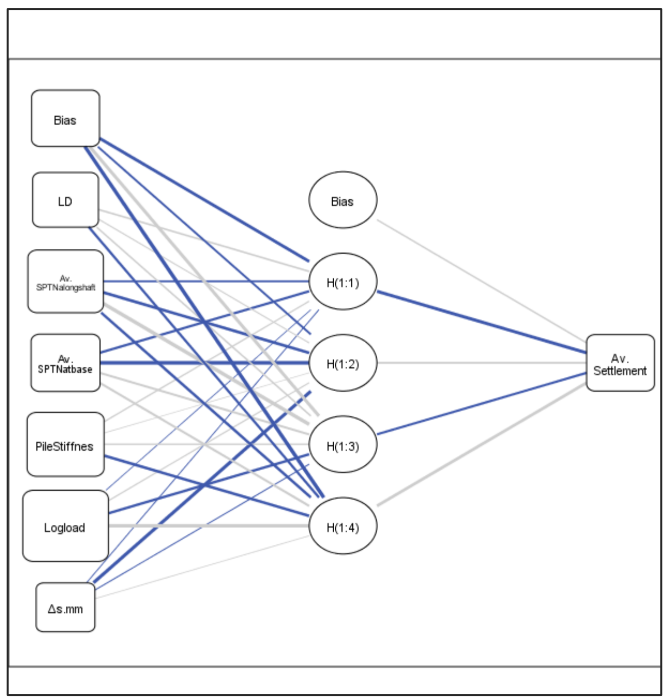


Figure 1. The ideal architecture of the ANN model (A.V Settlement mm)

1. L/D ratio (m).

2. Av. SPT(N) along the Shaft.

3. Av. SPT (N) under the base.

4. Pile Stiffness, EpAp/Lp.

5. log Load (kN).

6. Δs (MM)

The output of the model is the A.v settlement of the pile.

3.2 Model Architecture and Optimization*.*

Constructing the architecture of an Artificial Neural Network (ANN), which involves determining the number and connectivity of hidden layer nodes, is a crucial and challenging task. It has been shown that with a sufficient number of connection weights, a single hidden layer can approximate any continuous function[13]. Consequently, for this investigation, only one hidden layer was utilized. Multiple tests were conducted using the software's default parameters to determine the optimal network design and internal training process controls. These tests involved varying the number of hidden layer nodes from 1 to 13. It is important to note that 13 represents the maximum number of hidden layer nodes required to accurately map any continuous function for a network with 6 inputs. [14][15]. this study employed a sequence of tests using the program's preset configurations to identify the most effective network architecture and controls for the internal training procedure. The tests encompassed the following:

1. AUTOMATIC

2. TANH TANH

3. LOG-LOG

4. TANH LOG

5. LOG TANH

Metrics such as root mean square error (RMSE), coefficient of determination (R), and R-squared (R^2) were employed to assess the performance of the model. The study aimed to establish optimal and scientifically sound procedures for achieving successful outcomes in practical engineering techniques. Figure (2) displays the comparison between the measured settlement and the predicted settlement for both of these models. Figure (3) automatically visualizes the root mean square error (RMSE) values for both the training and test sets, allowing for an evaluation of the model's performance on both datasets. The link between RMSE and the number of hidden nodes is examined in Figure (4), offering insights into how network complexity affects prediction accuracy. The association between the number of concealed nodes and the coefficient of correlation (R) is explored in Figure (5).

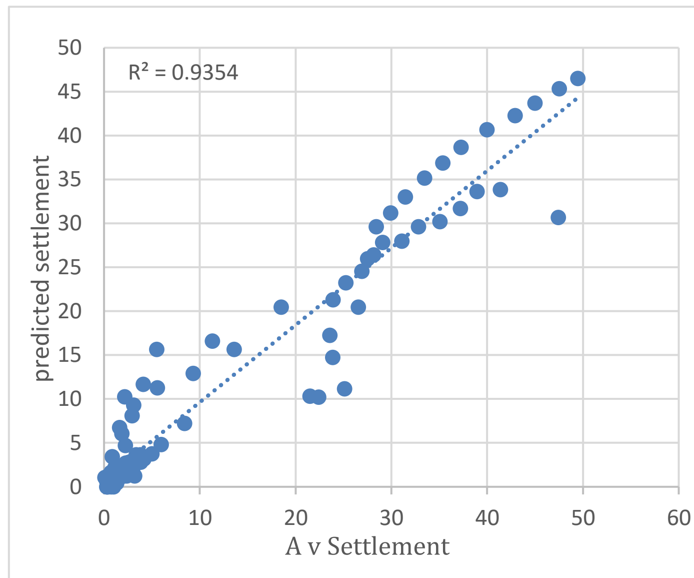


Figure (2) compares the ANN models' expected and observed settlements.

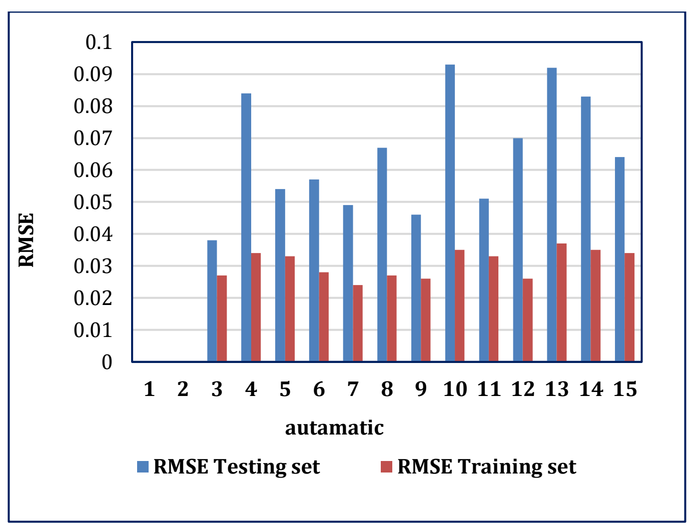


Figure 3: The Correlation between Training and Testing RMSE

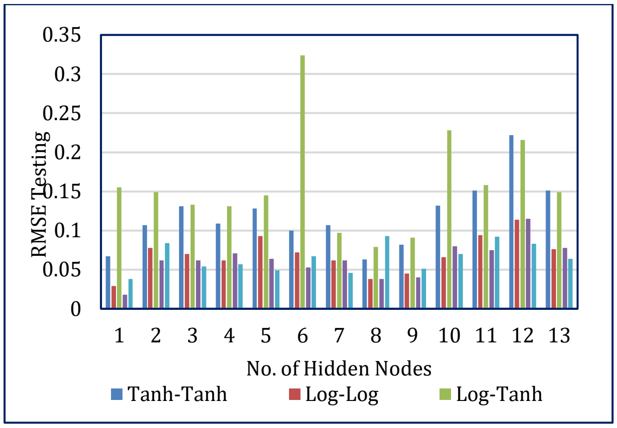


Figure (4) The Relation between RMSE &No. of Hidden Nodes

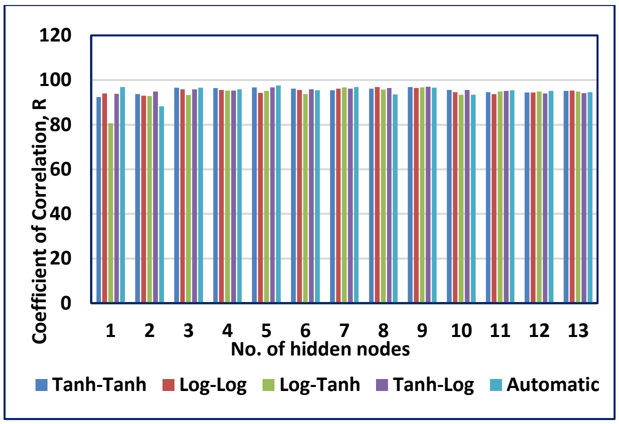


Figure 5: The Relationship between Correlation Coefficients and the Number of Hidden Nodes

3.3 Model validation and performance

Determining the accuracy and dependability of a model requires rigorous validation and verification processes. This study's artificial neural network (ANN) model was validated and verified using several statistical tests. The Root Mean Squared Error (RMSE) measures the difference between the expected and actual values, and the Coefficient of Correlation (R) measures the strength of the linear relationship between the expected and actual values. The amount of variance in the dependent variable that the independent variables account for is quantified by the coefficient of determination (R2). The results of several statistical tests, which shed light on the precision and dependability of the ANN model, are shown in Table (1). MPE (Mean Percentage Error) and MAPE (Mean Absolute Percentage Error) are a prediction model's accuracy metrics. They are frequently used to assess the performance of artificial neural networks (ANN). The average percentage difference between expected and actual values is MPE, while the average percentage difference between predicted and actual values is known as MAPE. The following formulas (1)(2) can be used to calculate these metrics:

$$MPE = \left(\frac{1}{n}\right) * \Sigma \left[\frac{y-\hat{y}}{y}\right] * 100 \quad (1)$$

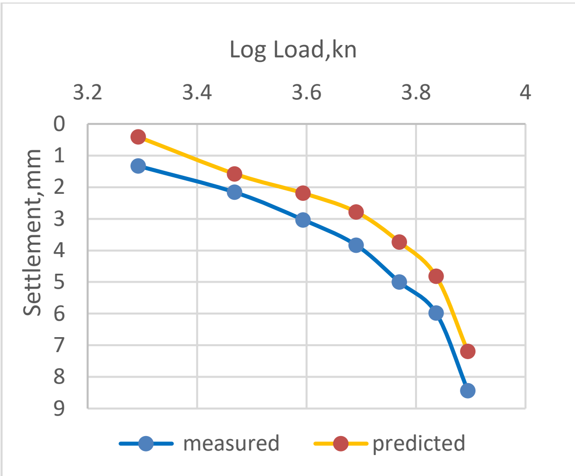
$$MAPE = \left(\frac{1}{n}\right) * \Sigma \left[\left|\frac{y-\hat{y}}{y}\right|\right] * 100 \quad (2)$$

Table 1: ANN model (A.V) statistical test results

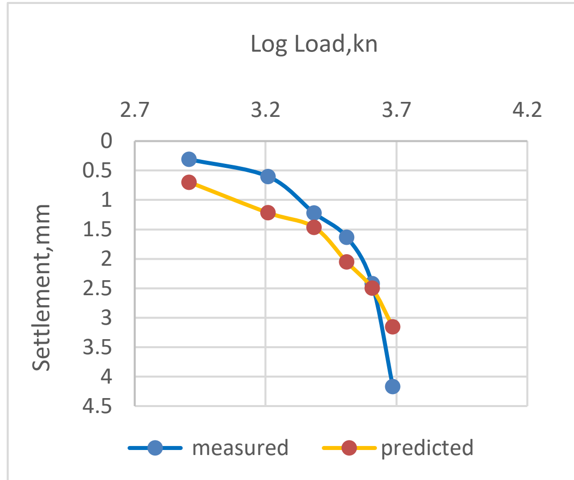
Statistical tests	Value
RMSE(Testing)	0.051
RMSE(Traning)	0.033
R	96.5
R^2	93.8
MPE	11 %.
MAPE	21.83%.

An effective artificial neural network (ANN) model was created in this work to forecast pile stability depending on a range of input parameters. The model was validated and calibrated by practical experimental data from 12 distinct projects with various soil types and geotechnical conditions. The L/D ratio, average SPT (N) under the base and along the shaft, pile stiffness, load, and settlement (Δs) were the input parameters, and the pile settlement was the output. The ANN model was trained through 13 iterations utilizing a trial and error technique to determine the ideal network geometry. The model showed good accuracy and reliability in predicting pile settlement using several statistical tests, such as RMSE, R, R2, MPE, and MAPE. With one hidden layer and four hidden nodes. It should be noted that the blue lines in Figure 6 represent.Experimental data while yellow lines are for ANN model predictions. For brevity only some representative curves have been selected and shown in Figure 6, which show well Performance of the developed ANN models

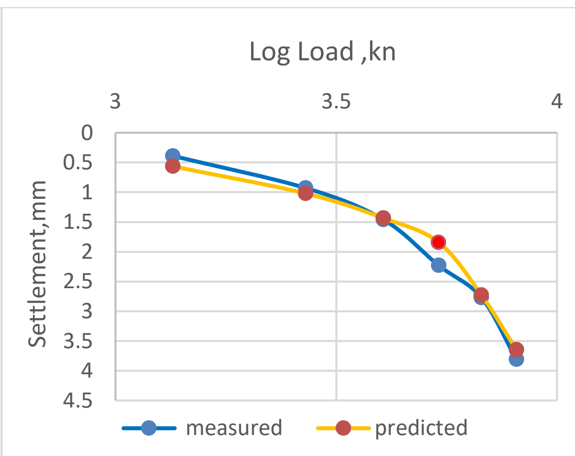
A



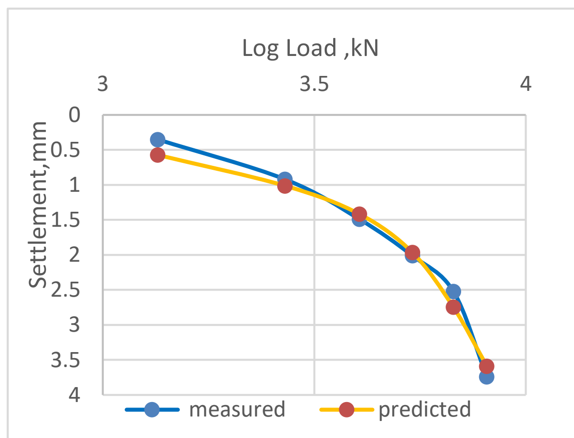
B



C



D



E

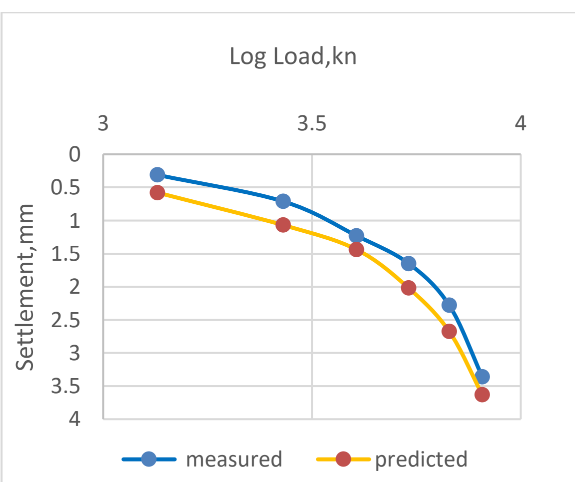


Figure (6) A some load settlement simulation results using the generated AN (A, B, C, D, E,)

3.4 ***Sensitivity Analysis***

The sensitivity analysis of the ANN model (A.V) showed that (Log load) has the highest effect, followed by (Pile Stiffness), (Av. SPT N along the shaft.), (Av. SPT N at the base.), Moreover, (L/D), with relative effects of (75.8%), (71.5%), (53.3%), and (44.2%), respectively, while the parameters (Δs.), have lower relative effects of (24.8%), as shown in Table2.

Table 2 Sensitivity analysis of the ANN model (c)

Independent Variable Importance	Importance	Relative Importance
L/D	0.119	44.2%
Av. SPT N along the shaft	0.193	71.5%
Av. SPT N at base	0.144	53.3%
Pile Stiffness	0.205	75.8%
Log load	0.271	100.0%
Δs. mm	0.067	24.8%

4. Conclusion

In conclusion, the developed artificial neural network (ANN) model effectively predicts the relationship between input and output variables in the context of pile settlement behavior. The model demonstrates accurate predictions, as indicated by the low values of root mean squared error (RMSE) and mean absolute error, as well as the high coefficient of determination (R-squared).

The RMSE values of 0.051 for testing data and 0.033 for training data suggest that the model can accurately estimate the average settlement of piles based on the input parameters. The strong positive correlation (96.5%) between the predicted and actual values further supports the reliability of the model's predictions. The coefficient of determination (R-squared) value of 93.8% indicates that the model effectively explains a significant portion of the variability observed in the average settlement values.

However, it is important to note that the model exhibits an average overestimation of 11% in the mean percentage error (MPE), indicating the presence of bias. This bias should be taken into account when interpreting the model's predictions. Additionally, the mean absolute percentage error (MAPE) of 21.83% provides a comprehensive measure of prediction accuracy, with higher values indicating a larger deviation between the predicted and actual values.The analysis of independent variable importance reveals the relative significance of each input parameter in predicting average settlement. The results suggest that log load, pile stiffness, Av. SPT N along the shaft, Av. SPT N at the base, L/D ratio and ΔS mm are important factors with varying degrees of influence. Overall, the ANN model performs well in predicting the average settlement of piles. However, it is crucial to consider the model's tendency to overestimate settlement values and the varying importance of input parameters. These findings provide valuable insights for utilizing the ANN model in predicting pile behavior. predict pile behavior more accurately than traditional approaches.

5. Funding

I declare that the manuscript was done depending on the personal effort of the author, and there is no funding effort from any side or organization.

6. Acknowledgements

I want to thank my supervisors, whose guidance and support made this paper. Thanks also to the Civil Engineering Department, University of Anbar.

7. Conflicts of Interest

The authors state no conflict of interest

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