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Machine Learning Model for Estimation of Local Scour Depth around Cylindrical Bridge Piers

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ABSTRACT

Scour around bridge piers is a well-known threat to bridge stability worldwide. It can cause losses in lives and the economy, especially during floods. Therefore, an artificial intelligence approach called artificial neural network (ANN) was used to predict the scour depth around bridge piers. The ANN model was trained with laboratory data, including pier width, flow velocity, particle diameter, sediment critical velocity, flow depth, and scour depth. The data was divided into 70% for training, 15 for validation, and 15% for testing. Besides, the ANN model was trained using various training algrthins and a single hidden layer with 20 neurons in the hidden layer. The results showed that the ANN model with Bayesian regularization backpropagation training algorithm provides a better predicted scour depth with a correlation coefficient (R) equal to 0. 9692 and 0.926 for training and test stages, respectively. Besides, it showed a low mean squared error (MSE), which was 0.0034 for training and 0.0066 for the test. These results were slightly better than the ANN with Levenberg-Marquardt backpropagation with R training equals 0.9552 (MSE training = 0.0047), and R test equals 0.838 (MSE test = 0.007).On the other hand, the ANN model with a scaled conjugate gradient backpropagation training algorithm showed worse predictions (R training = 0.7407 and R test = 0.6409). Besides, the ANN model shows better outcomes than the linear regression model. Finally, the sensitivity analysis has shown that the pier width is the most crucial parameter for estimating scour depth using the ANN model.

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1. Introduction

Streams near hydraulic facilities are represented by random geometric complexity due to active vortical structures overwhelming a broad combination of hydraulic facilities like bridge piers. Moreover, scour is a natural

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event that can happen suddenly, especially during floods. These whirlpools interact with sediments on the bed, directing to local scour and creating scour holes, which could jeopardize stability and sabotage structural reliability. Besides, scouring is one of the primary reasons for bridging piers' failure (Khosronejad et al., 2012), resulting in the destruction of highways (Iqbal et al., 2020), their reconstruction using concrete, and ultimately losses to the economy (Iqbal et al., 2019; Jahanzaib et al., 2021). The mechanisms of scouring around bridge piers are complex, and the discharge growths with the scour hole development (Ghodsian and Vaghefi 2009). The direct mechanism driving local scour around bridge piers is down-flow at the upstream front of the pier and creating the whirlpool or vortex at the bottom of the hydraulic structures like piers (Heidarpour et al., 2010), as shown in Figure 1 (Alasta et al.,2022). The mechanics of scouring around bridge piers were explained broadly in the literature by Chiew (1984) and Shen et al. (1969).

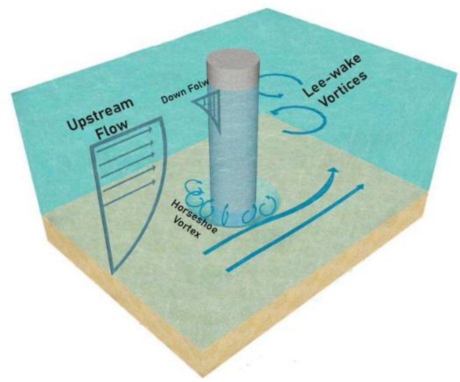

Figure 1 An illustration showing scouring around a bridge pier

Furthermore, scour at bridge locations is commonly categorized as a contraction and local scour. Contraction scour appears due to the existence of the hydraulic structure like a bridge pier, which raises the velocity over the entire cross-section of the stream, then creating erosion of the river's bed material. As flow accelerates near hydraulic structures like bridge piers, local scour occurs from the expanded velocities. In this study, we consider the scour depth an equilibrium scour, achieved when the river's bed material is dragged into the scour hole at the exact velocity it is carted out.

A report stated that in 1999, more than 1000 of about 600,000 bridges in the USA collapsed, and scour was responsible for 60% of these cases (Briaud et al.,1999). Wardhana and Hadipriono (2003) demonstrated that five hundred crumpled bridges in the USA from 1989 to 2000 were due to scouring. Thus, examining the lowering of the river's bottom is critical for designing bridges. D. Imhof (2004) revealed that data from various sources shows that the natural jeopardies are the most heightened reason for the bridge collapse, as shown in Figure 2. Also, they stated that the natural threat is the critical factor that leads to failure, and the most common cause is flooding or scouring. In addition, local scour could be critical in developing offshore wind and hydrokinetic turbine farms (Mutlu, 2007).

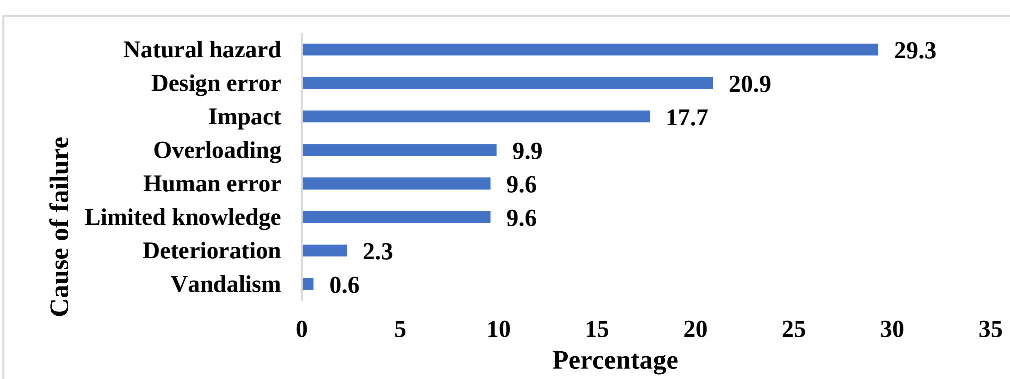

Figure 2 Failure of bridges due to various reasons (Imhof, 2004)

Various studies were conducted using numerical modeling, a mathematical model, to solve different problems (Ashiq and Khan, 2020; Ebrahimi and Khorram, 2021; Tunc et al., 2022). Hence, many studies were conducted to study scour around bridge piers. For instance, Khosronejad et al. (2012) used laboratory and mathematical models to investigate clear water scour types around various bridge piers. Omara and Tawfik (2018) used a numerical model to study and predict scour around bridge piers of multiple shapes. Ghaderi and Abbasi (2019) employed a CFD model using FLOW-3D software to examine the usefulness of airfoil-shaped piers on local scour. Wang et al. (2019) used experimental models to study local scour around cylindrical bridge piers and methods to reduce the scour, like collars around piers. Finally, Rasaei et al. (2020) employed experimental examination to examine the maximum scour depth and volume of holes around bridge piers. Alasta et al. (2022) used a FLOW -3D numerical model to simulate scour around bridge piers.

However, the recent development in data-driven models like machine learning models has attracted the attention of researchers to apply these advanced tools for various problems related to different engineering areas (Worden et al., 2007; Akhani et al., 2019; Sparks et al., 2020; Lange and Sippel, 2020; Zounemat et al., 2021; Gandomi et al.2021; Kashani et al., 2021; Akhani and Pezeshk, 2022; Azari et al., 2022; Ali et al., 2022). Machine learning models were adopted broadly for studying the scour around hydraulic structures because traditional methods like numerical or experimental models require a lot of data, and these models are costly. Therefore, multiple techniques applied machine learning models to study the scour around various hydraulic structures. Pal et al. (2011) used a support vector machine model to examine the machine learning model's performance to estimate the scour depth. They compared the outcomes with empirical equations, backpropagation, and generalized regression models and trained the models with field data. They showed that the support vector machine provides better results, especially in dimensionless data. Etemad-Shahidi et al. (2011) used a machine learning model to study and predict the scour near submarine pipelines for both scour conditions: clear-water and live-bed scour. They stated that the machine learning model could be a reliable tool for estimating scour depth. Pourzangbar et al. (2017) adopted two machine learning models, the support vector regression model and a tree algorithm (M5), to estimate maximum scour depth at breakwaters. They showed that these two models could provide accurate predictions and be used by coastal engineers to fix problems related to scouring, like a prediction of the depth of scour hole. Hu et al. (2021) used various machine learning approaches, such as the genetic algorithm, radial basis function, and support vector machine, to study and predict the scour depth around the pipelines. They demonstrated that the genetic algorithm model was the best compared to other machine learning models in this study. It showed good performance with a low error between measured and predicted scour depth. Yousefpour et al. (2021) used a machine learning model to predict the scour depth around bridge piers and trained the model with real-time scour depth data. They showed that the machine learning model could be used as a helpful tool for estimating scour depth by integrating the model with a monitoring system for observing the scour depth.

Hence, this study aims to adopt a machine learning model called the artificial neural network to predict the local scour depth around bridge piers and then examine the predicted scour depth with correlation coefficient and mean square error values to verify the accuracy of the ANN model. Besides, the outcomes of the ANN model were compared with a multiple linear regression model. Finally, the ANN model was used to examine the importance and effect of input parameters on the prediction performance by conducting a sensitivity analysis for the input parameters. It is essential to notice that this study is based on the article of Shakir Ali Ali and Günal (2021). The novelty of the current study is that the training data was used as raw data instated of normalizing the training data employed by Shakir Ali Ali and Günal (2021).

2. Methodology

2.1. Parameters Influencing Scour

Melville and Coleman (2000) indicated that the depth of scour around the bridge piers is affected by the river's flow, features of the particles like sediments, and the shape properties of the pier. Moreover, Choi et al. (2017) demonstrated that the depth of local scour around bridge piers (*dse*) is a function of the parameter like flow depth (y), flow velocity (V), sediment critical velocity (*Vc*), the diameter of the particle (d), and pier width or diameter (b), it can be written as follows:

$$\boldsymbol{dse} = \boldsymbol{f}\,(\boldsymbol{V}, \boldsymbol{Vc}, \boldsymbol{y}, \boldsymbol{d}, \boldsymbol{b}) \qquad (1)$$

Where dse is the scour depth, V is the flow velocity, Vc is sediment critical velocity, y is flow depth, d is particle diameter, and b is pier diameter. A dataset of local scour depth around a cylindrical bridge pier, which contains (V,Vc,y,d,b) , was used to train the ANN model. The dataset contains many laboratory data from various sources collected. These data were obtained from the PSDb-2014 report, consisting of prior experiments gathered by Sheppard et al. (2011), Benedict and Caldwell (2014). Sheppard et al. (2011) identified 441 laboratory measures that matched equilibrium scour and used them in their study of scouring. Besides, these data were used to enhance the initial Hydraulic Engineering Circular No. 18 (HEC-18) pier-scour equation (Richardson et al. 1991). The details of the training data are available in a published report and an excel file by Benedict and Caldwell (2014). Besides, the first 400 laboratory data were chosen out of 572 scour laboratory measurement data.

Table 1 - Training data.

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Pier width (ft)	400	0.094	2.510	0.269	0.278
Flow velocity (ft/s)	400	0.540	5.280	1.717	0.915
Sediment critical velocity (ft/s^2)	400	0.730	4.180	1.490	0.783
Flow depth (ft)	400	0.066	3.281	0.897	0.703
Particle diameter (mm)	400	0.240	7.800	1.302	1.554
Measured scour depth (ft)	400	0.049	1.497	0.367	0.232

2.2. Artificial Neural Network

Machine learning is a sort of artificial intelligence that lets computers learn and provide accurate outcomes. Besides, machine learning models use recorded data or other dataset types for training. Machine learning has advanced considerably within the last two decades from laboratory interest to practical approaches in across-the-board. Also, machine learning has appeared as the selection procedure for creating useful software for various purposes, robot control, and other applications (Jordan and Mitchell, 2015). Machine learning contains different approaches, and one of these approaches is an artificial neural network (ANN). ANN is a machine learning model boosted by the complex functionality of the biological system of the human intelligence system, where billions of connected neurons procedure information in parallel. Moreover, the ANN is trying to imitate the natural human system mathematically.

As shown in Figure 3, the neuron is the fundamental part of the ANN model, and it is a logical-mathematical model which tries to imitate the human biological neuron system. The neuron contains a bias computed with the weighted inputs to form the input, and it can be represented as follows (Ly et al., 2017):

$$n = \sum_{j=1}^{R} W_j P_j + b \qquad (2)$$

The part in the input vector P is weighted by the part of the weight matrix W. Then, the net input n passes via an operational process, which creates the outcome's neuron, as shown in Figure 3.

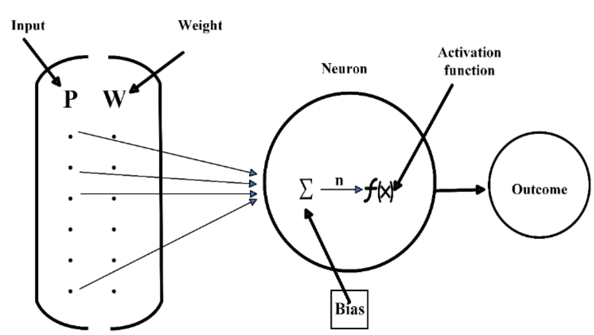

Figure 3 Artificial neuron (Ly et al.2017).

Commonly, the ANN model contains three layers with neurons. The first layer is the input layer, which takes the data or information for the problem. The second layer is the hidden layer, which can be one hidden layer or more. Finally, the last layer, called the output layer, provides the predicted value by the model, as shown in Figure 4. Besides, the connection between these layers is called weights. The weight values can initialize randomly, and it is updated during the training process based on the initial learning rate, which governs how much the values of the weights for the ANN model are to be adjusted based on the error between predicted and actual values.

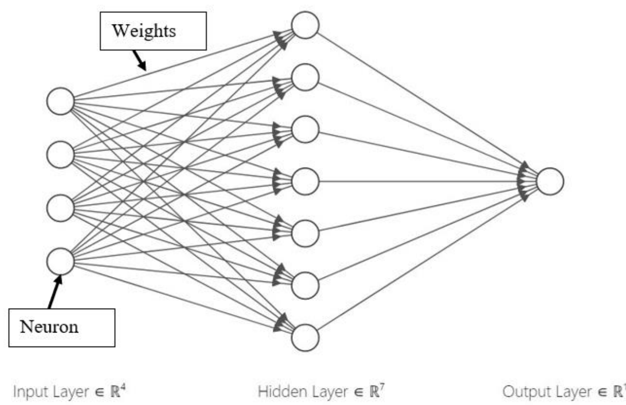

Figure 4 Typical artificial neural network

Besides, the ANN model contains activation functions. The objective of the activation function is to give the model the ability to solve the problem's nonlinearity and control the weight of the neuron (Wang 2003). This study used the tangent activation function between the input and hidden layer (Eq. 3). The tangent activation function was used because it demonstrates a more suitable training implementation during back-propagation for ANN models with various layers, and it has potent gradients (Nwankpa et al.,2018), The linear activation function was adopted between the hidden and the output layer (Eq. 4).

$$f(x) = \frac{2}{1+e^{(-2x)}} - 1 \tag{3}$$

$$f(x) = x \tag{4}$$

However, the activation function can be selected based on the type of the problem, and the most suitable one can be found by trial and error. Another crucial feature of a neural network model is called the training algorithm. A learning algorithm is a collection of teachings that helps a computer simulate the natural human learning ability to obtain better performance at describing knowledge. The mathematics that keeps learning can be revised over time as data is introduced to the computer. Besides, The ANN model learns from experience or data, comparable to the human capability of understanding by experience. Therefore, the training algorithm is adopted for training the model by inserting the data into the model, and these data are called training data. The expected outcomes of the problem are known. Thus, the training algorithm tries to reduce the differences between outputs of the ANN model and the measured or actual results by changing the weights between the neurons (Wang 2003) and the difference between actual and predicted called error, which is the mean square error in this study. A separate data set dubbed a validation set can be introduced to the trained ANN model. The validation data set aims to fairly assess the final tuned model's agility. Besides, another dataset is introduced to the ANN model after finishing the training stage, and these data are called test data. The test data are used to examine the accuracy of the ANN model, and these data are not used in the training stage. So, the ANN model treats these data as new data.

This study adopted the ANN approach to predict the scour depth bridge piers using MATLAB. The ANN models were built with an input layer with 5 neurons: pier width, flow velocity, flow depth, sediment critical velocity, and particle diameter. Also, a single hidden layer was used with 20 neurons. The number of neurons in the hidden layer was chosen based on the trial-and-error process. Finally, the output layer contains one neuron, the predicted scour depth.

As shown in Table 2, three ANN models were conducted using different training algorithms. The first one, called ANN-1, was trained with Bayesian regularization backpropagation, known as the TRAINBR function in

MATLAB. It is a linear hybrid of Bayesian techniques and ANN to automatically choose the values of the appropriate weights while training the ANN model (Okut, 2016). A more detailed discussion can be found in Gouravaraju et al. (2021). The second was called ANN-2 and trained with the Levenberg-Marquardt backpropagation, known as the TRAINLM function in MATLAB. The Levenberg-Marquardt algorithm is an adjusted version of Gauss-Newton approach, and more details are explained in Hagan and Menhaj (1994) and Reynaldi et al. (2012). Finally, the third model was called ANN-3 and trained with a scaled conjugate gradient backpropagation algorithm known as TRAINSCG function. The scaled conjugate gradient algorithm is founded on conjugate trends. Besides, it does not conduct a straight examination per iteration, which causes the procedure to become costly. Hence, SCG was created to bypass wasting time (Babani et al.2016).

The ANN model was trained with 400 laboratories scour depth data. The dataset was divided into 70% for the training stage, 15 % for the validation stage, and 15% for the test stage.

Table 2 ANN models.

Model	Training Algorithm	Neurons in the Hidden Layer	Epochs
ANN-1	TRAINBR	20	1000
ANN-2	TRAINLM	20	1000
ANN-3	TRAINSCG	20	1000

2.3. Multiple Linear Regression

Multiple linear regression (MLR) is a statistical approach that utilizes two or more additional independent parameters to forecast the result of a dependent parameter. Also, it can be used to choose the divergence of the approach and the proximate importance of each independent parameter. The multiple linear regression model was conducted using excel, and the coefficient values of the independent variables are as follows

$$y = 0.012 + 0.54\,B_1 + 0.0059B_2 + 0.13\,B_3 + 0.065\,B_4 - 0.052\,B_5 \qquad (5)$$

where y is the estimated value, B_1 is the pier diameter, B_2 is the flow velocity, B_3 is the sediment velocity, B_4 is the flow depth, and B_5 is the particle diameter.

2.4. Assessment of Model's Accuracy

The outcome of the ANN model, in which the predicted scour depth was assessed based on two criteria. The first one is the correlation coefficient; the correlation coefficient (r) is a statistical measurement of the strength of the connection between two variables like actual value and predicted value from the ANN model.

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

Where r is the correlation coefficient, n is the number in the given dataset, x is the first variable in the sample, and y is the second variable. For this study, x is the measured scour depth, y is the predicted scour depth, and the correlation coefficient examines the relationship between these two parameters. The second is the mean square error (MSE), which measures the average squared difference between the predicted and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x-y)^2 \qquad (7)$$

MSE is the mean squared error, x is the measure values, y is the predicted values, and n is the total amount of data.

3. Results and Discussion

The ANN model has shown promising results for estimating the scour depth around bridge piers. The ANN-1 model showed a high correlation between measured and predicted scour depth, which equals 0.9637, and the MSE value of 0.0038. Meanwhile, the ANN-2 model showed a similar performance with r correlation coefficient = 0.9416 and MSE = 0.006, but the ANN-3 model showed lower performance than the two ANN models with correlation coefficient = 0.7459 and MSE = 0.026. Furthermore, the R training was higher than the R test for three ANN models because the training data is introduced to the ANN model in the training stage. Therefore, it tries to reach results close to the training measurements as possible. Then, in the test stage, the ANN model makes predictions with new data set and compares the outcomes to examine the estimation accuracy based on the loss function like MSE. Figures 5 – 7 show the measured and predicted values of the scour depth using ANN models based on the final output of ANN models after finishing the training, validation, and testing process. While Table 3 shows the performance of the ANN molds for the training and test stages.

Table 1 Performance of ANN models.

Model	R training	MSE training	R test	MSE test
ANN-1	0.9692	0.0034	0.926	0.0066
ANN-2	0.9552	0.0047	0.838	0.007
ANN-3	0.7407	0.023	0.6409	0.0291

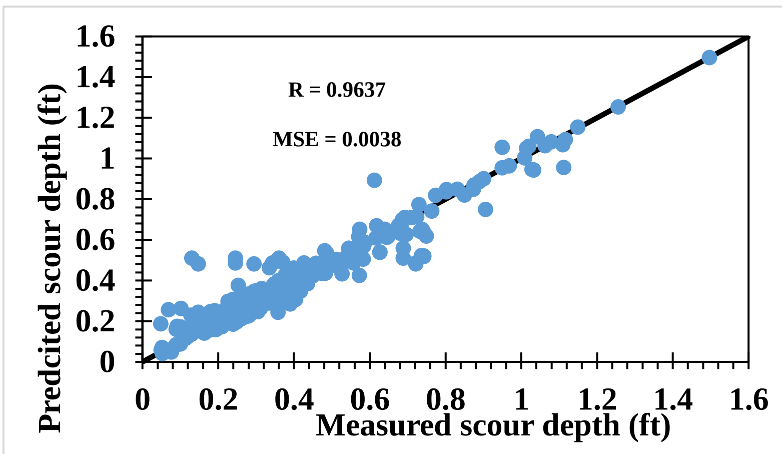

Figure 5ANN-1 model

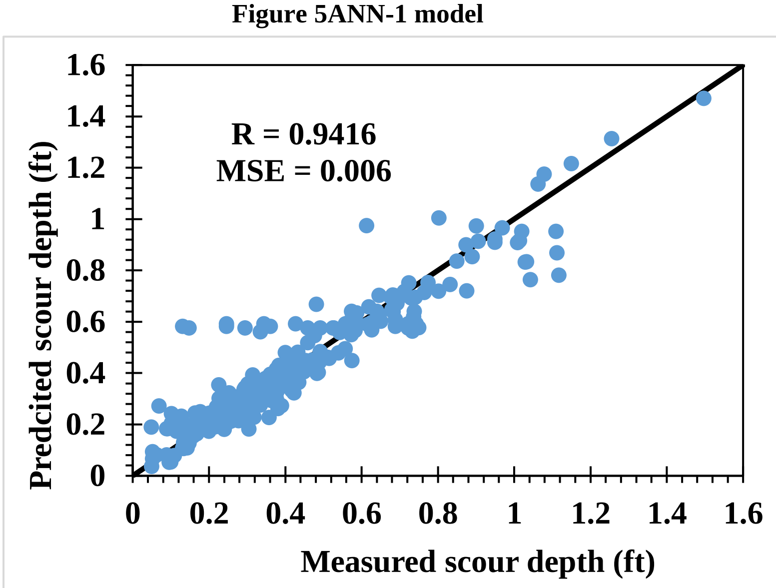

Figure 6 ANN-2 model.

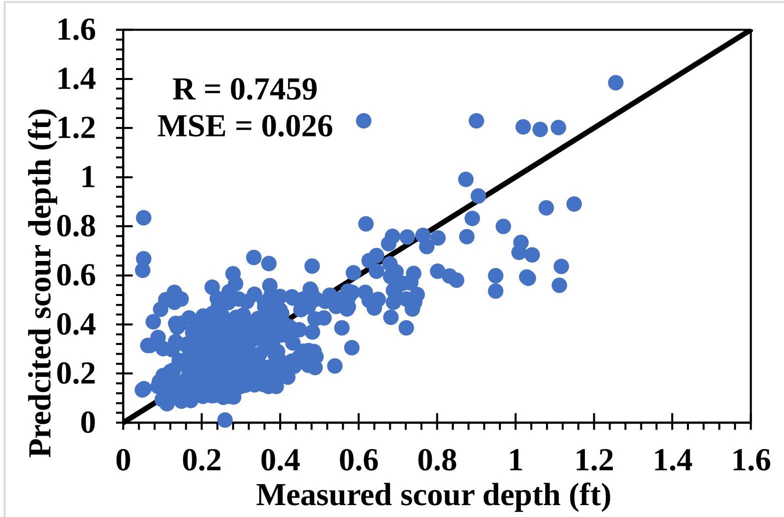

Figure 7 ANN-3 model

Moreover, the multiple linear regression model showed lower performance than the ANN-1 and ANN-2 models but similar to the performance of the ANN-2 model with a correlation coefficient = 0.7514 and MSE = 0.023. Besides, in the linear regression, all input variables were employed and considered in calculating the predicted scour as the ANN, which was trained with all parameters. Figure 8 shows the expected outcomes from the linear regression model.

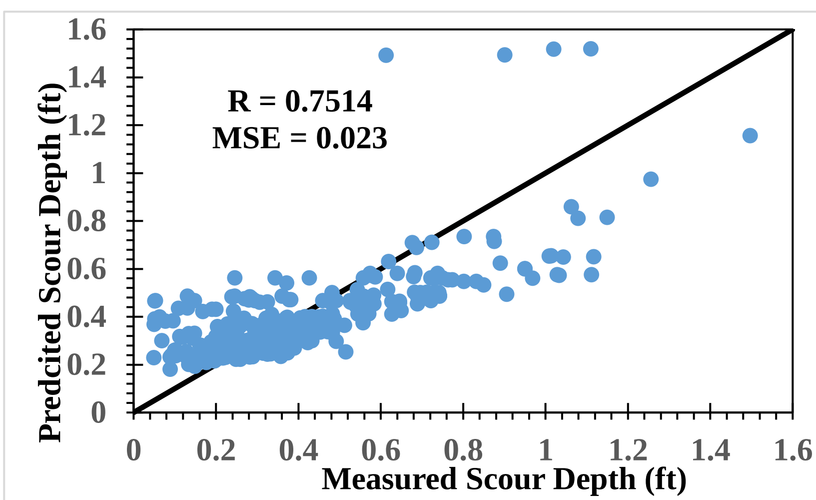

Figure 8 Linear regression model.

Besides, the ANN model was used to conduct a sensitivity analysis to examine the importance of five input parameters: pier diameter, flow velocity, flow depth, critical sediment velocity, and particle diameter. For this purpose, another five ANN model was run using the same structure of the ANN-1 model mentioned in the methodology section. The ANN-1 model was used as a reference model to examine the input parameters' impact. As shown in Figure 9 to Figure 13, the pier diameter has the most critical effect on the ANN model's accuracy, while removing other parameters has decreased the efficiency of the ANN-1 model slightly. Table 4 summarizes the performance of selectivity analysis ANN models during the training and test stage. Besides, the coloration analysis shows that the scour depth has strong with scouring depth, as shown in Table 5. It supports the outcome of sensitivity analysis by ANN models, which showed that removing a pier with decrees prediction efficiency.

Table 2 Sensitivity analysis.

Model	Removed parameters	R training	MSE test	R test	MSE test
ANN-1	None	0.9692	0.0034	0.926	0.0066
ANN-1a	Flow depth	0.9553	0.0047	0.8919	0.01
ANN-1b	Flow velocity	0.9429	0.0055	0.9311	0.0108
ANN-1c	Sediment critical velocity	0.969	0.0036	0.9012	0.0093
ANN-1d	Particle diameter	0.9409	0.006	0.9713	0.0058
ANN-1e	**Pier width**	**0.6178**	**0.031**	**0.4169**	**0.055**

Table 3 Correlation analysis for training parameters.

Variables	Pier width	Approach Flow Velocity	Sediment critical velocity	Approach flow depth	Particle diameter	Measured Scour Depth
Pier width	1	-0.129	0.035	0.081	0.046	0.669
Approach Flow Velocity	-0.129	1	0.588	0.083	0.594	0.019
Sediment critical velocity	0.035	0.588	1	0.473	0.951	0.260
Approach flow depth (ft)	0.081	0.083	0.473	1	0.306	0.366
Particle diameter	0.046	0.594	0.951	0.306	1	0.194
Measured Scour Depth (ft)	0.669	0.019	0.260	0.366	0.194	1

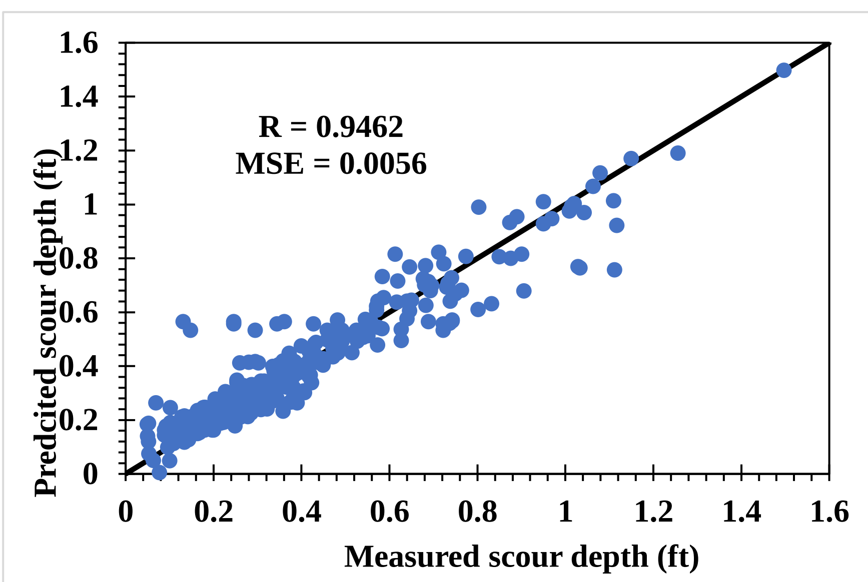

Figure 2 ANN-1a model trained without flow depth.

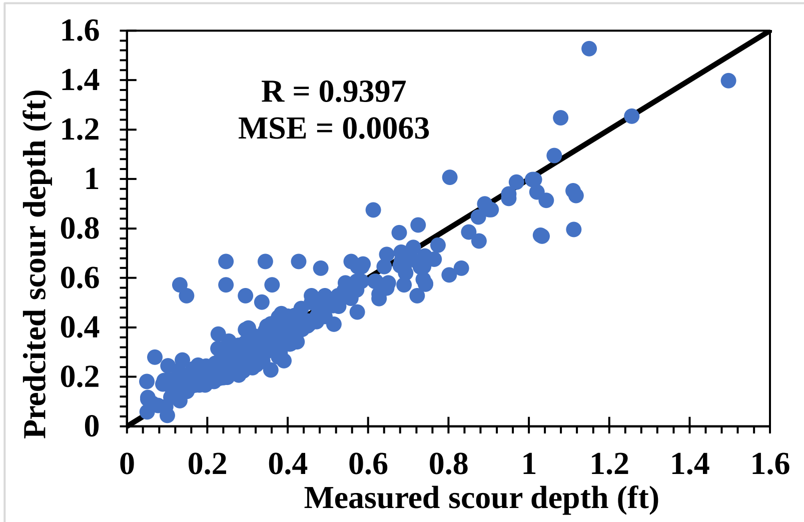

Figure 3 ANN-1b model without flow velocity.

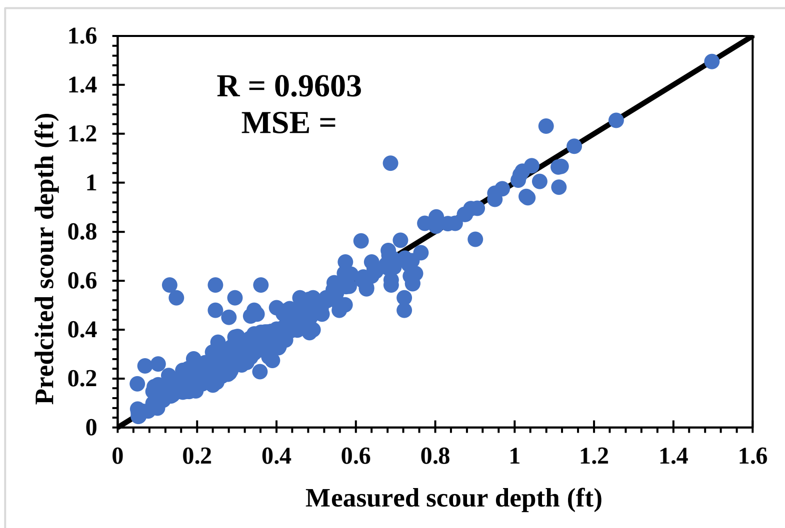

Figure 11 ANN-1c trained without sediment critical velocity.

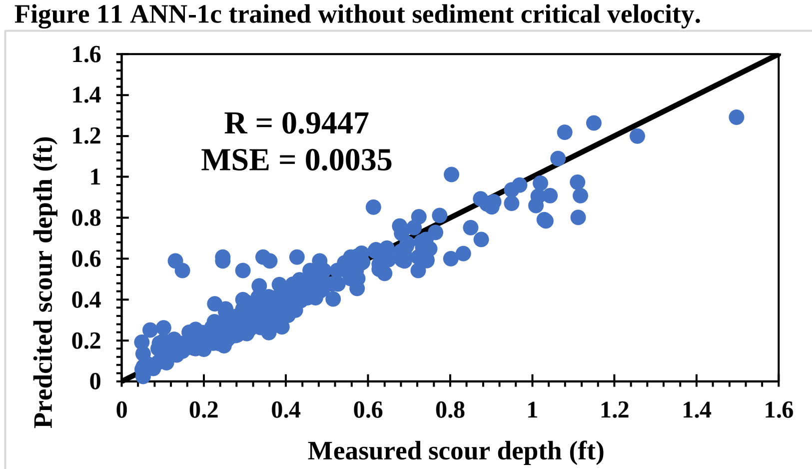

Figure 12 ANN-1d trained without particle diameter.

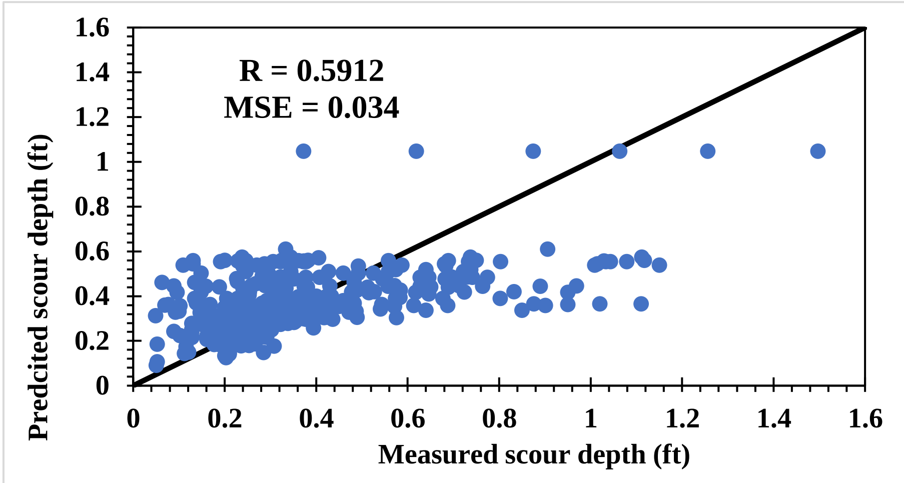

Figure 13 ANN-1e trained without pier width.

4. Conclusion

It is crucial to forecast the scour depth near bridge piers for hydraulic engineers concerned with the financial strategy of bridge pier bases. Hence, this study adopted an artificial neural network (ANN) model to predict scour around bridge piers. The ANN model trained laboratories scour measurement data collected from various studies. The dataset included five input data parameters: pier diameter, flow velocity, flow depth, sediment critical velocity, and particle diameter. Also, the output was the scour depth around bridge piers. The ANN model was trained with three backpropagation training algorithms: Bayesian regularization, Levenberg-Marquardtand, and scaled conjugate gradient algorithms, with a single hidden layer containing 20 neurons. In addition, another regression model called multiple linear regression was conducted to compare the outcome of the regression model with ANN. The main results of the study are as follows:

- ANN model has shown promising results for scour depth estimation around bridge piers with a high correlation coefficient (R = 0.9637) and low mean squared error (MSE = 0.0038).
- The multiple linear regression model showed worse results than the ANN-1 and ANN-2 models but better than the ANN-3 model trained with a scaled conjugate gradient algorithm. It is obvious that the ANN model can handle problems like prediction of scour better than multiple linear regsression.
- Pier diameter is the most critical input for training the ANN model and obtaining accurate scour depth prediction. However, other parameters like flow velocity can substantially impact the modeling of the scour depth around bridge piers. Still, the influence might appear clearly when the scour is simulated using numerical modeling, and the outcome can show the effect of velocity on removing of bed’s material.
- The correlation analysis showed that the pier width considerably correlates with the measured scour depth.
- The results showed that training ANN models with raw data could accurately predict the scour depth as normalized data. The normalized data was used in a study by Shakir Ali Ali and Günal (2021). The outcomes of the current study are similar to their results and performance of the ANN model's accuracy.

References

Akhani, M., & Pezeshk, S. (2022). Using metaheuristic algorithms to optimize a mixed model-based ground-motion prediction model and associated variance components. Journal of Seismology, 1-16.

Akhani, M., Kashani, A. R., Mousavi, M., & Gandomi, A. H. (2019). A hybrid computational intelligence approach to predict spectral acceleration. Measurement, 138, 578-589.

Alasta, M. S., Ali, A. S. A., Ebrahimi, S., Ashiq, M. M., Dheyab, A. S., AlMasri, A., Alqatanani, A., & Khorram, M. Modeling of Local Scour Depth Around Bridge Pier Using FLOW 3D.

Ali, A. S. A., Ebrahimi, S., Ashiq, M. M., Alasta, M. S., & Azari, B. (2022). CNN-Bi LSTM neural network for simulating groundwater level. Environ Eng, 8, 1-7.

Ashiq, M. M., & Khan, N. M. (2020). Impact of large diameter recharge wells for reducing groundwater depletion rates in an urban area of Lahore, Pakistan. Environmental Earth Sciences, 79(17), 1-14.

Azari, B., Hassan, K., Pierce, J., & Ebrahimi, S. (2022). Evaluation of machine learning methods application in temperature prediction. Environ Eng, 8, 1-12.

Babani, L., Jadhav, S., & Chaudhari, B. (2016, September). Scaled conjugate gradient based adaptive ANN control for SVM-DTC induction motor drive. In IFIP International Conference on Artificial Intelligence Applications and Innovations (pp. 384-395). Springer, Cham.

Benedict S., Caldwell A. (2014) A pier-scour database—2,427 field and laboratory measurements of pier scour, doi:10.3133/ds845

Briaud, J. L., Ting, F. C., Chen, H. C., Gudavalli, R., Perugu, S., & Wei, G. (1999). SRICOS: Prediction of scour rate in cohesive soils at bridge piers. Journal of Geotechnical and Geoenvironmental Engineering, 125(4), 237-246.

Chiew, Y. M. (1984). Local scour at bridge piers. Publication of: Auckland University, New Zealand.

Ebrahimi, S., & Khorram, M. (2021). Variability effect of hydrological regime on river quality pattern and its uncertainties: case study of Zarjoob River in Iran. Journal of Hydroinformatics, 23(5), 1146-1164.

Etemad-Shahidi, A., Yasa, R., & Kazeminezhad, M. H. (2011). Prediction of wave-induced scour depth under submarine pipelines using machine learning approach. Applied Ocean Research, 33(1), 54-59.

Gandomi, M., Kashani, A. R., Farhadi, A., Akhani, M., & Gandomi, A. H. (2021). Spectral acceleration prediction using genetic programming based approaches. Applied Soft Computing, 106, 107326

Ghaderi, A., & Abbasi, S. (2019). CFD simulation of local scouring around airfoil-shaped bridge piers with and without collar. Sādhanā, 44(10), 1-12.

Ghodsian, M., & Vaghefi, M. (2009). Experimental study on scour and flow field in a scour hole around a T-shape spur dike in a 90 bend. International Journal of Sediment Research, 24(2), 145-158.

Gouravaraju, S., Narayan, J., Sauer, R. A., & Gautam, S. S. (2021). A Bayesian regularization-backpropagation neural network model for peeling computations. The Journal of Adhesion, 1-24.

Hagan, M. T., & Menhaj, M. B. (1994). Training feedforward networks with the Marquardt algorithm. IEEE transactions on Neural Networks, 5(6), 989-993.

Heidarpour, M., Afzalimehr, H., & Izadinia, E. (2010). Reduction of local scour around bridge pier groups using collars. International Journal of Sediment Research, 25(4), 411-422.

Hu, K., Bai, X., Zhang, Z., & Vaz, M. A. (2021). Prediction of submarine pipeline equilibrium scour depth based on machine learning applications considering the flow incident angle. Applied Ocean Research, 112, 102717.

Imhof, D. (2004). Risk assessment of existing bridge structures (Doctoral dissertation, university of cambridge).

Iqbal, A., Rehman, H. S., Munir, M., Ashiq, M., Omar, A., Haider, Z., Akhtar, M., Javed, M., Rehman, O. U., Adnan, M., & Jahanzaib, M. (2019). Time and Cost Overrun in Construction Projects of Pakistan. Pakistan Journal of Engineering and Technology, 2(2), 22-29.

Iqbal, A., Yousuf, M., Ullah, K., Adnan, M., Ahmad, M., Ashiq, M., Shehzad, U., Munir, M., Rehman, S., Akhtar, M., Rizwan, M., Javed, & Akram, U. (2020). Utilization of Waste Plastic Polymers to Improve the Performance of Modified Hot Mix Asphalt. Pakistan Journal of Engineering and Technology, 3(2), 162-171.

Jahanzaib, M., Iqbal, A., Ashfaq, H., Munir, M., Akhtar, M., Ashiq, M., & Ibrahim, B. (2021). Partial Replacement of Coarse Aggregate by Using Pumice Aggregate in Lightweight Concrete-Experimental Investigation. Pakistan Journal of Engineering and Technology, 4(3), 27-30.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255-260.

Kashani, A. R., Akhani, M., Camp, C. V., & Gandomi, A. H. (2021). A neural network to predict spectral acceleration. In Basics of Computational Geophysics (pp. 335-349). Elsevier.

Khosronejad, A., Kang, S., & Sotiropoulos, F. (2012). Experimental and computational investigation of local scour around bridge piers. Advances in Water Resources, 37, 73-85.

Lange, H., & Sippel, S. (2020). Machine learning applications in hydrology. In Forest-water interactions (pp. 233-257). Springer, Cham.

Lv, C., Xing, Y., Zhang, J., Na, X., Li, Y., Liu, T., ... & Wang, F. Y. (2017). Levenberg–Marquardt backpropagation training of multilayer neural networks for state estimation of a safety-critical cyber-physical system. IEEE Transactions on Industrial Informatics, 14(8), 3436-3446.

Melville B. W., Coleman S. E. (2000) Bridge scour, Water Resources Publications, LLC, HighlandsRanch, Colo.

Mutlu Sumer, B. (2007). Mathematical modelling of scour: A review. Journal of Hydraulic Research, 45(6), 723-735.

Nwankpa, C., Ijomah, W., Gachagan, A., & Marshall, S. (2018). Activation functions: Comparison of trends in practice and research for deep learning. arXiv preprint arXiv:1811.03378.

Okut, H. (2016). Bayesian regularized neural networks for small n big p data. Artificial neural networks-models and applications, 21-23.

Omara, H., & Tawfik, A. (2018, May). Numerical study of local scour around bridge piers. In IOP conference series: earth and environmental science (Vol. 151, No. 1, p. 012013). IOP Publishing.

Pal, M., Singh, N. K., & Tiwari, N. K. (2011). Support vector regression-based modeling of pier scour using field data. Engineering Applications of Artificial Intelligence, 24(5), 911-916.

Pourzangbar, A., Brocchini, M., Saber, A., Mahjoobi, J., Mirzaaghasi, M., & Barzegar, M. (2017). Prediction of scour depth at breakwaters due to non-breaking waves using machine learning approaches. Applied Ocean Research, 63, 120-128.

Rasaei, M., Nazari, S., & Eslamian, S. (2020). Experimental investigation of local scouring around the bridge piers located at a 90 convergent river bend. Sādhanā, 45(1), 1-15.

Reynaldi, A., Lukas, S., & Margaretha, H. (2012, November). Backpropagation and Levenberg-Marquardt algorithm for training finite element neural network. In 2012 Sixth UKSim/AMSS European Symposium on Computer Modeling and Simulation (pp. 89-94). IEEE.

Shakir Ali Ali, A., & Günal, M. (2021). Artificial Neural network for estimation of local scour depth around bridge piers. Archives of Hydro-Engineering and Environmental Mechanics, 68(2).

Shen, H. W., Schneider, V. R., & Karaki, S. (1969). Local scour around bridge piers. Journal of the Hydraulics Division, 95(6), 1919-1940.

Sparks, T. D., Kauwe, S. K., Parry, M. E., Tehrani, A. M., & Brgoch, J. (2020). Machine learning for structural materials. Annual Review of Materials Research, 50, 27-48.

Tunc, G., Othman, M. M., & Mertol, H. C. (2022). Finite Element Analysis of Frames with Reinforced Concrete Encased Steel Composite Columns. Buildings, 12(3), 375.

Wang, S. C. (2003). Artificial neural network. In Interdisciplinary computing in java programming (pp. 81-100). Springer, Boston, MA.

Wang, S., Wei, K., Shen, Z., & Xiang, Q. (2019). Experimental investigation of local scour protection for cylindrical bridge piers using anti-scour collars. Water, 11(7), 1515.

Wardhana, K., & Hadipriono, F. C. (2003). Analysis of recent bridge failures in the United States. Journal of performance of constructed facilities, 17(3), 144-150.

Worden, K., & Manson, G. (2007). The application of machine learning to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 365(1851), 515-537.

Yousefpour, N., Downie, S., Walker, S., Perkins, N., & Dikanski, H. (2021). Machine learning solutions for bridge scour forecast based on monitoring data. Transportation Research Record, 2675(10), 745-763.

Zounemat-Kermani, M., Batelaan, O., Fadaee, M., & Hinkelmann, R. (2021). Ensemble machine learning paradigms in hydrology: A review. Journal of Hydrology, 598, 126266.