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Modeling of Scour Around Bridge Pier Using Artificial Neural Network

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***Abstract*—Numerical models are most useful for the prediction of scour around bridge pier due to its complexity. In this paper, soft computing technique such as Artificial Neural Network (ANN) model was developed for evaluating the scour around bridge pier. Feed forward back propagation learning algorithm was used as a learning technique. Data set used for the development of ANN model was from a technical report on "Field observations and evaluations of stream bed scour at bridges" published by FHWA, 2005. Various ANN models of observed pier scour depth on different choices of input variables were examined through sensitivity analysis. ANN model having best input combination for the prediction of scour depth was obtained as pier width, flow depth, flow velocity and d_{50} with a coefficient of determination of 0.88.**

Keywords— Artificial Neural Network; Back propagation; Skew

I. INTRODUCTION

Scour is a natural phenomenon caused by erosive action of the flowing water on the bed and banks of alluvial channels [5]. Determining the magnitude of scour is complicated by the cyclic nature of scour processes. The magnitude of local scour around piers is influenced by several factors, which include pier geometry, flow attributes, and bed-material characteristics etc. It has been highlighted that various design methods and formulae for the estimation of local scour depth around bridge piers have been proposed. The main problem with these formulae is that the existing equations are based on laboratory data. They do not accurately predict the actual field conditions and thus, tend to give conservative estimates.

The prediction of scour hole is estimated through physical and mathematical models. Artificial Neural Network (ANN) is an alternative method to overcome the variations involved with experimental and theoretical estimates. ANN act as universal function approximator, this making them useful in modelling problems in which the relationship between dependent and independent variables is poorly understood.

Begum et al. [1] has developed an ANN model and applied to the problem of scour around semicircular bridge abutments. Multilayer Perceptron (MLP) with single hidden layer and Radial Basis Function (RBF) network have been trained with the experimental data from literature and an appropriate model of each of the network was identified. Mohamed Soliman [4] has developed an ANN model using back-propagation learning technique. It was formulated to predict the maximum scour depth and length of downstream hydraulic structure. Results of ANN show good estimation of maximum scour hole in terms of both depth and length of the scour hole compared to the measured data from physical model. Homayoon et al. [3] has developed a multi-layer perceptron Artificial Neural Network (ANN), Ordinary Kriging (OK), and Inverse Distance Weighting (IDW) models for the estimation of local scour depth around bridge piers. These models have been developed by the data obtained from experiments conducted in a flume with curve shaped bedsill under different flow conditions and varying distances of bed sill from bridge pier. Gamal et al. [2] has developed an ANN model using back-propagation learning technique to predict the maximum scour depth around bridge piers due to the installation of aquatic weeds racks.

In the present study, efficiency of ANN models for estimating the observed scour depth from field with different combinations of input variables was tried. Best input- output combinations were determined through sensitivity analysis. About 494 data are used for the development of ANN model and are obtained from a technical report on "Field observations and evaluations of stream bed scour at bridges" published by FHWA in May 2005. Data includes the information about scour depth, pier characteristics and stream characteristics.

II. ARTIFICIAL NEURAL NETWORK

ANN is a digital model of the human brain and it imitates the way in which a human brain works. They are powerful tools for modelling, especially when the input- output relationship is unknown. ANN can identify and learn correlated patterns between input data set and corresponding target data set.

In this study Pier width, Pier length, Flow depth, Flow velocity, skew, d_{50} were taken as input variables and observed scour depth was assigned as output variable. A Multilayer feed forward neural network was used and is based on the Levenberg–Marquardt back-propagation algorithm. This MLP model consists of three layers. They are Input, hidden and output layer. A typical three layered feed forward neural network with back propagation training algorithm is shown in Fig 1.

Input layer accepts the input variables and output layer shows the system's response to the input variables. Hidden layer consist of input weights that biases and transfer functions relating the input variables to the output via ''neurons". Output of the network is the solution to the particular problem. The processes in developing the Neural Network Modelling (NNM) can be mainly divided into two phases, the training phase and the testing phase. Out of the total data, 80% of data is used for training and remaining 20% used for testing.

Three-layered Feed forward neural networks (FFNN) are based on a linear combination of the input variables, which are transformed by a nonlinear activation function. An explicit expression for an output value of FFNNs is,

$$\hat{y}_k = f_o\left[\sum_{j=1}^{M} w_{kj} \cdot f_h\left(\sum_{i=1}^{N} w_{ji} x_i + w_{jo}\right) + w_{ko}\right] \tag{1}$$

Where w_{ji} is the weight in the hidden layer connecting the i^{th} neuron in the input layer and the j^{th} neuron in the hidden layer, w_{jo} is the bias for the j^{th} hidden neuron, f_h is the activation function of the hidden neuron, w_{kj} is the weight in the output layer connecting the j^{th} neuron in the hidden layer and k^{th} neuron in the output layer, w_{ko} is the bias for the k^{th} output neuron and f_o is the activation function of the output neuron.

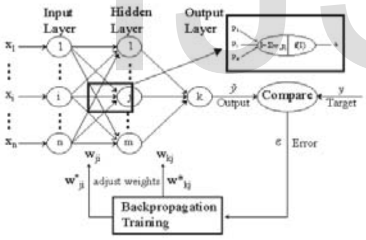

Figure 1: Three layered feed forward neural networks with back propagation training algorithm

A. Feed Forward Back Propagation Training

The back propagation network is to find the weight that approximate target values of output with a selected accuracy. The error between observed output and estimated output were reduced by modifying the weight in the hidden layer. Error was calculated in each forward pass. If an error is higher than a selected value, the procedure continues with a backward pass, otherwise, training is stopped. Least root mean square error method was used for optimizing the network. Fig.2. shows the learning cycle in ANN model.

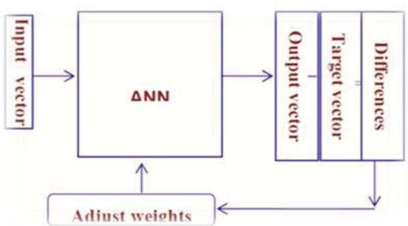

Fig.2. Learning cycle in ANN model

In training phase, number of neurons in hidden layer was varied from 1 to 20 for obtaining the optimum network with least Root Mean Square Error (RMSE) value. The number of epochs was selected as 70,000. Learning rate and momentum constant values are 0.5 and 0.1 respectively. Minimum gradient is selected as 10^{-20}.The transfer function used for the hidden layer was the Tan-sigmoid transfer function. The output layer uses a linear transfer function called purelin. Normalized input and the output data are used for the development of model. The models were analysed for different input-output combinations.

B. Performance Evaluation of the Models

Various parameters used for estimate the performance of ANN models are RMSE, Correlation Coefficient (r), Efficiency (E), Mean Absolute Error (MAE) and Standard Error of Estimate (SEE). The equations for the performance parameters are given by,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i\right)^2} \tag{2}$$

$$r = \frac{n\sum xy - \sum x \sum y}{\sqrt{n\sum x^2 - (\sum x)^2}\sqrt{n\sum y^2 - (\sum y)^2}} \tag{3}$$

$$E = \frac{E_1 - E_2}{E_1} \tag{4}$$

where, $E_1 = \Sigma\,(x_i - \overline{x}_i)^2$ and $E_2 = \Sigma\,(y_i - x_i)^2$

$$MAE = \frac{1}{n}\Sigma\left(y_i - x_i\right) \tag{5}$$

$$SEE = \left[\frac{\Sigma\,(x_i - y_i)^2}{n-1}\right]^{0.5} \tag{6}$$

Where x_i represents the observed values, y_i represents the predicted values and n represents the number of data.

III. RESULTS AND DISCUSSION

As a first estimate, six input variables such as pier length, pier width, flow depth, flow velocity, skew and d_{50} were used and the output variable was fixed as scour depth. During the training process, ANN with architecture of 6-20-1 was obtained as an optimum network with least RMSE value. Fig.3. shows the comparison of observed scour depth and ANN estimated scour depth using ANN1. This model shows a co-efficient of determination (R^2) of 0.7942.

Sensitivity analysis was performed to determine which of the input variables are more dominant in predicting scour depth. Various input-output combinations used in the sensitivity analysis are shown in Table I.

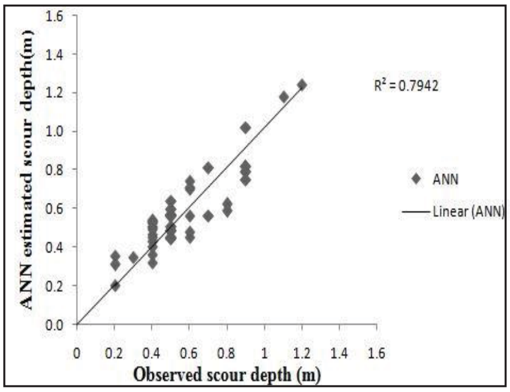

Fig.3. Comparison of observed scour depth and ANN estimated scour depth using ANN1

ANN2 model was developed by neglecting the pier characteristics such as pier length and pier width. Fig. 4 shows the comparison of observed scour depth and estimated scour depth by this model. The prediction performance of ANN2 model was found to be poor when comparing with ANN1, since its R^2 value is 0.7440. This is due to the absence of pier characteristics in the ANN2 model. Therefore in ANN3 model, Pier length was included as an input variable along with other input parameters in ANN2. Fig. 5 shows the comparison of observed scour depth and estimated scour depth using ANN3 model. But in this model R^2 value was obtained as 0.7120. It also shows poor performance when comparing with ANN1 model. From these two models, it was realised

TABLE I. DIFFERENT INPUT COMBINATIONS USED FOR ANN MODEL

Model	Input combinations
ANN2	Flow depth, Flow velocity, skew, d_{50}
ANN3	Pierlength, Flow depth, Flow velocity, skew, d_{50}
ANN4	Pier width, Flow depth, Flow velocity, skew, d_{50}
ANN5	Pier width, Flow depth, Flow velocity, d_{50}
ANN6	Flow depth, Flow velocity
ANN7	Flow depth, Flow velocity, d_{50}

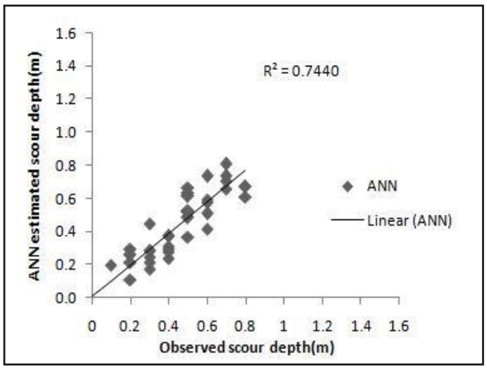

Fig.4. Comparison of observed scour depth and ANN estimated scour depth by ANN2

that the pier length has no significant effect on prediction of scour depth. Again the sensitivity analysis was done by replacing the pier length with pier width in ANN4 model. It was found that performance of ANN4 model was improved and its R^2 value obtained as 0.8194. Fig. 6 shows the comparison of observed scour depth and estimated scour depth by ANN4 model. It revealed that the pier width has a significant role in the prediction of scour depth.

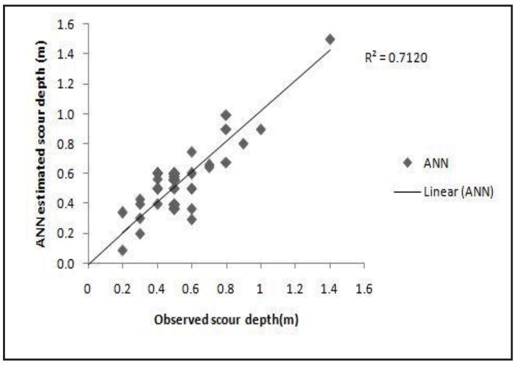

Fig.5. Comparison of observed scour depth and ANN estimated scour depth by ANN3

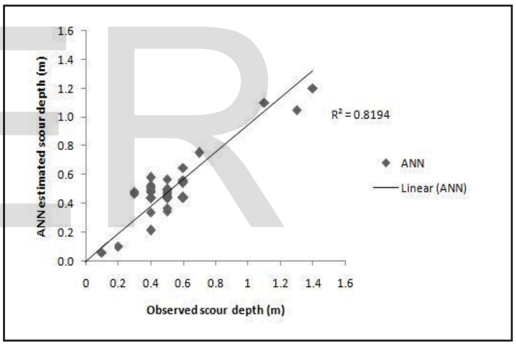

Fig.6. Comparison of observed scour depth and ANN estimated scour depth by ANN4

ANN 5 model shows that by removing the input variable skew, the prediction performance of ANN model was improved and its R^2 value is obtained as 0.8828. Fig. 7 shows the comparison of observed scour depth and estimated scour depth by ANN5 model. From this, it was clear that skew has not much effect on the prediction of scour depth around the bridge pier.

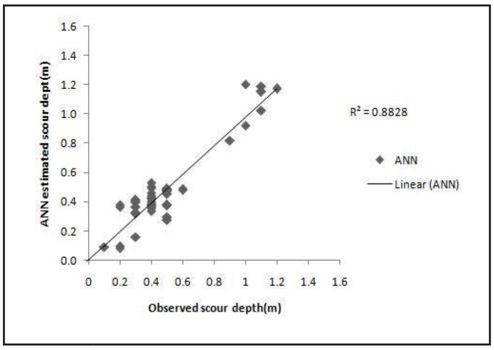

Fig.7. Comparison of observed scour depth and ANN estimated scour depth by ANN5

ANN6 model was developed by considering only the flow characteristics such as flow depth and flow velocity and its R^2 value is found as 0.7308. Fig. 8 shows the comparison of observed scour depth and estimated scour depth by this model. This indicates that these two parameters are insufficient for the prediction of scour depth. ANN7 was also indicating the same result such as stream and bed characteristics are not sufficient for the prediction of scour depth. Fig. 9 shows the comparison of observed scour depth and estimated scour depth using ANN7 model. Thus from all the seven ANN models, it was concluded that pier width, flow depth, flow velocity and d_{50} are the major input parameters influenced for the prediction of scour depth which are incorporated in the ANN5 model. Performance of ANN models after testing is shown in Table II.

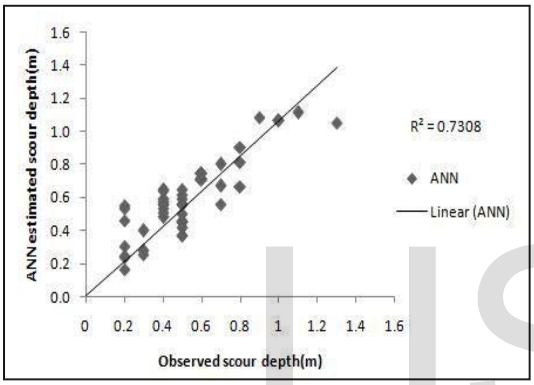

Fig.8. Comparison of observed scour depth and ANN estimated scour depth by ANN6

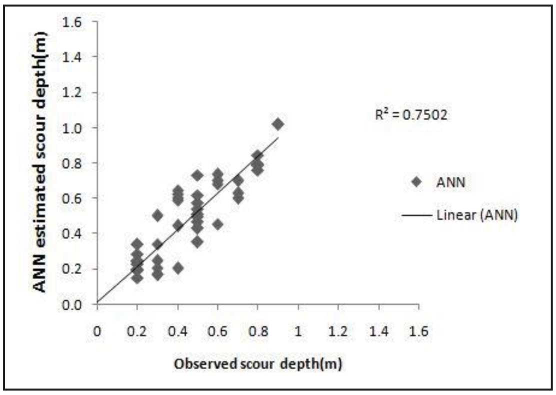

Fig.9. Comparison of observed scour depth and ANN estimated scour depth by ANN7

TABLE II. PERFORMANCE OF ANN MODELS FOR DIFFERENT INPUT- OUTPUT COMBINATIONS

Model	Optimum network	RMSE	R	E (%)	MAE	SEE
ANN1	6-20-1	0.115	0.8912	77.69	0.0275	0.1049
ANN2	4-19-1	0.1420	0.8627	69.73	0.0165	0.1009
ANN3	5-19-1	0.1921	0.8438	65.89	0.0227	0.1284
ANN4	5-16-1	0.0724	0.9052	81.56	0.0126	0.0998
ANN5	4-20-1	0.0563	0.9396	87.12	0.0087	0.0952
ANN6	2-17-1	0.1638	0.8549	65.49	0.0646	0.1416
ANN7	3-20-1	0.1265	0.8662	66.79	0.0278	0.1166

IV. CONCLUSION

ANN models were developed to analyze and predict the local scour depth around bridge pier. The models were developed for different input combinations and their performance was evaluated based on the statistical parameters. In this study seven ANN models were developed using different input combinations with scour depth. By comparing the performance of all the seven ANN models, ANN3 model shows that pier length has less significant effect on the prediction of scour depth and ANN6 model indicates that flow characteristics are insufficient for the prediction of scour depth. ANN5 model shows good performance comparing with other ANN models, since its R^2 value is obtained as 0.8828. Thus it is concluded that pier width, flow depth, flow velocity and d_{50} be the best input combination for the prediction of scour depth.

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