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Prediction of Local Scour Depth Around Bridge Piers in Clay-Sand Bed using The ANN Method

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ABSTRACT

Local scour is a primary cause of bridge collapse, presenting a complex challenge due to the numerous factors influencing its occurrence. The complexity of local scour increases with clay-sand beds, particularly in predicting scour depth, as empirical equations are inadequate for such calculations. This study aims to predict local scour around cylindrical bridge piers in clay-sand beds using an artificial neural network (ANN) model. The ANN model was developed using 264 observations from various laboratory experiments. Eight variables were included in the ANN model: clay fraction, pier diameter, flow depth, flow velocity, critical sediment velocity, sediment particle size, bed shear strength, and pier Reynolds number. Sensitivity and statistical analyses were conducted to evaluate the impact of each variable and the accuracy of the ANN model in predicting local scour depth in clay-sand beds. The findings indicate that the ANN model predicted local scour with high accuracy, achieving a mean absolute percentage error (MAPE) of 14.6%. All dimensional variables significantly influenced the prediction of local scour depth, particularly clay fraction and bed shear strength, which were identified as the most crucial parameters. Finally, the MAPE values for local scour depth calculated using empirical equations were significantly higher than those for the ANN model, leading to an overestimation of local scour depth by the empirical equations.

1. Introduction

Local scour is a primary cause of bridge collapses. In simple terms, it can be defined as a natural phenomenon that occurs in river systems near obstacles causing to erode the sediments surrounding the obstacles, such as piers and abutments. The multitude of variables that govern the occurrence of local scour development adds complexity to this matter. The factors are water velocity, water depth, pier shape, pier diameter, sediment types, and bed shear forces. Local scour occurs as a result of three-dimensional flow. Firstly, there is downward flow near the front of the pier. Secondly, horseshoe-vortices form at the base of the pier. Lastly, vortices form along the direction of the flow. Furthermore, wake vortices are generated downstream, specifically behind the pier. Fig 1 illustrates the mechanism of the local scour (Alasta et al., 2022; Ettema, Kirkil, & Muste, 2006).

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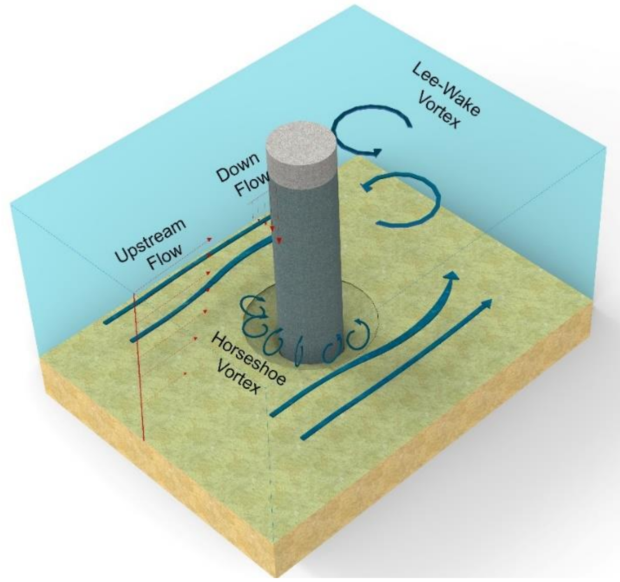

Fig 1. The mechanism of the local scour (Dheyab & Günal, 2023).

Local scour leads to many losses in the financial aspects, people life, and operational disruptions. Therefore, researchers investigated the potential scenarios of local scour in order to fully comprehend all aspects related to this issue and ensure the long-term viability and sustainability of infrastructure systems (De Falco & Mele, 2002; Schaap & Caner, 2022).

Numerous studies have been carried out in recent years to investigate the impact of sediment type on local scour. Based on the research outcomes, the sediments can be classified into three different types: cohesive sediments (clay and silt), noncohesive sediments (sand), and mixed sediments (sand and clay bed) (Baykal, Sumer, Fuhrman, Jacobsen, & Fredsoe, 2015; Chaudhuri & Debnath, 2013; Chaudhuri, Pandey, Debnath, & Oliveto, 2022; K. Debnath & Chaudhuri, 2010a, 2010b; Ismael, Gunal, & Hussein, 2015; Liang, Du, Pan, & Zhang, 2020; Molinas & Hosni, 1999; Najafzadeh & Barani, 2014; Roulund, Sumer, Fredsøe, & Michelsen, 2005; Sumer, Hatipoglu, & Fredsøe, 2007; Wang, Yu, & Liang, 2017; Zhang, Sun, Yao, & Yu, 2022; Zhao, Cheng, & Zang, 2010).

Indeed, the rivers bed sediments are not limited to sand or clay alone. Observations in the field indicate that the ocean floor can contain fine sand or silt particles with varying densities. Based on statistical data from China, it has been observed that the bed materials in the Yangtze River estuary mainly consist of cohesive soil and sand with relatively large particle sizes. However, the bed materials found in the Yellow River Delta consist mainly of silt and clay (Wang et al., 2017). Therefore, it is crucial to investigate the methods of predicting local scour in clay-sand beds.

Several formulas have been developed through regression analysis to predict the local scour depth based on experimental data, leading to the development of an empirical formula that can be used under specific circumstances. Nevertheless, the derived formulations of this methodology have faced criticism for their tendency to overestimate scour depth in real-world applications (S.-U. Choi, Choi, & Lee, 2017; Ettema, Melville, & Barkdoll, 1998; Sonia Devi & Barbhuiya, 2017).

In the past, numerous investigations were conducted to predict the local scour around bridge piers in non-cohesive and cohesive beds. According to S. U. Choi and Cheong (2006), the artificial neural network (ANN) model is more accurate than empirical methods in predicting the local scour depth in a non-cohesive bed. Bateni, Borghei, and Jeng (2007) employed artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models to predict the local scour depth. Their findings indicated that the ANN model provided more accurate predictions of the local scour depth compared to the ANFIS model and empirical formulas. On the other hand, according to Muzzammil (2010), the ANFIS model accurately predicts local scour more than the ANN model. Muzzammil, Alama, and Danish (2015) applied Gene Expression Programming (GEP) to predict the local scour around bridge piers in cohesive beds by using laboratory data, Their findings indicated that (GEP) model is more accurate than empirical methods in predicting the local scour depth in cohesive beds.

S.-U. Choi and Choi (2022) utilized support vector machines (SVMs) and adaptive neuro-fuzzy inference system (ANFIS) models to forecast the depth of local scour in cohesive beds by using dimensional variables. Their findings demonstrated that the model training utilizing the ANFIS method was effectively conducted with a very low MAPE (Mean Absolute Percentage Error). Nevertheless, the model validation revealed that the ANFIS technique was unable to accurately predict the maximum scour depth in the cohesive bed due to overfitting. In contrast, the training and validation of SVMs were carried out with a moderate degree of accuracy.
Regarding clay-sand beds, no research has been conducted to predicate local scour. The objective of this study is to predict the depth of local scour in clay-sand beds using an artificial neural network (ANN). The predictions of the ANN models were generated using six datasets consisting of experimental data obtained from literature. Sensitivity analysis is employed to comprehend the underlying patterns and correlations among the variables. Additionally, comparisons are carried out with existing formulas, including one for the erosion of piers in a clay-sand bed. Finally, the forecasted outcomes are presented and analyzed.

2. Local Scour Around Bridge Piers

Several factors govern the local scour. The primary factors can be summarized as follows.:

$$ds = f\begin{pmatrix} Flow\left(h, V, Re_p, g, \rho, \mu\right), Sediments\ properties\left(d_{50}, \tau_c, \rho_s, \sigma_g, S_s, V_c\right), \\ Pier\ geometry(D, \alpha, \beta) \end{pmatrix} \dots\dots\dots\dots\dots 1$$

Where: h flow depth, V velocity, V_c critical velocity, Re_p Pier Reynolds number, g gravitation acceleration, D pier diameter, α flow direction, β correction factors for pier shape, τ_c bed shear strength, σg standard deviation of particle size, d_{50} median particle size, ρ water density, ρ_s sediment density, S_s specific gravity of sediment, and μ dynamic viscosity of water.
The most significant parameters of local scour in the clay-sand bed are mentioned in Eq. 2, as stated by (Chaudhuri et al., 2022; Das, Chaudhuri, Barman, Roy, & Debnath, 2022; Das, Roy, Barman, Chaudhuri, & Debnath, 2019; K. Debnath & Chaudhuri, 2010a).

$$ds = f\left(h, V, d_{50}, \tau_c, C_p, V_c, Rep\right) \dots\dots\dots\dots\dots 2$$

In this study, The data in this study were carefully collected from experimental studies conducted by (Chaudhuri et al., 2022; K. Debnath & Chaudhuri, 2010a, 2010b; S. C. V. K. D. K. Debnath, 2020; Kho, Valentine, & Glendinning, 2004; Molinas, Jones, & Hosny, 1999). These studies aimed to experimentally investigate the local scour depth in the clay-sand bed. The dataset included 264 observations. Table 1 demonstrates the range of dimensional variables. Table 2 presents the equations employed to calculate the depth of local scour in a clay-sand bed. These equations were derived using the regression method based on experimental data.

Table 1. Range of dimensional variables.

Variable	Observations	Minimum	Maximum
Flow depth h (cm)	264	15	35
Pier diameter D (cm)	264	2.5	15.24
Sand median particle size d_{50} (mm)	264	0.081	0.55
Clay fraction C_p (%)	264	0	100
Local scour depth d_s (cm)	264	0	24.77
Velocity V (m/s)	264	0.2177	0.8273
Critical velocity V_c (m/s)	264	0.1755	0.736
Pier Reynolds number Re_p	264	6323	96571
Bed shear strength τ_c (kN/m^2)	264	1.1	12.7

Table 2. Local scour formulas in clay-sand bed.

Source	Equation	Eq. no.
Molinas et al. (1999)	$\frac{d_s}{D} = 18.92\left[\frac{F_r^{2.08}}{\left(1 + C_p\right)^{1.88}}\right]$	3
K. Debnath and Chaudhuri (2010a)	$d_s = 8.2F_{rp}^{0.79}C_p^{-0.28}W_c^{0.15}\tau_s^{-0.38}$	4
K. Debnath and Chaudhuri (2010b)	$d_s = 2.05F_{rp}^{1.72}C_p^{-1.29}\tau_s^{-0.37}$	5

3. ANN Method

Artificial neural networks (ANNs) are a class of machine learning models that draw inspiration from the intricate operations of the human brain. Artificial Neural Networks (ANNs) seek to simulate the collaborative processing and analysis of data in the brain, where billions of interconnected neurons work. This is achieved through the use of mathematical methods (S.-U. Choi et al., 2017). Fig. 2 illustrates the basic structure of the Artificial Neural Network (ANN).

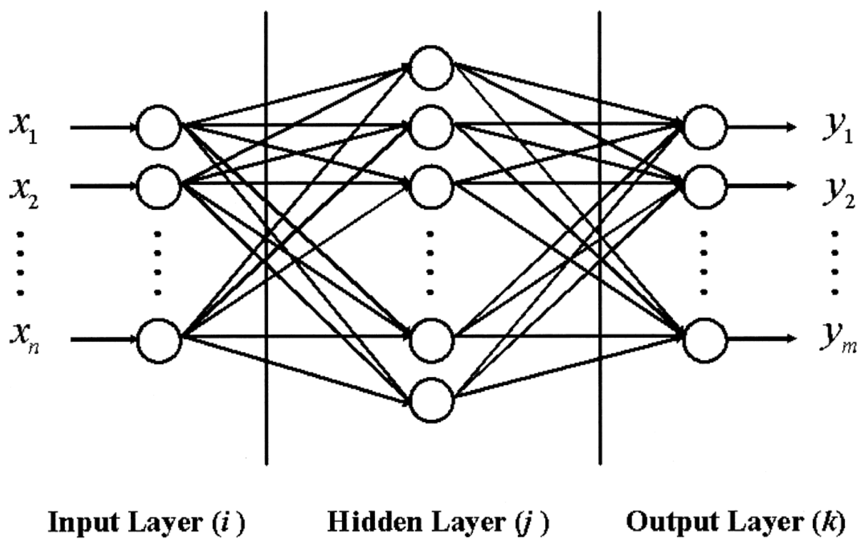

Fig 2. The general structure of ANN (S. U. Choi & Cheong, 2006).

An artificial neural network (ANN) consists of three separate layers, which are the input layer, the hidden layer, and the output layer. The input layer is responsible for collecting essential data. The hidden layer, whether it consists of singular or multiple sections, remains unreported and performs calculations. The output layer represents the predicted result. Linkages are formed among these levels using weights. The initial learning rate is a critical factor in determining how the weight values are adjusted in the neural network model. This element helps to minimize the difference between the expected and actual values. The weight values can be assigned randomly. However, these parameters are adjusted as the training progresses (S.-U. Choi et al., 2017).

The nodes in the network receive input signals, perform computations on them, and transmit output signals to other nodes in the network. The effectiveness of these nodes' interactions varies.

In this study, the ANN model was trained using the error back-propagation approach, as proposed by Rumelhart, Hinton, and Williams (1986). This approach is employed to measure errors, facilitating efficient monitoring of the model's efficacy. Subsequently, it modifies the weights according to these evaluations. Detailed descriptions regarding the ANN model can be found in (S. U. Choi & Cheong, 2006).

4. ANN Training and Prediction

An artificial neural network (ANN) was used to predict the depth of local scour in a clay-sand bed. The training dataset for the Artificial Neural Network (ANN) model included 264 experimental observations. The training was conducted using the dimensional variables which are listed in Table 1. The Artificial Neural Network (ANN) model included 8 input nodes.

In order to identify the optimal ratio for dividing the data set into training, testing, and validation, various ratios were evaluated, such as 60:40, 70:30, and 80:20. In addition, many layers were carefully examined to determine the optimal fit for the prediction. Consequently, it was found that the most accurate predictions were achieved by dividing the data into training (70%), testing (15%), and validation (15%) and 20 hidden layers.

The Levenberg–Marquardt backpropagation training algorithm was utilized in this study. According to S.-U. Choi et al. (2017) and Ali and Günal (2021), using this algorithm improved the accuracy of predicting the local scour depth. The Levenberg–Marquardt backpropagation is a modified version of the Gauss–Newton method. The error back-propagation algorithm estimates errors to monitor the model's performance and recalculates the weight values accordingly. During the learning process, the artificial neural network (ANN) model adjusts its own code to fit the particular circumstance. Additional information about Artificial Neural Networks (ANNs) and The Levenberg–Marquardt backpropagation can be found in the research conducted by (Reynaldi, Lukas, & Margaretha, 2012).

Figure 3 illustrates the significant results of the Artificial Neural Network (ANN) model in predicting the local depth in a clay-sand bed. The training phase yielded a correlation coefficient (r) of 0.94967 and a Mean Squared Error (MSE) of zero. Throughout the next testing phase, the correlation coefficient (r) constantly maintains a high value of 0.84323, while the mean squared error (MSE) remains at zero. During the validation phase, 15% of the dataset was utilized. The correlation coefficient (r) was recorded at 0.88393, along with a mean squared error (MSE) of 0.0016. The average correlation coefficient (r) across all stages is 0.91336.

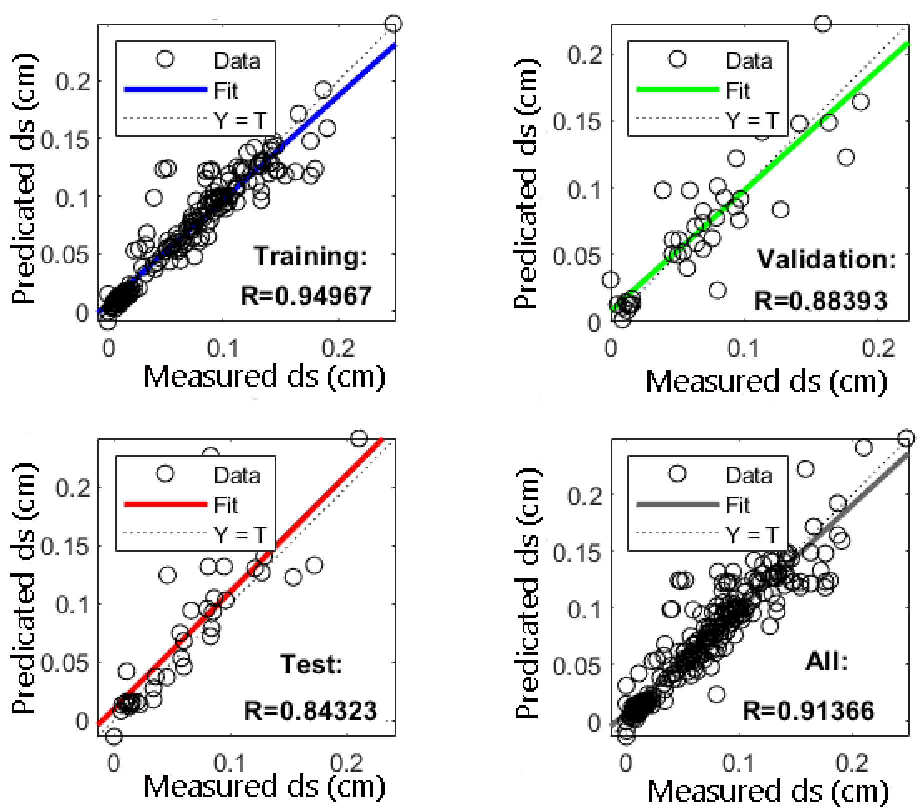

Fig 3. ANN model with dimensional variables.

The artificial neural network (ANN) model incorporating dimensional variables has exhibited commendable performance in accurately forecasting the scour depth proximate to bridge piers within clay-sand beds. The outcomes depicted in Figure 3 demonstrate notable efficacy, as evidenced by a correlation coefficient (r) of 0.94967 during the training phase and a Mean Squared Error (MSE) of zero. During the subsequent testing phase, the correlation coefficient (r) remains consistently high at 0.84323, with MSE persisting at zero. In the validation phase, the attained correlation coefficient (r) registers at 0.88393, accompanied by an MSE of 0.0016. Cumulatively, across all phases, the correlation coefficient (r) averages at 0.91336.

According to these results, the utilization of the ANN model with dimensional variables predicted the local scour depth with a high degree of accuracy due to the utilization of a large number of variables. These findings align with previous studies conducted by (Bateni, Jeng, & Melville, 2007; S.-U. Choi et al., 2017; Muzzammil, 2010).

5. Sensitivity Analysis and Statistical Analysis

A sensitivity analyze was carried out to assess the impact of the specified variables on the ANN model. In order to evaluate the impact of each variable, eight models were developed following the same approach for first ANN model. The dataset was divided into 70% for training, 15% for testing, and 15% for validation. The hidden layers contained 20 layers, and the Levenberg–Marquardt backpropagation training approach was applied. For each model, one variable was selectively removed and the comparison was conducted based on the R-value. Table 3 displays the models labelled as ANN1-ANN8. Additionally, Figure 4 illustrates the fitting of training of each model. Overall, the sensitivity analysis demonstrated that all variables have significant impacts on predicting local scour in a clay-sand bed. Furthermore, the most significant variables might be ranked in the following order: shear stress, clay fraction, flow depth and velocity.

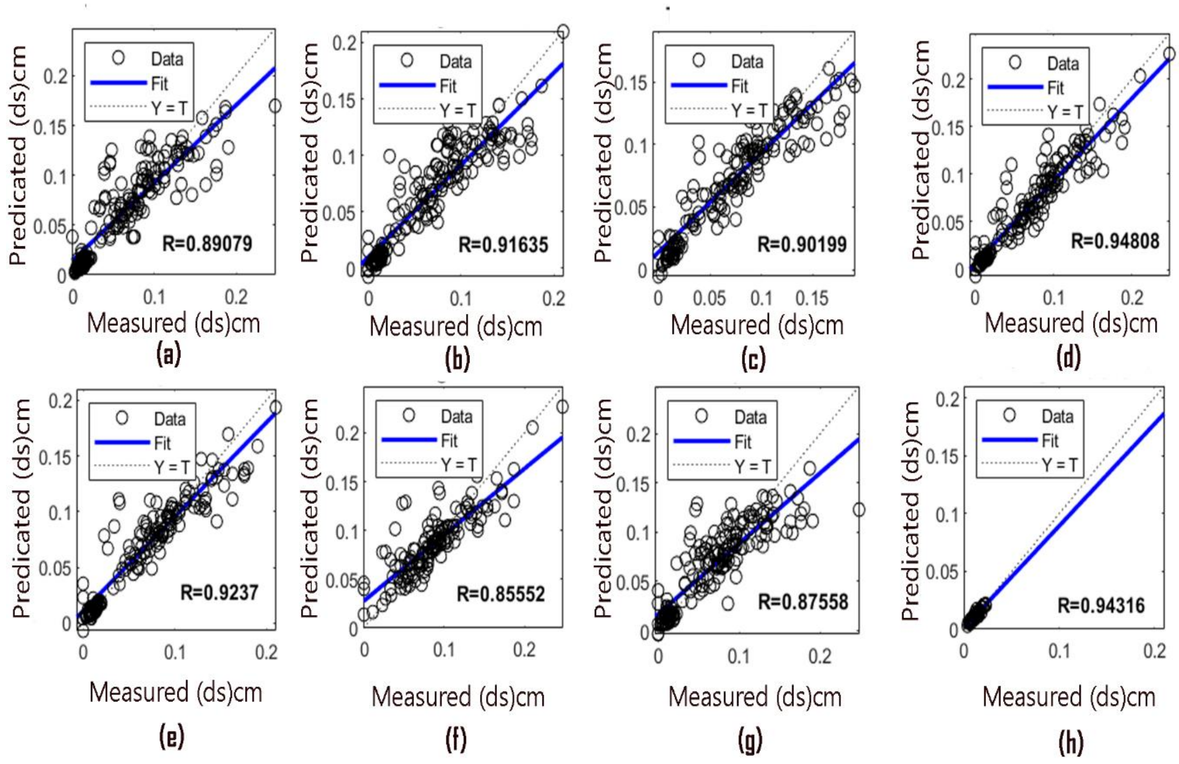

Fig 4. Models training with dimensional variables a. ANN1 model, b. ANN2 model, c. ANN3 model, d. ANN4 model, c. ANN5 model, d. ANN6 model, e. ANN7 model, f. ANN8 model.

Table 3. Sensitivity Analysis

Model	R Training	R Testing	R Validation	Removed Parameter
ANN1	0.89	0.891	0.889	CP%
ANN2	0.91	0.78	0.91	D
ANN3	0.90	0.95	0.96	d_{50}
ANN4	0.94	0.81	0.76	h
ANN5	0.92	0.84	0.876	Re_p
ANN6	0.85	0.50	0.7	τ_c
ANN7	0.87	0.85	0.89	V
ANN8	0.94	0.86	0.94	Vc

A Pearson correlation analysis was carried out to assess the eight-dimensional variables used in the ANN model. The correlation coefficient is a measure of the degree of relationship between variables and is represented on a scale ranging from -1 to 1. This continuum represents the corresponding P value linked to the correlation.

$$r = \frac{n\sum(xy)-(\sum x)(\sum y)}{\sqrt{n[\sum x^2-(\sum x)^2][\sum y^2-(\sum y)^2]}},\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 6$$

where r is the correlation coefficient; n represents the sample size; and x and y are the first and second variables in the given dataset, respectively.
Figure 5 demonstrates the significant correlation between the local scour depth ds and the eight-dimensional variables. The results of the Pearson correlation analysis are similar to the obtained results from the sensitivity analysis. Additionally, all variables have statistically significant relationships with depth of local scour according to the P value as presented in the Table 5.

Table 5. Pearson correlation between the dimensional variables and d_s

	Cp (%)	D	d_{50}	V	Vc	h	Re_p	τ_c
r	-0.621^{**}	0.063^{**}	0.320^{**}	-0.492^{**}	0.264^{**}	-0.29^{**}	0.094^{**}	-0.83^{**}
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

**Correlation is significant at the 0.01 level (two-tailed).

The performance of the ANN model for predicting the local scour depth in a clay-sand bed was evaluated using the following statistical analysis:
The Nash-Sutcliffe efficiency (NSE) is a statistical method used to assess the performance of a model. The purpose of this evaluation is to assess the degree of agreement between the predicted values and the observed data (Nash & Sutcliffe, 1970). The NSE can be calculated by use Equation 7. Table 4 indicates that the NSE values of the ANN model were near to 1, indicating that the ANN model accurately predicted the local scour depth.

$$NSE = \frac{\sum_{i=1}^{n}(OBS_i-PRE_i)^2}{\sum_{i=1}^{n}(OBS_i-\overline{OBS})^2},\ldots\ldots\ldots\ldots\ldots\ldots\ldots 7$$

Where OBS is the observed data, and PRE is the predicated data.
Additionally, the ANN model was evaluated using the root mean square deviation (RMSD). The root mean square deviation (RMSD) result is presented in Table 4, throughout the obtained results for all phases. The RMSD values demonstrate the high level of accuracy of predicting the local scour depth in clay-sand bed by using the ANN model.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\hat{x}_i)^2}{N}},\ldots\ldots\ldots\ldots\ldots\ldots\ldots 8$$

Where N is the number of observations, x_i is observed value, $\hat{x}_i$ is predicted value.

Table 4. Statistical analysis (ANN Model)

	ANN		
	r	**NSE**	**RMSD**
Training	0.949	0.959	0.109
Testing	0.843	0.897	0.126
Validation	0.88	0.901	0.101
All	0.913	0.928	0.038

Lastly, A Mean Absolute Percentage Error (MAPE) was used to determine the error percentage and is calculated using Eq.9.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 9$$

Where n is the number of observations, A_i is the actual value, F_i is the forecasted value.

A comparison was carried out between the predicted scour depth using the ANN model and the computed scour depth using the empirical formulas listed in Table 2. Figure 6 presents a box plot illustrating the errors in scour depth predictions. The error is calculated as the difference between predicted and observed scour depths. The dotted line represents the zero error of the local scour depth. The positive value of errors indicates overprediction by the respective formula. The Mean Absolute Percentage Errors (MAPE) are also depicted in the figure. All formulas tend to overpredict scour depths. Nonetheless, the ANN method demonstrates significantly superior predictive accuracy compared to the empirical formulas.

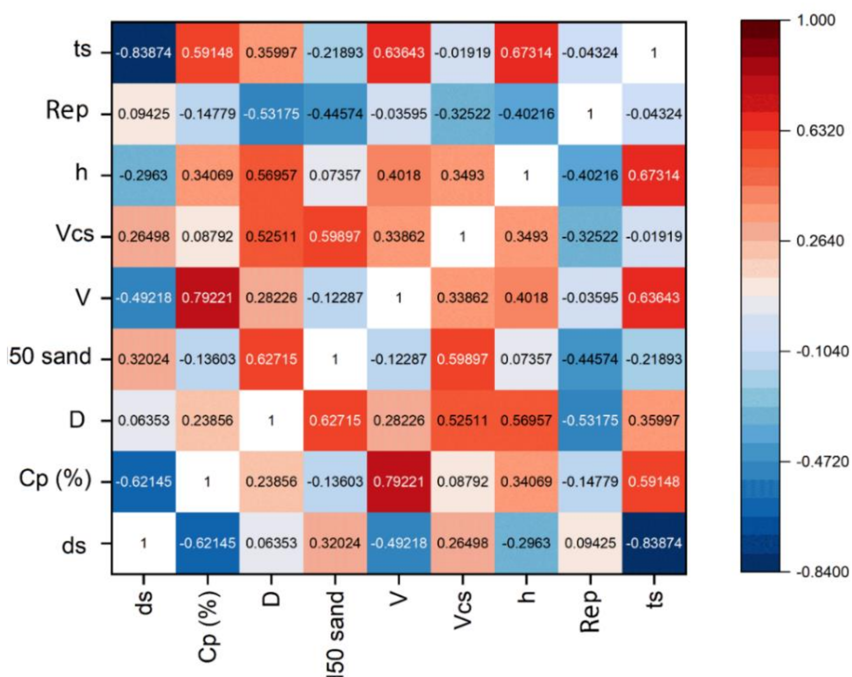

Fig 5. Correlation coefficient for the dimensional variables.

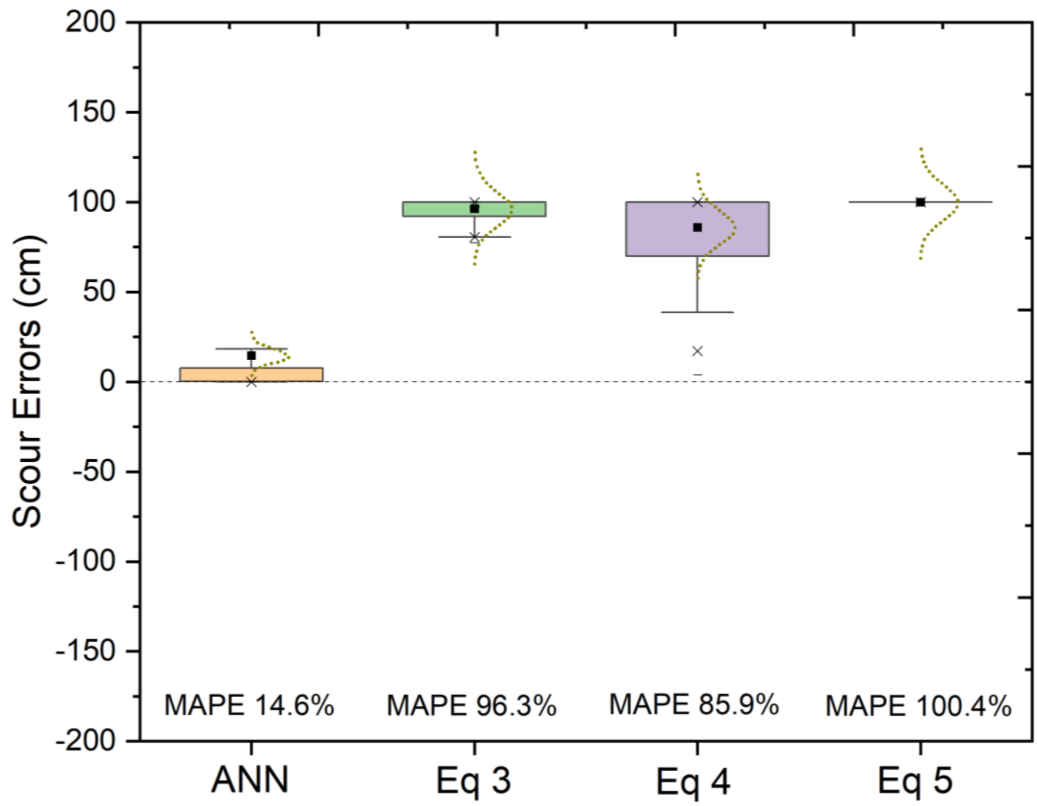

Fig 6. Box plot of prediction errors of ANN model and various formulas in application to experimental data.

6. Conclusion

This study aimed to predicate the local scour depth in clay-sand bed using the ANN method with eight-dimensional variables, namely mean velocity, clay fraction, sand median particle size, critical velocity, flow depth, pier diameter, pier Reynolds number, and bed shear strength.

The results demonstrated that the artificial neural network (ANN) model achieved a high level of accuracy in predicting the depth of local scour in a clay-sand bed. The Mean Absolute Percentage Error (MAPE) in this prediction was 14.6% when using eight-dimensional variables. The study demonstrated that the optimal ratio of the training-to-testing data is 70:30. Furthermore, the applying of a 20-hidden-layer and Levenberg–Marquardt backpropagation training method greatly enhanced the accuracy of predictions. The results of sensitivity analysis and Pearson correlation analysis showed that all dimensional variables have a significant impact on predicting local scour depth. Among these variables, clay fraction and bed shear strength were found to be the most significant parameters. Finally, the comparison of the predicted local scour depth using artificial neural networks (ANN) yielded superior results compared to the calculated local scour depth using empirical formulas.

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