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Artificial Neural Network for Estimation of Local Scour Depth Around Bridge Piers

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Abstract

Local scour around bridge piers impairs the stability of bridges' structures. Therefore, a delicate estimation of the local scour depth is vital in designing the bridge piers foundations. In this research, MATLAB software was used to train artificial neural network (ANN) models with four hundred laboratory datasets from different laboratory studies, including five parameters: pier diameter, flow depth flow velocity, critical sediment velocity, sediment particle size, and equilibrium local scour depth. The outcomes present that the ANN model with the Levenberg-Marquardt algorithm and 11 nodes in the single hidden layer gives an accurate estimation better than other ANN models trained with different training algorithms based on the regression results and mean squared error values. Besides, the ANN model accurately provides predicted local scour depth and is better than linear and nonlinear regression models. Furthermore, sensitivity analysis shows that removing pier diameter from training parameters diminishes the reliability of prediction.

Key words: artificial neural network, bridge pier, hydraulics, local scour

1. Introduction

Local scour is a natural phenomenon generated by the denudation of silty ducts' bottom and edges due to the water's flow (Khwairakpam and Mazumdar 2009). Besides, scour takes place in the coastal regions as a result of the waves. The procedure of scouring mechanizations is well established. However, it is not manageable to quantify the quantity of scour at the bridge pier because of the complexity of the cyclic nature of the event and the fact that geometry of the bridge, morphology, the channel of the river, and the hydrologic process is different at each bridge. Scour at bridge piers is generally the outcome of the combined influences of three separate scour procedures (local, contraction, and general scour at abutments and piers) that could occur either at the specific moment or independently. As shown in Figure 1, researchers have ordered total scour into the general scour and localized scour. The localized scour includes constriction scour, which is the decrease in the cross-sectional area of the flow of water due to the presence of piers and abutments; leading to an increase in the flow velocity, as a consequence, increase erosion due to flow, and hence reduce the bed elevation across the area concerned by the constriction.

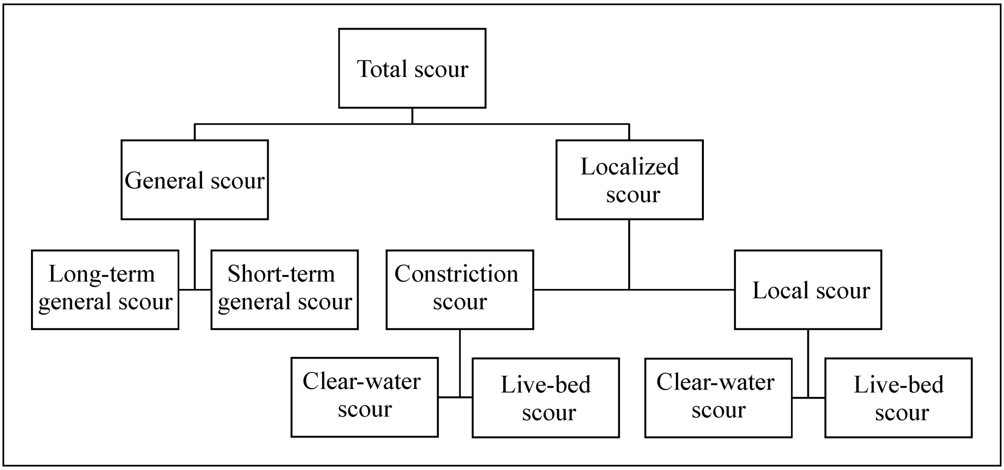

Fig. 1. Scour classification (Cheremisinoff et al 1987)

Another type of localized scour is the local scour, which is directly influenced by a pier or abutment of the bridge that interrupts water flow and combines live bed scour and clear water scour situations. The principal factor distinguishing between the live bed scour and clear water conditions is that the mean velocity (V m/s) of the flow upstream of the bridge is less or more significant than the scour-critical velocity (V_s m/s) needed to relocate the bed material. Therefore, the clear water scour condition happens in $V < V_S$. The bed material upstream of the bridge is at ease, referred to as the clearwater condition, because the approach flow does not sustain sediment, while live-bed scour does not occur when the $V > V_S$. Additionally, the equilibrium scour depth is accomplished when the material is carried into the scour hole at the same rate at which it is transported out. In the clear water scour condition, the depth of the scour hole extends to grow till equilibrium is reached. Hence, it occurs when the combination of the temporary mean bed shear stress and the turbulent near the bed can no longer eliminate the bed substance from the scour hole at the pier. In live-bed scour, the equilibrium scour depth is reached when the time that sediment enters the scour hole is equivalent to the time that is leaving the hole. Therefore, the depth of scour is an essential parameter for determining the minor depth of foundations as it minimizes the lateral capacity of the foundation. For this purpose, inclusive laboratory researches were carried to understand the complex scour process and establish a method of predicting scour depth for various pier locations. However, no generic description has been revealed that can be used in all pier cases to determine the quantity of scour that will happen. Numerous empirical formulae were presented to predict equilibrium scour depth at bridge piers, including Laursen and Toch (1956), Shen (1971), Hancu (1971), Breuser et al (1977), Melville and Sutherland (1988). Besides, improving soft computing techniques supported researchers in utilizing advanced methods to estimate the scour depth around various structures. Jeng et al (2005) employed an artificial neural network to predict equilibrium scour depth and time-dependent scour depth. They developed two Bayesian models with single hidden layers and multiple hidden layers, and they trained ANN models with the combination of dimensional and dimensionless parameters. They noted that the Bayesian neural network model provides more precise scour depth predictions than the current methods. The sensitivity analysis revealed that pier diameter has the most significant influence on equilibrium scour depth. Additionally, predictions based on the original (dimensional) scour data were more accurate than those based on dimensionless data. Bateni et al (2007) applied ANN models with multilayer perceptron (MLP/BP), radial basis function (RBF/OLS), and adaptive neuro-fuzzy inference system (ANFIS) in the calculation of equilibrium and time-dependent scour depth around piers. The research comprised the laboratory data to train and verify the networks, and they trained ANN models with dimensional and non-dimensional parameters. They observed that the neural networks and neuro-fuzzy approaches predict scour depth much more precisely than the present methods, especially multilayer perception with one hidden layer and raw data. They also pointed out that the pier diameter has the most influence on equilibrium scour depth. Guven et al (2012) developed gene-expression programming (GEP) and a multilayer perception model with one hidden layer and a backpropagation algorithm to predict the scour depth around a circular pile due to tides. The models are trained with dimensional and non-dimensional parameters. They concluded that the GEP predicted the scour depth around the pile with better precision than MLP, linear regression, and nonlinear regression models. Sarshari and Mullhaupt (2015) used ANN and empirical methods to predict equilibrium scour depth at bridge piers. They applied a multilayer neural network and the popular backpropagation algorithms in MATLAB, and they trained ANN models with dimensional parameters. They noticed that the neural network prediction results are more precise than the outcomes gained from the empirical models. The training algorithm Levenberg-Marquardt BPG (trainlm) presents more desirable outcomes than other algorithms in MATLAB. Khassaf and Abdulwhab (2016) employed ANN with feed-forward backpropagation algorithms in MATLAB to estimate the maximum local scour depth at cylindrical bridge piers. They observed that ANN gives better outcomes than empirical formulas, particularly the ANN model with Levenberg-Marquardt BPG (trainlm), which includes a single hidden layer and two hidden layers. Besides, the pier diameter has the most significant impact on predicting local scour depth based on sensitivity outcomes. Amini et al (2020) used an ANN model with a single hidden layer and three neurons to predict the scour depth at the composite piers of the bridges. They found that the proposed ANN model provides better results than the empirical methods, and the pile cap location and the flow depth have the most effects on the scour depth. However, the literature on applying artificial neural networks to estimate the scour depth at the bridge's abutment has not been reported over an extensive range. This study aims to utilize Artificial Neural Networks trained with laboratory data and various backpropagation algorithms in MATLAB for predicting equilibrium local scour depth around bridge piers. Besides, examining the most critical factors that affect the prediction and performance of modeling with dimensional and non-dimensional variables and comparing the outcomes with linear and nonlinear regression models.

2. Parameters Governing Scour

The depth of equilibrium local scour around the bridge piers is influenced by flow, sediment properties, and the geometry of the pier (Melville and Coleman 2000), as shown in the following functional relationship:

$$d_{se} = f_n \left[\text{flow}\,(\rho, \mu, V, y, g, \gamma)\,, \text{sediment}\,(d_{50}, \sigma_g, \rho_s, V_C), \atop \text{pier geometry}\,(b, \alpha, \beta) \right], \tag{1}$$

where d_{se} is the equilibrium scour depth, μ and ρ are dynamic viscosity of water (m^2/s) and fluid density (kg/m^3), respectively, y and V are flow depth (m) and mean velocity (m/s^2), respectively, g is the gravitational acceleration, γ is the correction factor for bed form, σ_g and d_{50} are standard deviation and median of the particle size distribution (mm), respectively, V_C is the critical mean velocity for entrainment of bed sediment (m/s), ρ_s is the sediment particle density (kg/m^3), b is the pier width or pier diameter, and β and α are correction factors for flow angle of attack and pier shape. However, the number of parameters in (Eq. 1) can be reduced, as γ and σ_g can be ignored and subscript in d_{50} can be removed from Equation 1 in the case of uniform sediment and abandoned influence of bedform. Moreover, when the angle of flow attack is assumed to be zero, β and α parameters could be taken away. Furthermore, ρ_s and ρ can be removed due to constant values of these parameters, and the meager effectiveness of viscous, (Eq. 1) could be written as follows (Choi et al 2017):

$$d_{se} = f_1\,(V, y, d, V_C, b)\,. \tag{2}$$

The dimensional analysis of Equation 2 leads to (Eq. 3) (Choi et al 2017), as shown:

$$\frac{d_{se}}{b} = f_2 \left(\frac{V}{V_c}, \frac{y}{b}, \frac{d}{b} \right). \tag{3}$$

3. Artificial Neural Network

An artificial neural network (ANN) is a comprehensive parallel-distributed information-processing framework that has a valid task feature similar to the brain's biological neural network systems in the human being (Haykin 1999), which is provided by McCulloch and Pitts (1943). The strength of the artificial neural network in distinguishing a relationship from a presented method makes it advantageous in resolving complex wide-ranging problems such as modeling, classification, and nonlinear problems. The characterizes of an ANN are known by determining the connection weight, the structure of the neural network, and activation function. The principles and components of ANN modeling and training steps are exceedingly introduced in the published works of Haykin (1999); Dolling and Varas (2002); Azmatullah et al (2005). Commonly, an artificial neural network contains three layers: input layer, hidden layer, and output layer, and each of these layers acting as a separate computational part, as shown in Figure 2.

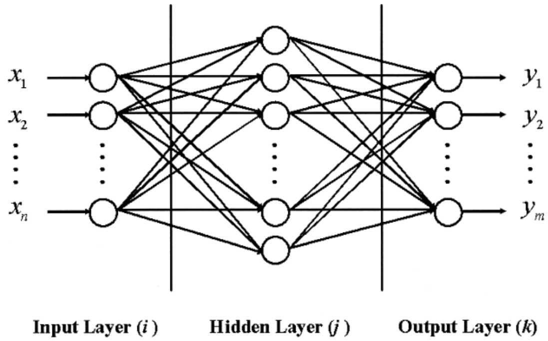

Fig. 2. Architecture of an ANN model (Choi and Cheong 2006)

The number of neurons in the hidden layer is a critical parameter determining ANN models' accuracy. Fletcher and Goss (1993) recommended that the suitable number of neurons in the hidden layer range from ($2n1/2 + m$) to ($2n + 1$), where n is the number of input neurons and m is the number of output neurons. Commonly, the number of hidden layer neurons is decided by a trial-and-error process. Finally, the model with the most precise results will be applied, which contains the most relevant number of neurons in the hidden layers. In this study, eight ANN feed-forward neural network models with backpropagation algorithms were established to predict the equilibrium local scour depth around bridge piers using a deep learning toolbox in MATLAB. Besides, these ANN models included a single hidden layer with 2 – 12 nodes to figure out the appropriate number of nodes in the hidden layer. Table 1 shows the backpropagation algorithms used in the training ANN models in MATLAB and the parameters of each ANN model.

Table 1. ANN models

Model name	Function name	Algorithm	Variables
DM-1	TRAINLM	Levenberg-Marquardt backpropagation	d_{se}, b, V, y, V_c, d
DM-2	TRAINRP	Resilient backpropagation	d_{se}, b, V, y, V_c, d
DM-3	TRAINGDA	Gradient descent with adaptive *lr* backpropagation	d_{se}, b, V, y, V_c, d
DM-4	TRAINCGF	Fletcher-Powell conjugate gradient backpropagation	d_{se}, b, V, y, V_c, d
DM-5	TRAINCGP	Polak-Ribiere conjugate gradient backpropagation	d_{se}, b, V, y, V_c, d
DM-6	TRAINCGB	Powell-Beale conjugate gradient backpropagation	d_{se}, b, V, y, V_c, d
DM-7	TRAINBFG	BFGS quasi-Newton backpropagation	d_{se}, b, V, y, V_c, d
NDM-1	TRAINLM	Levenberg-Marquardt backpropagation	$\frac{d_{se}}{b}, \frac{V}{V_c}, \frac{y}{b}, \frac{d}{b}$

The log-sigmoid transfer function (LOGSIG) was utilized in the hidden layer that outfits a graded nonlinear response and supports the ANN to transact with any non-linear cases. The linear transfer function (PURLIN) was utilized as a transfer function between the hidden and output layer (Prasad et al 2012):

$$\text{LOGSIG} = f(n) = \frac{1}{1 + \exp(-n)}, \tag{4}$$

$$\text{PURLIN} = f(n) = n, \tag{5}$$

where $f(n)$ is the output of the transfer function, and n is the weighted sum of inputs. Moreover, the evaluation of the accuracy of ANN models in the prediction was assessed according to regression value (R) (best value = 1) and mean squared error (MSE) (best value = 0) (Hagan et al 2002, Hagan et al 2009).

$$R = \frac{\sum_{k=1}^{n} \left(T_K - \bar{T}\right)\left(O_K - \bar{O}\right)}{(n-1) S_T S_o}, \tag{6}$$

$$S_T = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} \left(T_K - \bar{T}\right)}, \tag{7}$$

$$S_T = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} \left(O_K - \bar{O}\right)}, \tag{8}$$

$$\bar{T} = \frac{1}{n} \sum_{k=1}^{n} T_K, \tag{9}$$

$$\bar{O} = \frac{1}{n}\sum_{k=1}^{n} O_K, \tag{10}$$

$$\text{MSE} = \frac{1}{n}\sum_{k=1}^{n} (T_K - O_K)^2\,, \tag{11}$$

where n is the number of data, O_K is the network outcome, T_K is the actual target, $\bar{O}$ is the mean value of the network output, $\bar{T}$ is the mean value of the targets.

4. Dataset

ANN models were trained with 400 laboratory measurements of the pier scour dataset. These data were taken from the laboratory data available in the PSDb-2014, consisting of 569 measures taken from 17 previous investigations collected by Sheppard et al (2011), Benedict and Caldwell (2014). Throughout a screening method that included data review and statistical study, Sheppard et al (2011) recognized 441 of the laboratory measurements that approximated equilibrium scour depths and applied that data in their research of pier scour. Some of the laboratory measurements compiled by Sheppard et al (2011) are of historical interest. In particular, various of the data collected by Chabert and Engeldinger (1956) and Shen et al (1969) was employed to improve the original Hydraulic Engineering Circular No. 18 (HEC-18) pier-scour equation (Richardson et al 1991). The data consist of variables which are pier width (b), flow velocity (V), flow depth (y), the sediment critical mean velocity (Vc), the particle diameter (d), and equilibrium scour depth (dse). Table 2 shows the sources of data used in the training ANN models.

Table 2. Dataset

Source of dataset	Number of datasets
Chabert and Engeldinger (1956)	93
Chee (1982)	37
Chiew (1984)	101
Coleman (unpublished)	6
Dey et al (1995)	18
Ettema (1980)	97
Ettema et al (2006)	6
Ettema (1976)	19
Graf (1995)	3
Jain and Fischer (1979)	20

Table 3 presents the range of dimensional variables, while Table 4 shows the range of non-dimensional variables.

Besides, all variables were normalized according to the min-max normalization method to increase prediction efficiency (Dogan et al 2008).

Table 3. Dimensional dataset

Dimensional variable	Range
V (ft/s^2)	0.54–5.28
y (ft)	0.066–3.281
d (mm)	0.24–7.8
V_c (ft/s)	0.73–4.81
b (ft)	0.095–2.5
d_{se} (ft)	0.049–1.497

Table 4. Dimensionless dataset

Dimensionless variable	Range
d_{se}/b	0–3.084
V/V_C	0.445–4.690
y/b	0.052–20.947
d/b	0.304–82.978

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{12}$$

where X_{norm} is the normalized value of a variable, X is any value of the dataset, $X_{\max}$ is the maximum value of the whole dataset, and $X_{\min}$ is the minimum value of the whole dataset. The dataset was divided randomly into 70% for training, 15% for validation, and 15% for test.

5. Results and Discussion

ANN models with various backpropagation algorithms and 2–12 nodes in the single hidden layers were run in MATLAB using a deep learning toolbox. Each ANN model provided different results, and the performance of ANN models was assessed according to the regression value (R) and mean squared error (MSE) of the training and test data set. The ANN model DM-1 with training algorithm Levenberg-Marquardt backpropagation (TRAINLM) and 11 nodes in the hidden layer showed the best results among ANN models. Moreover, model DM-1 performance is better than ANN model NDM-1, trained with the same training algorithm, the number of nodes in the hidden layer (11 nodes), and dimensional and non-dimensional parameters, as shown in Table 5. Figure 3 – Figure 9 demonstrates the performance of ANN models. Besides, ANN model DM-1 provided better predicted local scour depth results than ANN model NDM-1, linear regression model, and nonlinear regression model, as shown in Figure 10 – Figure 12.

6. Sensitivity Analysis

Artificial neural networks could be used to assess the significance of dimensional and non-dimensional input variables in estimating the local scour depth. For this purpose,

Table 5. Performance of ANN model DM-1 and NDM-1

Models	R training	MSE training	R test	MSE test	Nodes	Function name
DM-1	0.9585	0.0025	0.9290	0.0032	11	TRAINLM
NDM-1	0.7023	0.009	0.7128	0.0088	11	TRAINLM

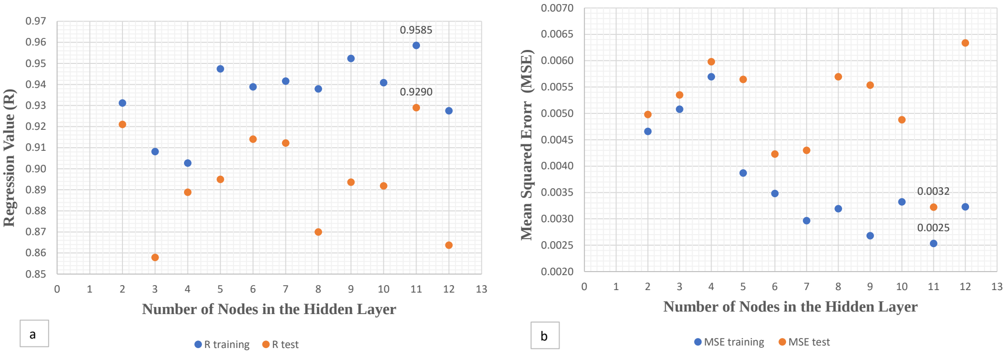

Fig. 3. Performance of ANN model DM-1: (a) R values; (b) MSE

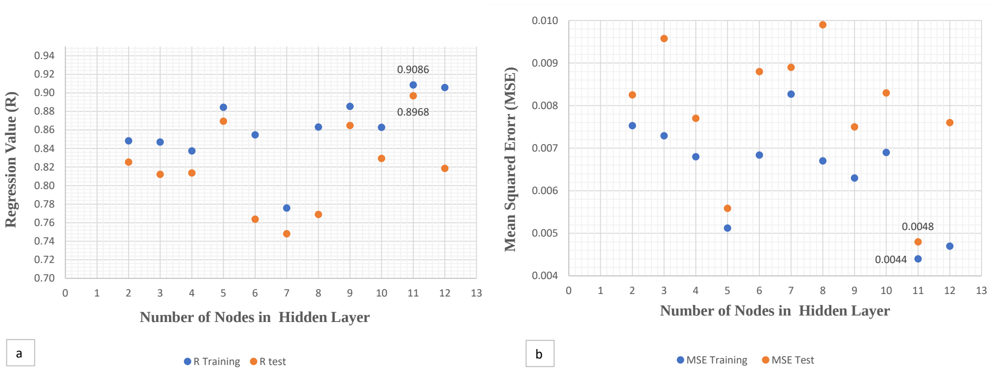

Fig. 4. Performance of ANN model DM-2: (a) R values; (b) MSE

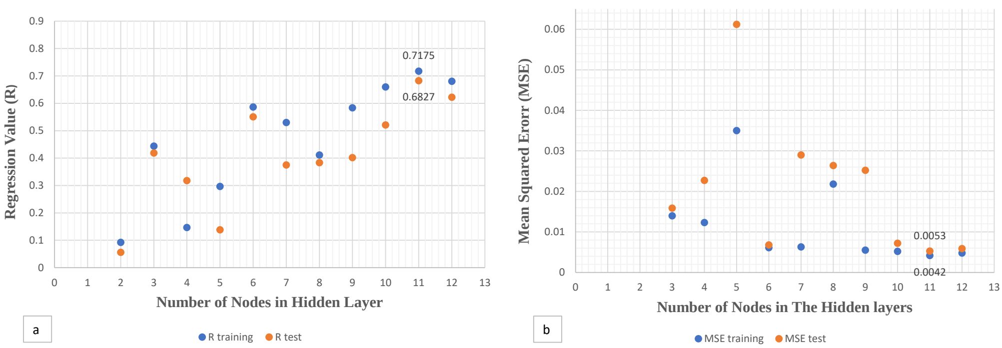

Fig. 5. Performance of ANN model DM-3: (a) R values; (b) MSE

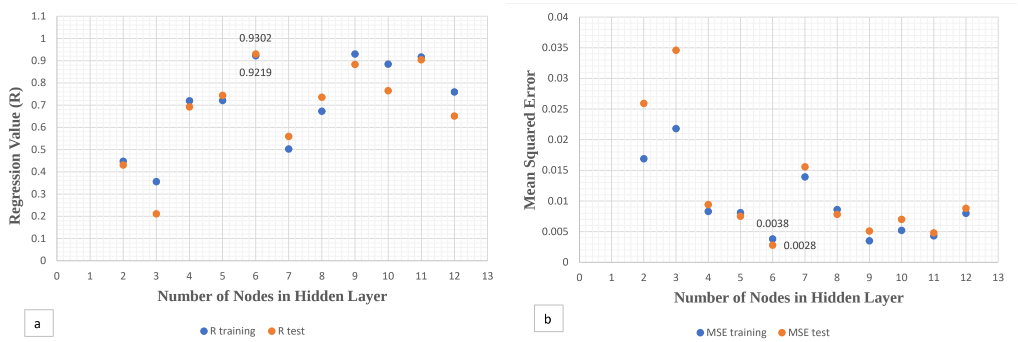

Fig. 6. Performance of ANN model DM-4: (a) R values; (b) MSE

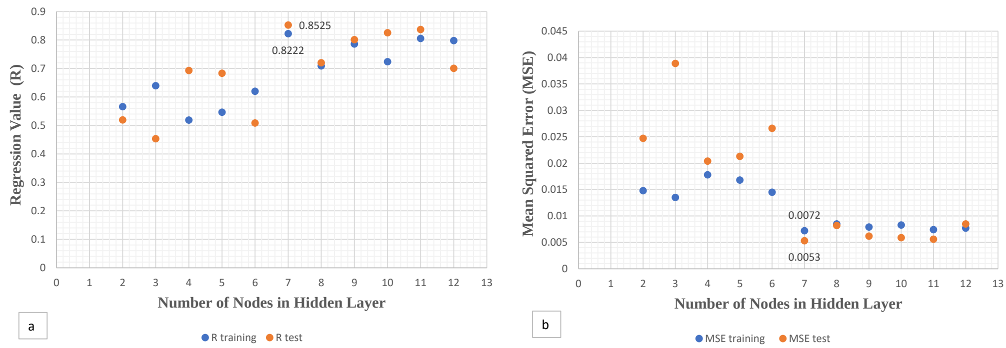

Fig. 7. Performance of ANN model DM-5: (a) R values; (b) MSE

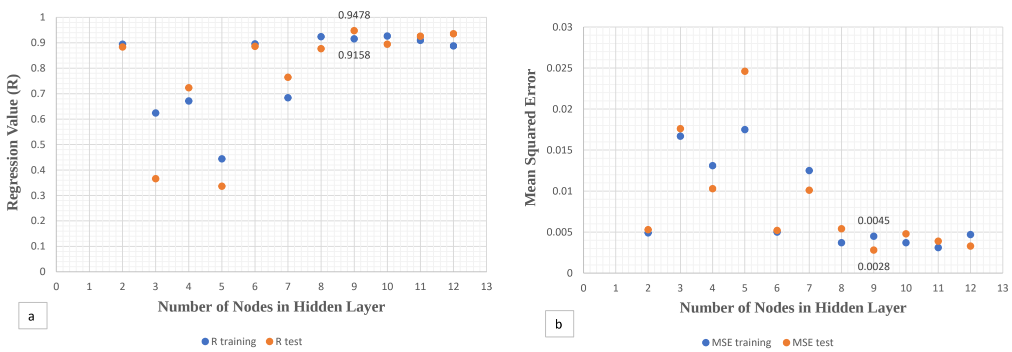

Fig. 8. Performance of ANN model DM-6: (a) R values; (b) MSE

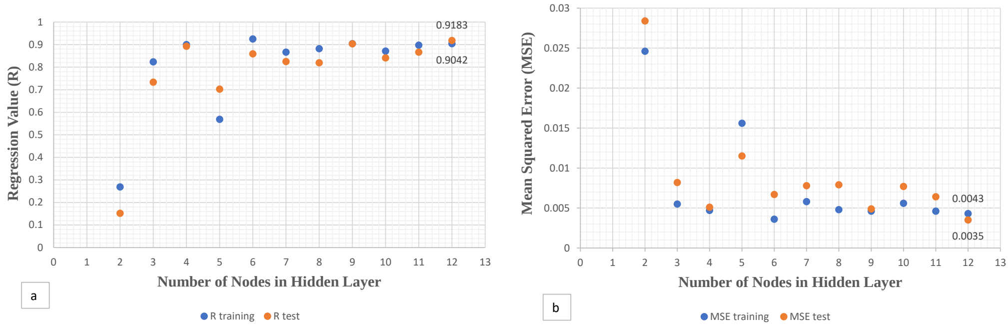

Fig. 9. Performance of ANN model DM-7: (a) R values; (b) MSE

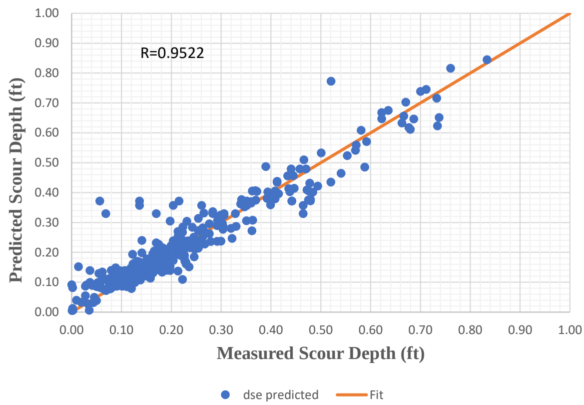

Fig. 10. Predicted equilibrium local scour depth obtained from ANN model DM-1

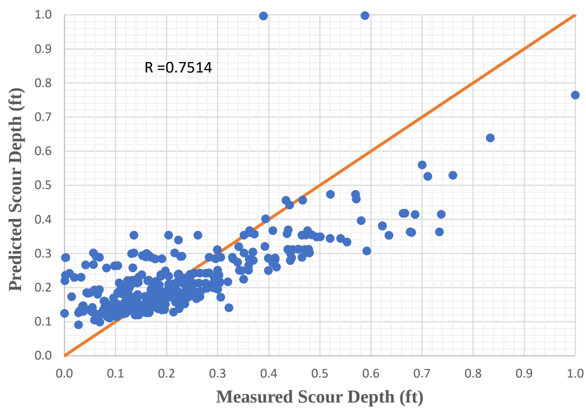

Fig. 11. Predicted equilibrium local scour depth obtained from linear regression model

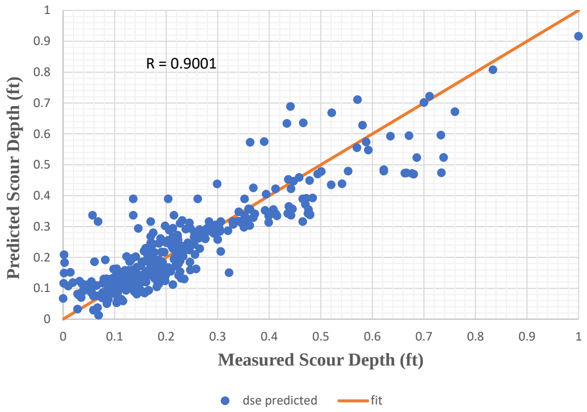

Fig. 12. Predicted equilibrium local scour depth obtained from nonlinear regression model

additional 8 ANN models were established, and each model contained one missed input parameter. Table 6 and Table 7 show the importance of each input parameter in the modeling. It is clear from the results that the pier width (b), as shown in Table 6, has the most impact on prediction accuracy more than other input parameters. In contrast, the removal of each non-dimensional parameter shows the same effect on the performance of the ANN NDM-1 model.

Table 6. Sensitivity analysis of dimensional parameters

Model	R training	MSE training	R test	MSE test	Nodes	Removed Parameter
DM	0.9585	0.0025	0.9290	0.0032	11	
DM1-a	0.9225	0.0028	0.9177	0.0044	11	Vc
DM1-b	0.939	0.0027	0.9078	0.005	11	V
DM1-c	0.5619	0.017	0.415	0.0212	11	b
DM1-d	0.9453	0.0026	0.9284	0.0034	11	y
DM1-e	0.9411	0.0025	0.9267	0.004	11	d

Table 7. Sensitivity analysis of non-dimensional parameters

Model	R training	MSE training	R test	MSE test	Nodes	Removed Parameter
NDM	0.7023	0.009	0.7128	0.0088	11	
NDM-1a	0.4994	0.015	0.4549	0.011	11	$\frac{V}{V_c}, \frac{y}{b},$
NDM-1b	0.5286	0.014	0.3519	0.02	11	$\frac{V}{V_c}, \frac{d}{b},$
NDM-1c	0.5578	0.136	0.4858	0.018	11	$\frac{V}{V_b}, \frac{b}{b},$

7. Conclusions

Artificial neural network models demonstrated a reliable result in predicting equilibrium local scour depth around bridge piers. ANN model DM-1 trained with Levenberg-Marquardt backpropagation (trainlm) algorithm and 11 neurons in the single hidden layer has provided a precise estimation of local scour depth compared to ANN models in this research. Also, the trial-and-error process was used in determining the appropriate number of nodes in the hidden layers. ANN model DM-1 demonstrated better performance than linear and nonlinear regression models. ANN models DM-1, DM-2, and DM-3 provided good performance with 11 nodes in the hidden layer. ANN model DM-4 provided considerable results with 6 and 11 nodes in the hidden layer, while ANN models DM-5 and DM-6 showed promising results with 6 and 9 nodes in the hidden layer, respectively. ANN model DM-7 presented good outcomes with 12 nodes in the hidden layer. It is clear from the results that the small number of nodes in the single hidden layer provides good performance. The sensitivity analysis showed that the availability of the pier width or pier diameter is significant to predicting the equilibrium local scour depth at bridge piers and is more critical than other parameters such as flow depth, flow velocity, and sediment particle size.

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