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GRNN BASED MODELLING OF PIER SCOUR DEPTH USING FIELD DATASET

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Abstract: *This paper investigates the potential of generalized regression neural network approach to model the local scour around piers using field data. Four predictive equations as proposed in literature were used to compare the performance of generalized regression neural network. A dataset of consisting of 232 pier scour measurements were used for this analysis. A total of 154 data were used to train whereas remaining 78 data were used to test the created model. A correlation coefficient value of 0.914 (root mean square error = 0.438) was achieved by generalized regression neural network. Comparison of results with four predictive equations suggests an improved performance by generalized regression neural network in predicting the scour depth.*

Keywords: *pier scour, field scour data, generalized regression neural network, predictive equations.*

INTRODUCTION

Scour is a natural phenomenon caused by the removal of sediments near the structures by the action of turbulent flows. Scour reduces the bed elevation near the piers and abutments, exposing the foundations of a bridge, which may result in structural collapse as well as loss of life and property. The amount of this reduction below an assumed natured level is termed scour depth. Failure of bridges due to scour at abutments and piers is a common occurrence. Bridge scour is a function of flow energy, sediment-transport characteristics, and bridge characteristics. Richardson and Davis (2001) suggested that total scour at a bridge can be divided into aggradation or degradation, contraction scour and local scour. Local scour is defined as the removal of bed material from around piers, abutments, spurs, and embankments. Local scour can be either clear-water or live-bed. Local scour at piers is caused by the formation of vortices known as the horseshoe vortex at their base. The horseshoe vortex is caused by the accumulation of water on the upstream surface of the obstruction thus causing flow to accelerate around the nose of the pier. This acceleration of flow removes bed material from around the base of the pier. Thus, the amount of the sediments carried away from the base region is greater than the amount being brought into the region, consequently, causing a scour hole.

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Accurate measurement of equilibrium depths of local scour around bridge piers is a vital issue in the design of bridges concerned to the hydraulics engineering. The physical process of scour around bridge piers is quite complicated which makes the development of methodology for predicting scour at bridge piers difficult. Most of the research in the field of local scour at bridge piers is based on dimensional analysis using small-scale laboratory experiments with non-cohesive, uniform bed material under steady-flow conditions. A number of equations are proposed to estimate the local scour at bridge piers by carrying out laboratory experiments (McIntosh, 1989; Mueller and Wagner, 2005). The equations developed using laboratory research have not been adequately verified by using field data and the scour prediction methods developed this way did not always produce good results for field conditions (Melville, 1975; Dargahi, 1990; Jones, 1984). Due to the scale effect, the scour-depth equations based on laboratory flume data found to overestimate scour depth measured at bridge piers (Mueller and Wagner, 2005).

Soft computing techniques, like artificial neural network is being widely used in prediction of pier scour (Trent et al., 1993; Trent et al., 1999; Kambekar and Deo 2003; Choi and Cheong, 2006; Bateni et al. 2007, Bateni et al. 2007; Lee et al. 2007). Results obtained by using a neural network were compared with different equations and found to be working well in comparison to the empirical relations. A neural network based modeling algorithm requires setting up of different learning parameters (like learning rate, momentum), the optimal number of nodes in the hidden layer and the number of hidden layers. A large number of training iterations may force a neural network to over train, which may affect the predicting capabilities of the model. Further, presence of local minima is another problem with the use of a back propagation neural network.

Within last decade, several studies reported the use of generalized regression neural network for several civil engineering problems (Nawari et al., 1999; Abu Keifa, 1998; Cigizoglu, 2005; Kurup and Griffin, 2006). This modeling approach requires setting of few user-defined parameters and do not face the problem of local minima. Within last few years, another modeling approach called as support vector machines is also utilized to solve various civil engineering problems (Dibike et al., 2001; Gill et al., 2006; Pal and Goel, 2006; Pal, 2006) and found to be working well in comparison to neural network approach.

Keeping in view the usefulness of a generalized regression neural network, this study explores its potential in predicting the pier scour and compares its performance with four empirical relations. A study by Mueller and Wagner, (2005) suggests that out of 26 predictive equations used in their study, no single equation is conclusively better than the rest. So, in present study, four predictive equations namely HEC-18, HEC-18_Mueller, Froehlich, (1988) and Froehlich Design (1988) are used. Details of all these four predictive equations can be found in Mueller and Wagner, (2005).

DATASET

Out of the total 493 pier scour measurements available in the bridge scour data management system (Mueller and Wagner, 2005), 232 data for upstream scour were selected for this study. The time required for scour to reach its maximum depth in cohesive material is considerably longer than in noncohesive material. Therefore, observations with scour in cohesive material (a total of 5 data out of 493 measurements) were removed from this analysis. Data sets with pier type group, unknown bed material, missing value of any input variable and having zero scour were also removed from the total data set. Further, data sets with scour measurements at the downstream side of piers were also removed. The effect of debris on the scour depth was also provided in the data set and grouped in four categories (i.e. unknown, insignificant, moderate and substantial). As debris buildup near the piers often make measurement of maximum scour impossible as well as may increase the scour near the pier due to a larger obstruction to flow (Song et al., 1989). So, all scour measurements with substantial and moderate effect (a total of 40 data, having 14 data with scour measurement at the downstream side and 3 data with pier type group) were removed from the data set. Finally, the dataset was divided randomly in a way that 154 data were used for training purposes whereas the remaining 78 data to test the model.

Seven input parameters namely pier shape factor (Ps), pier width (Pw), skew of the pier to approach flow (skew), velocity of the flow (V), depth of flow (h), D50 (i.e. the grain size of bed material in mm for which 50 percent is finer) and gradation of bed material (σ) were used to predict the upstream scour depth. Minimum, maximum, mean and standard deviation values of all input and output parameters used in this study are provided in table 1.

Table 1.Characteristics of the train and test data used in this study

Input parameter	Train data				Test data			
	Min	Max	Mean	St.	Min	Max	Mean	St.
Ps	0.7	1.3	0.973	0.210	0.7	1.3	0.988	0.202
Pw	0.3	5.5	1.558	1.156	0.3	5.5	1.397	1.151
Skew	0	85	9.260	18.629	0	65	9.897	18.373
V	0.2	4.5	1.639	0.891	0	3.2	1.301	0.675
h	0.3	22.5	4.552	4.019	0	22.4	3.796	3.579
D50	0.12	95	18.978	26.758	0.15	95	19.473	25.097
σ	1.2	20.3	3.650	3.294	1.2	21.8	3.605	2.901
Scour	0.1	7.1	1.121	1.272	0.1	6.2	0.938	1.059
The unit of measurements for pier width, depth of flow and scour depth is meter, skew is measured in degree and velocity of flow is in meter/second								
Ps = 1.3 for square nosed-piers, 1.0 for round-nosed piers and 0.7 for sharp-nosed piers.								

GENERALIZED REGRESSION NEURAL NETWORK

The generalized regression neural network (GRNN) proposed by Specht (1991), is a normalized radial basis function (RBF) network with a hidden unit centered at every training example. These RBF units are called kernels and are usually probability density functions such as the Gaussian. The hidden-to-output weights are just the target values, so the output is simply a weighted average of the target values of training cases close to the given input case. The weights that need to be learned are the widths of the RBF units. GRNN is a universal approximator for smooth functions, so it should be able to solve any smooth function-approximation problem given enough data.

A GRNN configuration consists of four layers. The first layer consists of input whereas the second layer has the pattern units, the outputs of this layer are passed on to the summation units in the third layer, and the final layer covers the output units. The first layer is fully connected to the second layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The optimal value of spread parameter (s) is often determined experimentally. Larger values of spread indicate a smoother function approximation. The GRNN does not require an iterative training procedure as in the back-propagation method. For further detail of the GRNN readers are referred to Specht (1991) and Wasserman (1993).

RESULTS

To assess the usefulness of GRNN in predicting the scour depth 154 data for training and 78 for testing were used. Correlation coefficient and root mean square error (RMSE) were used to compare the performance of GRNN with four predictive equations. For GRNN, only one parameter i.e. spread of radial basis functions need to be determined for a given dataset. After number of trials a value of 0.62 was found to be performing well for this dataset. Table 2 provides the value of correlation coefficient and RMSE obtained by GRNN. A correlation coefficient value of 0.914 (RMSE = 0.438 m) suggests that GRNN can effectively be used in predicting the scour depth of the bridge piers.

Table 2. Correlation coefficient and RMSE with predictive equations and GRNN

Name	Equation	Correlation coefficient	RMSE	R^2
Generalized regression neural network	Spread = 0.62	0.914	0.438	0.835
Froehlich Equation (1988)	$0.32\ P_s\ g^{-0.1}\ V^{0.2}\ h^{0.36}\ P_w^{0.62}\ D_{50}^{-0.08}$	0.62	0.957	0.433
Froehlich Design (1988)	$0.32\ P_s\ g^{-0.1}\ V^{0.2}\ h^{0.36}\ P_w^{0.62}\ D_{50}^{-0.08} + P_w$	0.658	1.540	0.389
HEC-18	$2.0\ K_1\ K_2\ K_3\ g^{-0.215}\ V^{0.43}\ h^{0.135}\ P_w^{0.65}$	0.565	1.670	0.320
HEC-18/Mueller Equation (1996)	$2.0\ K_1\ K_2\ K_3\ K_4\ g^{-0.215}\ V^{0.43}\ h^{0.135}\ P_w^{0.65}$ Where $K_4 = 0.4\left(V - V_c' / V_c' - V_{c95}'\right)^{0.15}$	0.628	1.360	0.394

Figure 1 provides the graph plotted between actual and predicted value of scour depth obtained by using GRNN with the test dataset. This figure suggests that most of the predicted values are lying within or closer to ±25% error from the line of perfect agreement. A higher value of (i.e.0.835) with GRNN also confirms that this approach works well in predicting the scour depth.

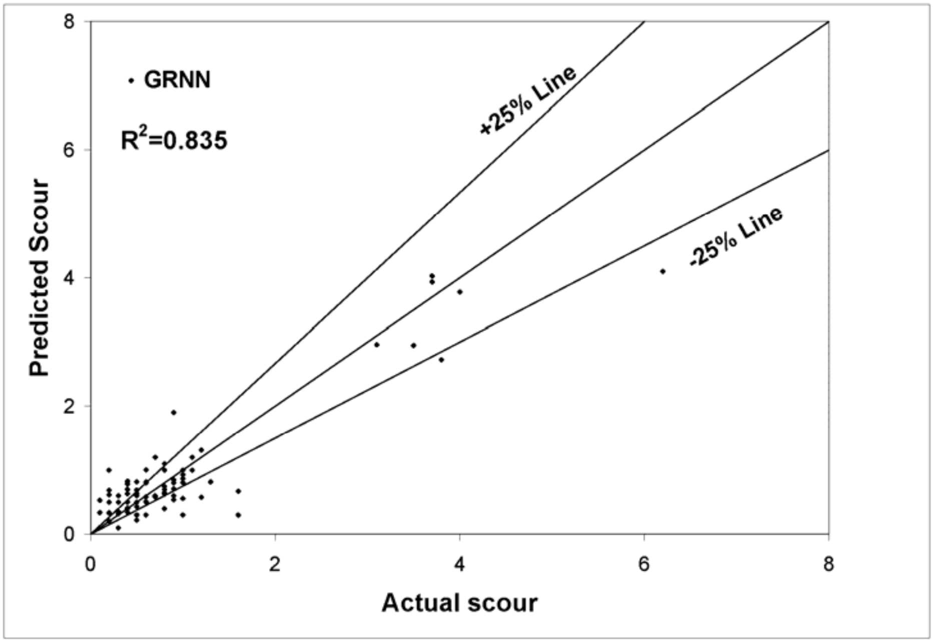

Fig. 1. Actual vs. predicted scour using GRNN.

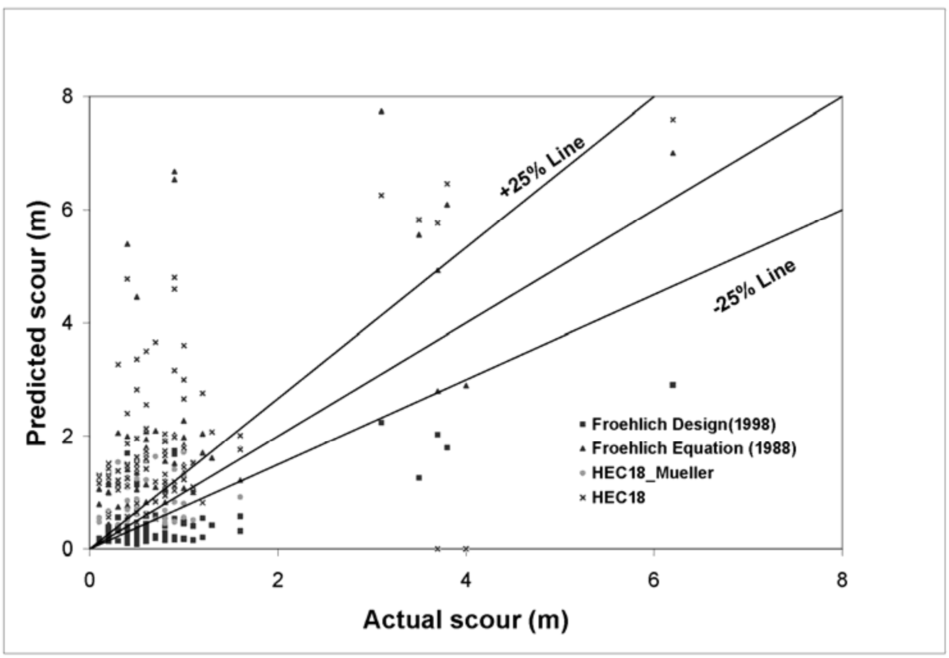

Fig. 2. Actual vs. predicted scour using four empirical relations.

COMPARISON WITH EXITING RELATIONS

Same training and test data set were used to compare the performance of GRNN model with four predictive equations in modeling the scour depth (Table 2). A comparison of correlation coefficients and RMSE values (Table 2) indicate that GRNN predictions are more consistent in comparison to all four predictive equations. Figure 2 provides a graph between actual and predicted values of scour depth using Froehlich (1988), Froehlich Design (1988), HEC-18 and HEC-18_Mueller equations. Comparisons of results in figure 2 suggest that out of the four empirical relations used in this study, Froehlich (1988) under predicts most of the values whereas remaining three equations over predict the scour depth. Further, a comparison of values as well as the correlation coefficient and RMSE values also suggests a better performance by GRNN approach. The GRNN results in Figure 1 shows less scatter in the data points in comparison to the predictive equations (Figure 2).

CONCLUSIONS

This paper investigates the potential of GRNN in predicting the local scour using the field data in comparison to four empirical relations. The results presented in this work are quite encouraging. A major conclusion from this study is that GRNN approach works well in predicting the pier scour depth in comparison to all four empirical relations thus suggesting that GRNN based neural network models has good ability in predicting the scour depth.

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