Modelling of Scour Depth Around Bridge Piers using Artificial Neural Network (ANN)

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Abstract- **Scour is defined as the erosion of streambed around an obstruction in a flow field. The prediction of scour depth around bridge piers is estimated quite often through physical and mathematical models. However, physical models are costly and not easily available for testing all hydraulic conditions and mathematical models were derived to represent certain hydraulic conditions. In this paper, Artificial Neural Network (ANN) modelling using back-propagation learning technique was formulated to predict the maximum scour depth around bridge piers. The data used to train the ANN was obtained from a technical report on "Field observations and evaluations of streambed scour at bridges" published by Federal Highway Administration in May 2005. The pier width, pier length, skew, velocity, depth, D50 and D84 were used as input parameters to ANN while scour depth as the output parameter. Results of ANN show good estimation of maximum scour depth compared to the measured data from physical model. An advantage of the use of ANN in the prediction of maximum scour depth that it will certainly decrease the cost and time for physical modelling and help in simulating different hydraulic conditions of the hydraulic structure.**

Key words: Artificial neural network, scour depth, mean square error, coefficient of correlation

I. INTRODUCTION

Scour is the local lowering of stream bed elevation which takes place in the vicinity or around a structure constructed in flowing water. Scour takes place around bridge piers, abutments, around spurs, jetties and breakwaters due to modification of flow pattern in such a way as to cause an increase in local shear stress. This in turn dislodges the material on the stream bed resulting in local scour. The concern about safety of bridges is primarily due to three reasons which are: (1) inadequate knowledge about scour phenomenon when the bridges were constructed, (2) inadequate data on which the design flood was chosen, and (3) increase in the loading on the bridge due to increase in size of trucks, wagons, and their frequency of operation.

It is for this reason that extensive experimental investigation has been conducted in an attempt to understand the complex process of scour and to determine a method of predicting scour depth for various pier situations. To date, no generic formula has been developed that can be applied to all pier cases to determine the extent of scour that will develop. In this project, an alternative approach, Artificial Neural Network models, will be established for the prediction of local scour around bridge piers.

ANN models are attractive in the area of estimation of local scour around bridge piers in this study. This is because of their adaptive nature where learning by example replaces programming or making functions in solving problems. This feature renders computational models very appealing in domains, where one has little or incomplete understanding of the problem to be solved but where training data examples are available. In the reviewed papers it was concluded that ANN provides a higher level of accuracy in solving a particular problem when compared to experimental and theoretical results. ANN act as universal function approximator, thus making them useful in modelling problems in which the relationship between dependent and independent variables is poorly understood. ANN may therefore be a viable alternative in the estimation of local scour depth around bridge piers, provided a reliable database is available. Hence, in this project, the efficiency of artificial neural network models in estimating maximum scour depth with different combinations of input variables is tried.

II. LOCAL SCOUR

Scour is defined as the erosion of streambed around an obstruction in a flow field (Chang, 1988). The amount of reduction in the streambed level below the bed level of the river prior to the commencement of scour is referred as the scour depth. A scour hole is defined as depression left behind when sediment is washed away from the riverbed in the vicinity of the structure. Local scour refers to the removal of sediment from the immediate vicinity of bridge piers or abutments. It occurs due to the interference of pier or abutment with the flow, which results in an acceleration of flow, creating vortices that remove the sediment material in the immediate surroundings of the bridge pier or abutment.

The process of scour is affected by a large number of variables. The flow, fluid, pier and sediment characteristics are the main variables affecting the pier scour time and spacing between the piers. Depending upon whether the flow approaching the pier is transporting sediment or not, the pier scour is classified as (i) clear-water scour; when approaching flow does not carry any sediment (ii) live-bed scour; when approaching flow carries sediment.

The local scour has the potential to threaten the structural integrity of bridge piers, ultimately causing failure when the foundation of the pier is undermined. Besides the human loss, bridge failures cost crores of rupees in direct expenditure for replacement and restoration in addition to the indirect expenditure related to the disruption of transportation facilities.

The basic mechanism causing local scour at piers is the down-flow at the upstream face of the pier and formation of vortices at the base. The flow decelerates as it approaches the pier coming to rest at the face of the pier. The approach flow velocity is reduced to zero at the upstream side of the pier, which results in a pressure increase at the pier face. The associated pressures are highest near the surface, where the deceleration is greatest, and decrease downwards. Since the velocity is decreasing from the surface to the bed, the pressure on the face of the pier also decreases accordingly forming a downward pressure gradient. The pressure gradient hence forces the flow down the face of the pier, resembling that of a vertical jet. The resulting down flow impinges on the streambed and creates a hole in vicinity on pier base. The down flow impinging on the bed is the main scouring agent.

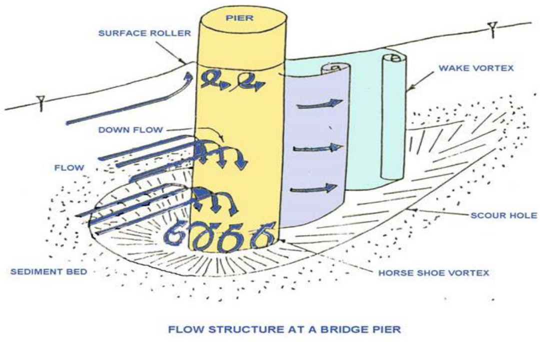

Fig.*1: flow structure at a bridge pier*

Fig.2: *a picture showing the local scour around a bridge pier*

I. ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a form of artificial intelligence, which by means of try to simulate the behaviour of the human brain and nervous system. A typical structure of ANNs consists of a number of nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers, as shown in Fig.4. Each node in a specific layer is fully or partially joined to many other nodes via weighted connections. The input from each node in the previous layer is multiplied by an adjustable connection weight. At each node, the weighted input signals are summed and a threshold value or bias is added. This combined input is then passed through a non linear transfer function to produce the output of the node. The output of one node serves as the input to the nodes in the next layer. The actual output of the network is compared with the desired output and an error is calculated. Using this error and utilizing a learning rule, the network adjusts its weights until it can find a set of weights that will produce the input/output mapping that has the smallest possible error.

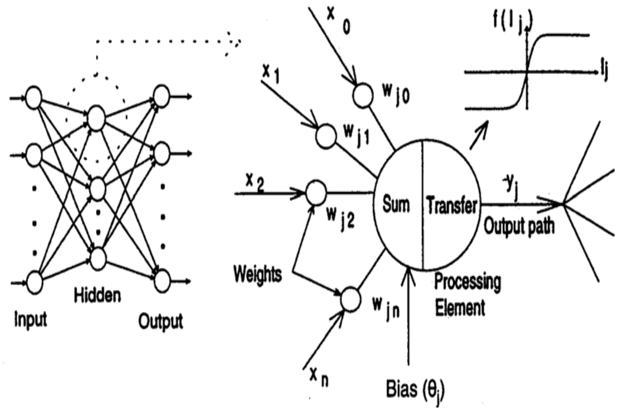

Fig.3: *structure and operation of ANN*

II. ANN ARCHITECTURE

The ANN models developed in this paper use single layer perceptrons (MLP) that are trained with the back-propagation training algorithm for feed forward ANNs. The ANN model developed in this study consists of input nodes of effective grain size (d_{50} & d_{84}), pier length, pier width, velocity, skew and depth. This model was used for predicting the scour depth around bridge piers. The structure of the ANN model used in the study is shown in Fig.5. The model consists of an input layer with 7 nodes and an output layer with a single node. In order to determine the optimum number of nodes in the hidden layer, a trial-and error procedure was adopted. The procedure is discussed in the following sections.

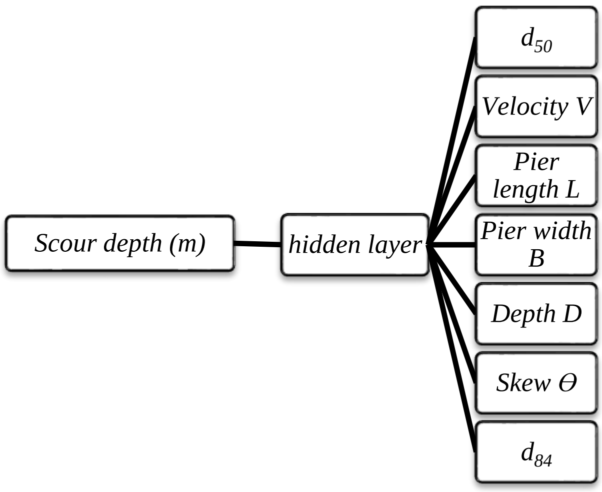

Fig.*4: ANN hierarchy*

III. ANN DATABASE

In the present study, ANN models were developed for modelling the scour around bridge piers. Data set of scour depth, pier characteristics and stream characteristics are obtained from a technical report on "Field observations and evaluations of stream bed scour at bridges" published by Federal Highway Administration in May 2005. For the development of ANN model pier length, pier width, flow depth, flow velocity, skew, d_{50} and d_{84} are selected as input variables and scour depth is assigned as output variable. The models were analyzed for different input-output combinations.

IV. DATA DIVISION

The ranges of the data used for the input and output variables are summarised in Table 2. The available data was divided into three sets (i.e. training, testing and validation) in such a way that they are statistically consistent and thus represent the same statistical population. In total, 80% of the data were used for training and 20% were used for validation. The training data were further divided into 70% for the training set and 30% for the testing set. Before presenting the input and output variables for ANN model training, they were scaled between 0.0 and 1.0 to eliminate their dimension and to ensure that all variables receive equal attention during training.

The simple linear mapping of the variables' practical extremes to the neural network's practical extremes is adopted for scaling as it is the most common method for data scaling. Using this method, for each variable x with minimum and maximum values of x_{min} and x_{max}, respectively, the scaled value x_n is calculated as follows:

$$x_n = \left(\frac{x - x_{min}}{x_{max} - x_{min}} \right) \quad (1)$$

TABLE 1: DATA RANGES USED FOR ANN VARIABLES

Model variable	**Minimum value**	**Maximum value**
Grain size, d_{50}	0.12	108
Grain size, d_{84}	0.25	233
Pier length, L	0	27.4
Pier width, B	0.3	5.5
Flow velocity, V	0	4.5
Flow depth, D	0.1	22.5
Skew, Θ	0	85

V. TRAINING AND TESTING

The neural network tool *(nntool)* in MATLAB was used to formulate the ANN model. Training of the model was performed using gradient descent with momentum and adaptive learning rate backpropagation technique. In order to determine the number of hidden nodes in the hidden layer, the models were trained for 10000 epochs with 6,8,10,12 and 14 nodes in the hidden layer. The statistics are given in Table 1.

TABLE 2 ANN TRAINING STATISTICS

No. of nodes	Mean square error	R value	Elapsed time
6	0.00147	0.92	0.4
8	0.00158	0.91	2.6
10	0.00103	0.93	2.37
12	0.000702	0.87	2.4
14	0.007	0.871	2.55
16	0.000595	0.91	3.14

The mean squared error, elapsed time and correlation coefficient are plotted against the number of hidden nodes in Fig.6a, Fig.6b and Fig.6c. It can be seen that 10 nodes in the hidden layer gives optimum values for mean squared error and coefficient of correlation. Hence, a 7-10-1 configuration is adopted for the ANN models. The initial weights and biases were randomly selected. Training was continued for until one of these conditions occurs:

a. The maximum number of epochs is reached

b. The maximum amount of time is exceeded.

c. Performance is minimized to the goal.

d. The performance gradient falls below minimum gradient, fixed as 10^{-5}.

Once the training is completed, optimized connection weights and biases for the model is obtained. They are summarized in Table 3.

TABLE.3 OPTIMIZED CONNECTION WEIGHTS OF THE MODEL

i/j	i=1	i=2	i=3	i=4	i=5	i=6	i=7	To o/p	Bias 1	Bias 2
j=1	-0.87707	-0.01342	-0.56657	0.18758	1.0021	-0.99641	-0.5953	-0.26451	2.0298	-0.10977
2	1.1757	0.49117	0.078774	-0.97309	-1.0311	-0.11071	-0.30065	-0.72213	-1.5768	-
3	-0.45661	0.87925	-0.94307	-1.1178	0.36125	0.29829	0.82976	-0.6315	0.96003	-
4	-0.33954	0.074799	1.3938	0.32102	0.3879	-0.8345	-0.88925	-0.14145	0.65992	-
5	0.97745	-0.36973	-0.18324	-0.58922	1.248	-0.15219	0.91711	0.56926	-0.2235	-
6	0.92349	1.3817	-0.37558	-0.58054	0.43141	-0.7566	0.21742	0.53078	0.18057	-
7	1.0251	-0.5383	0.97624	0.40937	0.42088	-0.48124	-0.79489	0.23028	0.70392	-
8	-0.80239	0.45766	-0.04099	1.0738	0.78727	0.39391	0.91179	0.27106	-1.1524	-
9	-0.94662	0.9589	-0.40985	-0.35688	-0.25881	1.108	0.46787	0.1835	-1.5809	-
10	-0.27284	0.47881	-1.0405	1.1237	-0.63124	0.88978	0.14553	-0.2717	-1.9327	-

VI. RESULTS AND DISCUSSION

The ANN model formulated was used to predict the scour depth around bridge piers. In order to determine the number of hidden nodes in the hidden layer, the models were trained for 10000 epochs with 6,8,10,12 and 14 nodes in the hidden layer. In the present study, the optimum values from the graphs (fig. 6a, 6b & 6c) is obtained for 10 number of nodes. Hence, a 7-10-1 configuration is adopted for the ANN models. The effect of various parameters on scour depth has been calculated. Scatter plots between the estimated and predicted values of scour depth of the model was plotted.

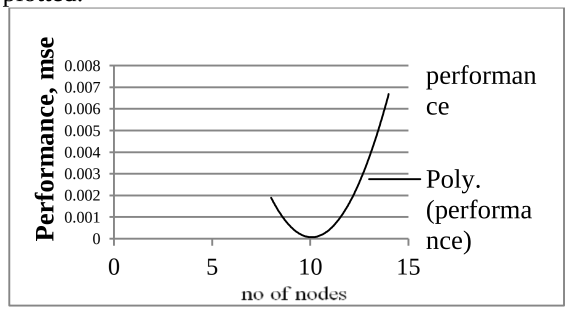

Fig. 5a*: performance vs. no.of nodes*.

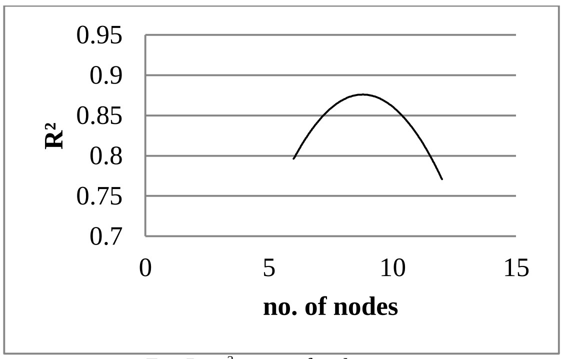

Fig. 5c*: r^2 vs. no.of nodes.*

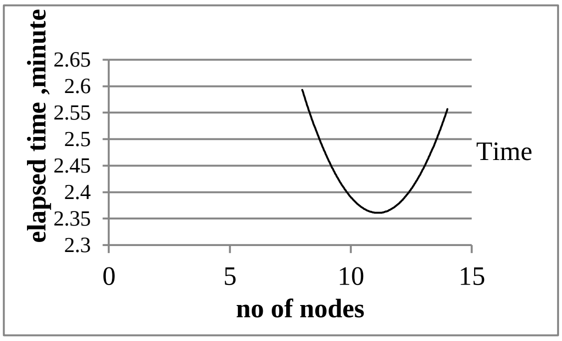

Fig. 5b*: elapsed time vs. no.of nodes.*

After training, testing of the ANN model is done. The predicted values of scour depth was obtained from the ANN model. The actual values and the predicted values are plotted in a graph and it has been seen that the actual and predicted value of the scour depth are very close to one another and a considerable degree of scatter is observed around the 45 ° line.

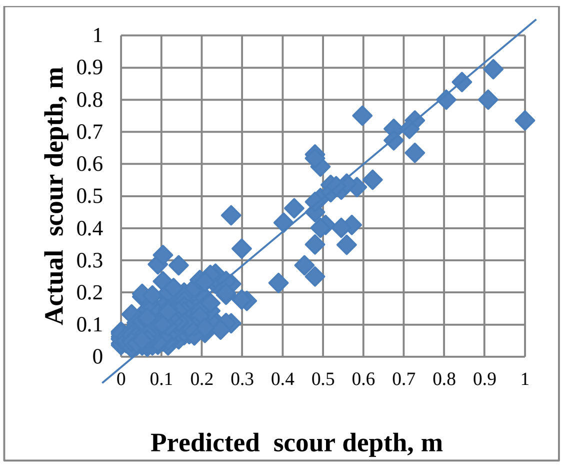

Fig.6*: actual value of scour depth vs. predicted value of scour depth.*

A. Sensitivity analysis

The experimental dataset not used for training were used to validate the predicted and experimental result . Sensitivity analysis is carried out by varying the value of any one parameter from its minimum to maximum value from the dataset, while fixing the values of all the other variables and hence we can identify the effect of each of the input variables on the estimated scour depth

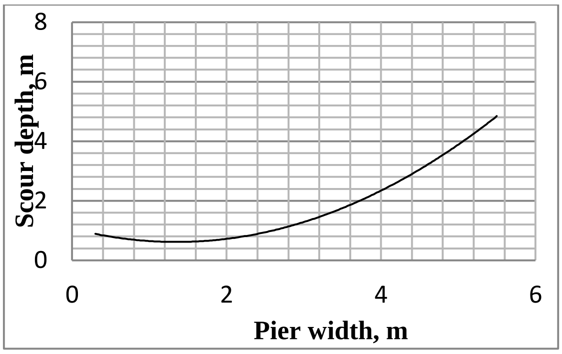

Fig.16*: Scour depth vs. pier width*

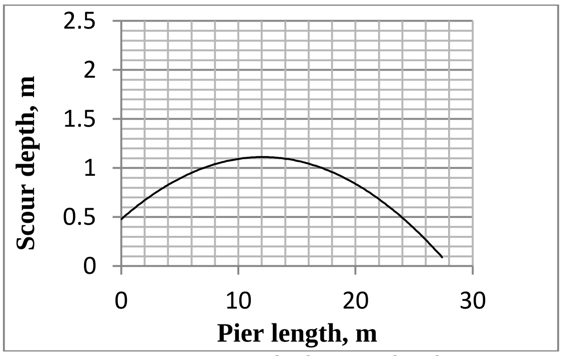

Fig.17: *Scour depth vs. Pier length*

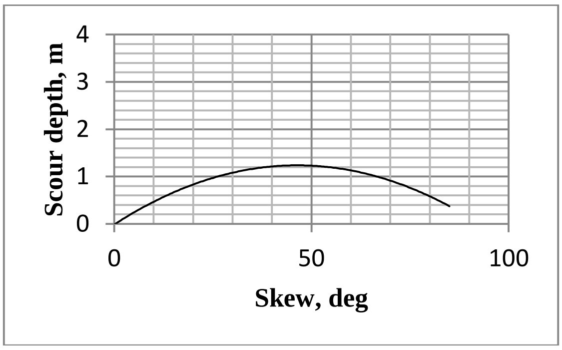

Fig.18*: Scour depth vs. Skew*

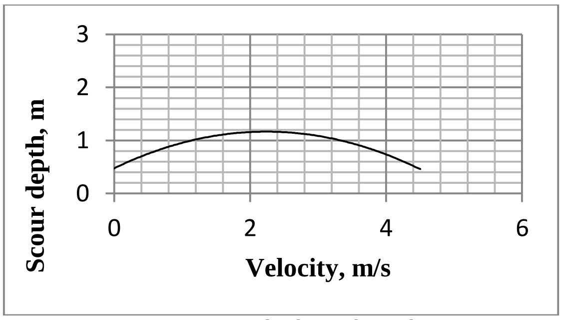

Fig.19*: Scour depth vs. Flow velocity*

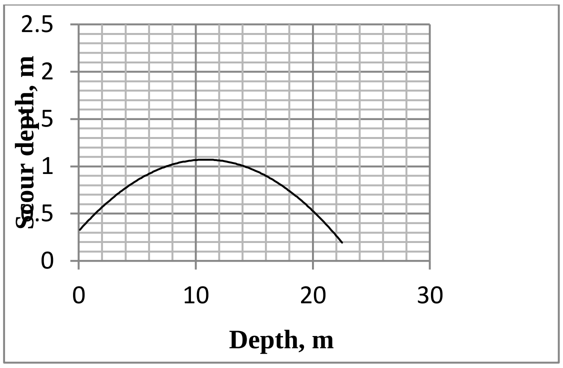

Fig. 20: *Scour depth vs. Depth*

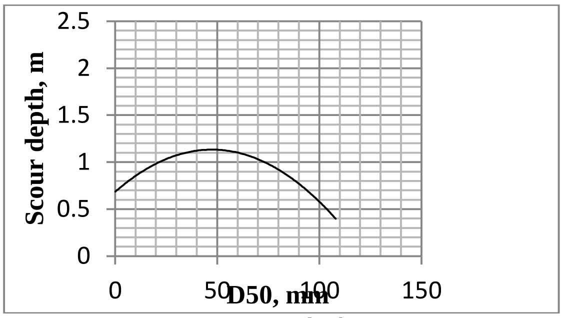

Fig. 21: *Scour depth vs. D50*

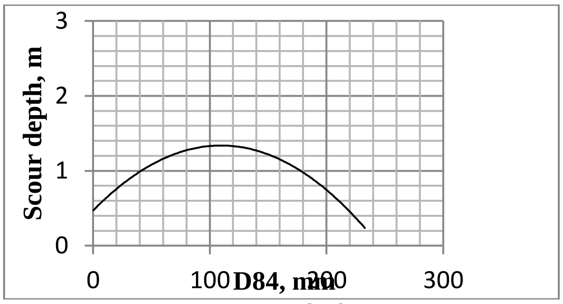

Fig. 22: *Scour depth vs. D84*

From the graph, as the D84 value increases, scour depth rises initially and then suddenly decreases after reaching a maximum value.

B. comparative study

In this we are using six equations for the comparative study

i. Mean absolute error (MAE)

$$\text{MAE} = \frac{1}{N}\sum_{1}^{N}(\text{Oi} - \text{ti}) \qquad (2)$$

MAE is the average over the verification sample of the absolute values of the differences between the forecast and corresponding observation. The MAE is a linear score which means that all the individual differences are weighted equally in the average.

ii. Root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_{1}^{N}(\text{Oi}-\text{ti})2}{\text{N}}} \qquad (3)$$

The RMSE is a quadratic scoring rule which measures the average magnitude of the error.

where: Oi and ti are observed and predicted for the ith output, and is the average of predicted, and N is the total number of events considered.

TABLE 4 MAE&RMSE VALUES FOR VARIOUS EQUATIONS

EQUATION	MAE VALUE	RMSE VALUE
1. Blench-Inglis scour depth equation: Ys=1.8b0.25Y00.75-Y0	0.29429	6.434118
2. Laursen I scour depth equation : Ys= 1.11Y00.5b0.5	1.57889259	34.5196621
3. Laursen scour depth equation: Ys=1.5b0.7Y00.3	1.776475531	38.83945956
4. Breuser's equation: Ys=1.4b	0.910334728	19.90284034
5.Inglis-Poona I equation: Ys=1.7b0.22Y00.52V00.52-Y0	-1.117323872	24.4282877
6.Inglis-Poona II equation: Ys=1.73b0.22Y00.78-Y0	0.287492118	6.285500862
7. ANN MODEL	0.017295246	0.378129613

VII. CONCLUSIONS

In this study, the authors attempt to predict the scour depth around bridge piers using artificial neural networks. A three layer ANN with a 7-10-1 configuration was used for the study. A procedure to determine the optimum number of nodes in hidden layer is detailed. The following points are concluded from the study:

1. ANN models are trained with the dataset available and the number of nodes in the hidden layer is obtained as 10.

2. The models could effectively predict the scour depth around the bridge pier since it shows small variation from the actual value of scour depth.

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