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APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN ASSESSING THE EQUILIBRIUM DEPTH OF LOCAL SCOUR AROUND BRIDGE PIERS

Ehsan Sarshari
Institute of Mechanical Engineering
École Polytechnique Fédérale de Lausanne EPFL
Lausanne, Switzerland
Email: ehsan.sarshari@epfl.ch

Philippe Mullhaupt
Institute of Mechanical Engineering
École Polytechnique Fédérale de Lausanne EPFL
Lausanne, Switzerland
Email: philippe.muellhaupt@epfl.ch

ABSTRACT

Scour can have the effect of subsidence of the piers in bridges, which can ultimately lead to the total collapse of these systems. Effective bridge design needs appropriate information on the equilibrium depth of local scour. The flow field around bridge piers is complex so that deriving a theoretical model for predicting the exact equilibrium depth of local scour seems to be near impossible. On the other hand, the assessment of empirical models highly depends on local conditions, which is usually too conservative.

In the present study, artificial neural networks are used to estimate the equilibrium depth of the local scour around bridge piers. Assuming such equilibrium depth is a function of five variables, and using experimental data, a neural network model is trained to predict this equilibrium depth. Multilayer neural networks with backpropagation algorithm with different learning rules are investigated and implemented. Different methods of data normalization besides the effect of initial weightings and overtraining phenomenon are addressed. The results show well adoption of the neural network predictions against experimental data in comparison with the estimation of empirical models.

1 INTRODUCTION

Every year a considerable number of bridges is destroyed due to the scour phenomenon with their piers and abutments. For instance, seventeen bridges were destroyed during the flash flood in 1987 in the United States [1]. The costs of damages to the bridges and highways of the United States caused by local floods during an eight year period studied in [2], were estimated around 100 million U.S. dollars per disaster. Scour is a phenomenon during which the river bed sediments run from the upstream to the downstream and causes damage in the marine structures foundation. Shoreline protection manual spotted the word "scour" instead of the word "erosion" in 2001 to distinct these two kinds of damages in marine structures.

The appropriate estimation of equilibrium depth of local scour is of paramount importance in bridge construction. Underestimating the scour depth can result in the destruction of the bridges. However, an overestimated prediction can lead to extra expenses in the construction of the bridges. It is therefore imperative to make a proper estimation of the equilibrium depth of local scour in an effective design of a bridge. Several methods have been proposed in the literature to predict the equilibrium depth of local scour. These methods can be broadly categorized in three classes, namely the methods associated with the empirical, theoretical, and those based on soft computing.

1.1 Empirical and theoretical prediction methods

The shear stress at the bottom of the scour hole has been approximated in [3]. A model has been presented in [4] to assess the flow field around the upstream of the scour hole. It has been shown that the scour hole width is related to the flow depth as well as the pier diameter. Making a physical model and applying clear water scour conditions, the effects of river bed sediment was investigated in [5].

Predictions from different empirical methods are somewhat different when compared. On the other hand, these methods usually result in conservative predictions [6]. Making physical models is expensive as well as time consuming. However, the validity of the results from these methods highly depends on the local data.

The theoretical methods have stronger analytical reasoning as compared to the empirical methods. Different parameters which affect the scour have been investigated in [7].

1.2 Soft computing based prediction methods

Empirical and theoretical methods can provide a comprehensive intuition about different aspects of a phenomenon. However, the progress made in the development of the soft computing methods led to a widespread use of these methods in most engineering fields [8, 9]. Artificial neural networks have been also utilized in the field of river management [10]. The bayesian neural networks applied in [11] to assess the time-dependent scour depth.

In this paper, a neural network model is applied to assess the equilibrium depth of local scour. The experimental data of bridges with circular piers are used to train the neural networks (see 'Section 4'). These data were obtained under steady state and clear water conditions in rivers with uniform bed sediments.

Neural networks consist of simple elements which operate in parallel and simultaneously. These elements have been inspired from biologic systems and have several connections with weights. Through a proper set of these connection weights determined by the use of an appropriate learning rule such as the well-known backpropagation, the neural network will be able to mimic a desired function. The purpose in the training of a neural network is usually to track output vectors (targets) against given input vectors. This is done during certain numbers of epochs in the training process. In each epoch the network output vector is compared to the corresponding target vector and the error is used to modify the connection weights [12].

The paper is organized as follows. In Section 2 the mathematical models of the scour are briefly introduced. Section 3 serves to spell out the architecture of the neural networks model. The model is developed in Section 4 and the results are also discussed at the same section. Eventually, the argument is concluded in Section 5.

2 Local scour and its mathematical model

The river flow regime changes once the flow contacts the bridge piers. This change causes local shear stresses which lead to piers scour. In fact, a three dimensional vortex flow system is created and causes separation of the sediment from the river bed [13]. As shown in fig. 1, the two main reasons for such vortex flows are the wrapping of the flow around the piers and the separation of the flow from these piers. Horseshoe vortex is resulted once the flow is in contact with the piers. On the other hand, the separation of the flow from the piers lead to wake vortex [13, 14].

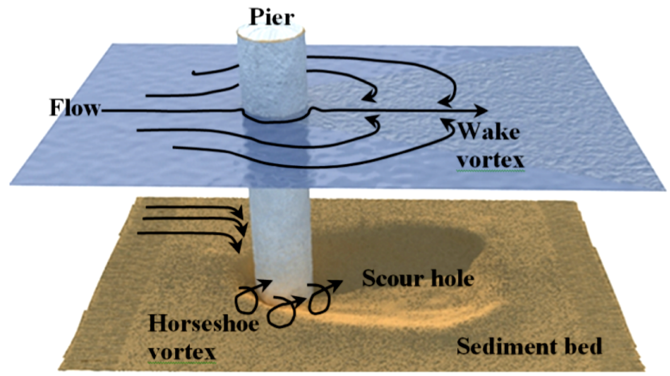

FIGURE 1: river flow regime changes once the flow is in contact with the piers, and separates from the piers as well.

The scour is divided into two classes, namely clear water scour and live bed scour [14]. The manner in which the scour hole extends with time, and the way in which the scour depth relates to the flow velocity depend on the two scour classes.

The mostly referred models presented in [15–17] are used to evaluate the prediction results obtained from the neural networks model in this study. These models are tabulated in table 1.

TABLE 1: models for predicting the equilibrium depth of local scour.

Model name	Description	
Laursen [15]	$d_{se} = 1.35\ D^{0.7}\ Y^{0.3}$	
Hancu [16]	$2.42\ D\ (2\ \frac{U}{U_c} - 1)\left(\frac{U_c^2}{gD}\right)^{1/3}$	
	$d_{se} = D\ f\ (\frac{U}{U_c})\ [2\tanh(\frac{Y}{D})]$	
Breusers [17]	$f(\frac{U}{U_c}) = 0$	$, \frac{U}{U_c} < 0.5$
	$f(\frac{U}{U_c}) = (2\ \frac{U}{U_c} - 1)$	$, 0.5 < \frac{U}{U_c} < 1.0$

Where, D is the pier diameter, U is the average flow velocity, U_c is the critical flow velocity, Y is the flow depth, g is the acceleration due to gravity, and d_{se} is the equilibrium depth of local scour.

3 NEURAL NETWORK ARCHITECTURE

Assuming clear water scour, steady state flow, and homogeneity and non-viscous effect for the bed sediments, the equilibrium depth of the local scour for circular bridge piers is estimated in the present study. The equilibrium depth of the local scour is therefore can be estimated as a function of certain variables [18], given in eq. (1).

$$d_{se} = \phi(\rho, \mu, U, Y, g, d_{50}, U_c, D) \tag{1}$$

Where ρ is the fluid density, μ is the fluid dynamic viscosity, and d_{50} is the average diameter of the bed sediments.

Though the effect of these variables on the equilibrium depth of the local scour is remarkable, the geometry of the piers as well as the flow contact angle are also parameters that affect the scour depth [19]. In the present study, the equilibrium depth of the local scour is considered to be a function of the variables given in eq. (2).

$$d_{se} = \Omega(d_{50}, D, U, Y, U_c) \tag{2}$$

Use of the data with dimensions in the development of the neural network model can lead to a better estimation of the scour depth [11, 20]. Therefore, in this study, data with dimensions as those of eq. (2) are used to train the multilayer neural network (MLP) model. The five arguments of the function Ω and d_{se} are used as the neural network input and output variables, respectively.

4 NEURAL NETWORK DEVELOPMENT AND THE RESULTS

A multilayer neural network along with the well-known backpropagation of error with five input variables from eq. (2) and d_{se} as the output were used in the development of the network. In order to train and test the network, the experimental data presented in references [3, 4, 6, 21–23] were employed.

The equilibrium depth of the local scour is a stochastic variable. Hence, the analysis of the estimation results is done in the probability domain of the occurrence. To do this, two mathematical expectations known as the root mean square of error (RMS) and the correlation coefficient (CC) are used. These parameters are defined in eq. (3).

$$\begin{aligned} RMS &= \sqrt{\sum_{i=1}^{n} (\rho_i - t_i)^2 / n} \\ CC &= \sum_{i=1}^{n} (\rho_i - \bar{\rho}_i)(t_i - \bar{t}_i) \Big/ \sqrt{\sum_{i=1}^{n} (\rho_i - \bar{\rho}_i)^2 (t_i - \bar{t}_i)^2} \end{aligned} \tag{3}$$

Where t_i and p_i are, respectively, the actual (target) and estimated values for the equilibrium depth of the local scour.

An important factor in the performance of the neural network is the proper pre-processing of the data used in the network training. These data are often normalized in an appropriate range such as [-1,+1]. Two different methods were used in the normalization process in this study. In the first method, based on eq. (4), the data are normalized in such a way as to have a zero mean and standard deviation equal to unity. The second method assumes eq. (5) in normalizing the data in the range [-1,+1].

$$p_n = \frac{p - p_{min}}{\mathrm{std}(p)} \tag{4}$$

$$p_n = \frac{2(p - p_{min})}{p_{max} - p_{min}} - 1 \tag{5}$$

Where p_n and p are the matrices of the normalized and un-normalized inputs, respectively, p_{min} and p_{max} are the vectors containing the smallest and largest row elements of matrix p, and $\mathrm{std}(p)$ is the vector containing the standard deviation of each row of matrix p. The un-normalized data relating to the critical flow velocity along with the normalized data from the two methods are depicted in fig. 2.

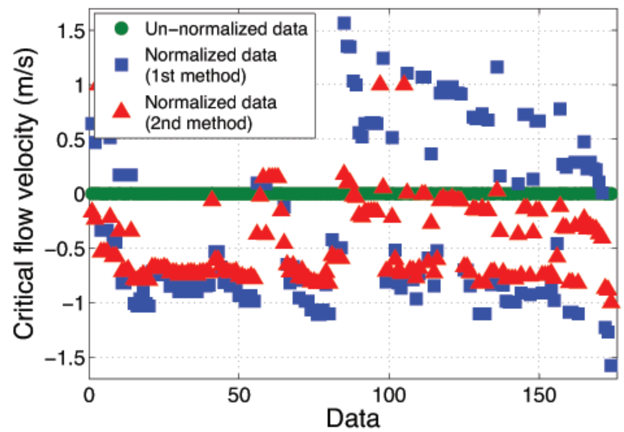

FIGURE 2: the un-normalized data relating to the critical flow velocity along with the normalized data.

Two neural networks were designed and trained using each of the two normalized data explained earlier. Comparison of the performance results obtained by these two networks helps determine the better data normalization method. fig. 3 shows the estimation results of these two neural networks. This figure indicates that the second method of data normalization as the preferred one.

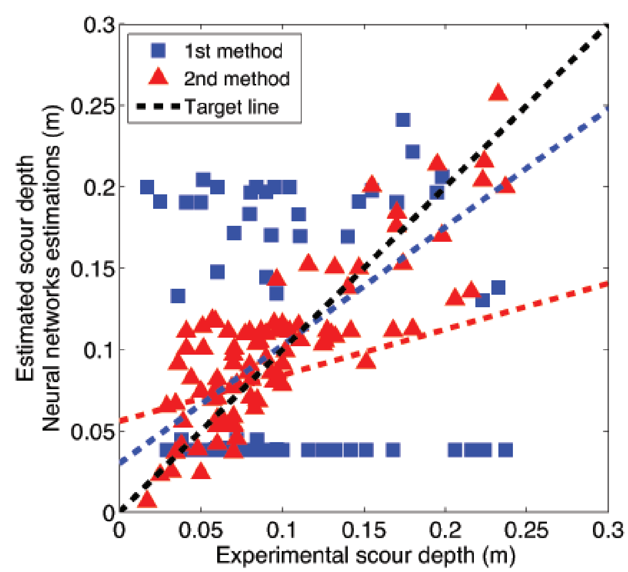

FIGURE 3: comparison of the two different data normalization methods used in this study.

TABLE 2: choosing the combination set of initial weights and number of hidden neurons resulting in the best network performance from the cases examined.

number of neurons	2	3	4	5	6	7	8	9	10	11	12
initial weight index number	3	23	3	17	4	11	37	31	21	32	28
RMS	0.040	0.043	0.042	0.030	0.076	0.063	0.065	0.253	0.073	0.135	0.247
CC	0.675	0.675	0.741	0.821	0.569	0.566	0.587	0.441	0.467	0.504	0.388

The network initial weights were randomly assigned, as normally done. This was done for a set of 41 different initial weight values along with different number of neurons in the hidden layer so as to choose the set leading to the best result. The number of hidden neurons was changed from 2 to 12, leading to a total combination of 451 cases. According to the results given in table 2, among the cases examined, the combination set with the best results corresponds to the case with 5 hidden neurons and weight values of no. 17.

The RMS and CC for the networks with different number of hidden neurons are depicted in fig. 4. It can be observed that the best network estimate corresponds to the case with 5 hidden neurons.

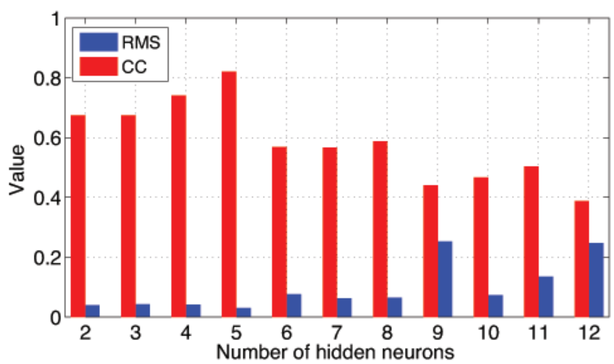

FIGURE 4: the bar chart showing the number of hidden neurons resulting in the best network performance from the cases examined.

Once the "best" combination set was determined with respect to the number of hidden neurons, the next step was to find the best number of epochs to train the network while at the same time avoiding the network overtraining. To do this, different training sessions were performed changing the epochs from 25 to 1000. It was observed that the best network estimate was obtained with the case of 286 epochs.

Having obtained the best network performance among the cases examined, the final task was to determine which learning rule among the limited number of rules, given in table 3, was the most proper for this problem.

The performance of the developed neural network was shown in fig. 5 in terms of the RMS and CC for the different

TABLE 3: the learning rules used in the present study from Matlab®. software.

Abb.	Description
OSS	one step secant BPG (backpropagation)
GDA	gradient Descent with Adaptive lr BPG
GDX	gradient Descent with momentum and adaptive lr BPG.
RP	resilient BPG
CGF	conjugate Gradient BPG with Fletcher-Reeves updates
CGP	conjugate Gradient BPG with Polak-Ribiere updates
CGB	conjugate Gradient BPG with Powell-Beale restarts
SCG	scaled Conjugate Gradient BPG
LM	levenberg-Marquardt BPG

learning rules examined. It demonstrates that the Levenberg-Marquardt rule (LM) offers the best estimate. This rule was also shown to have the fastest convergence rate as well.

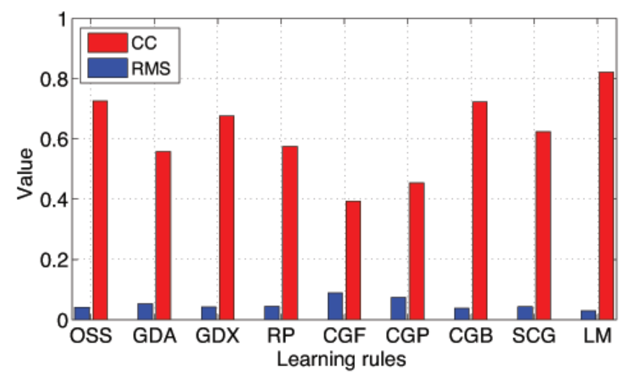

FIGURE 5: choosing the most proper learning rule from among a limited number of rules.

The results for the estimate of the equilibrium depth of the local scour are depicted in fig. 6. In addition, the results obtained from the empirical models introduced in table 1 are also shown in figs. 6 to 8.

As can be observed from these figures, the neural network model offers the best estimate for the equilibrium depth of the

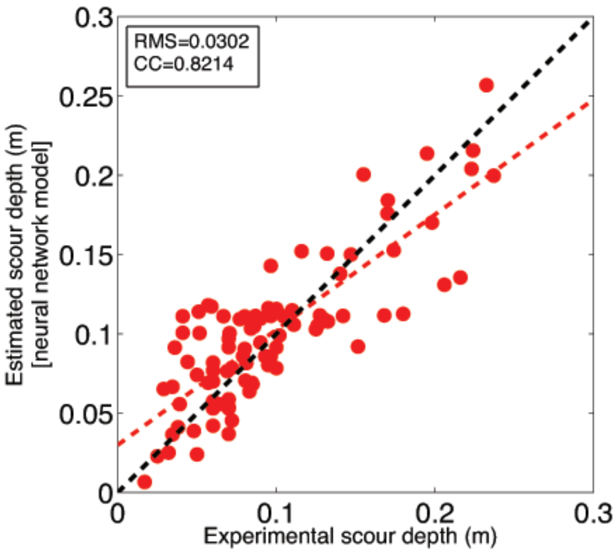

FIGURE 6: estimate for the equilibrium depth of the local scour from the neural network model.

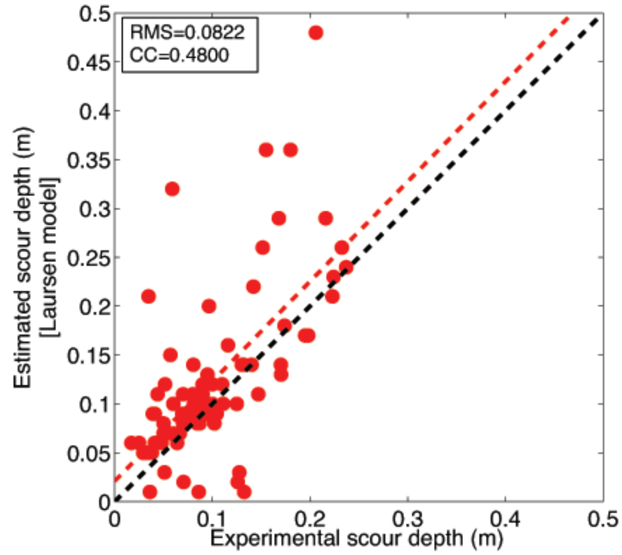

FIGURE 7: estimate for the equilibrium depth of the local scour from the Laursen model.

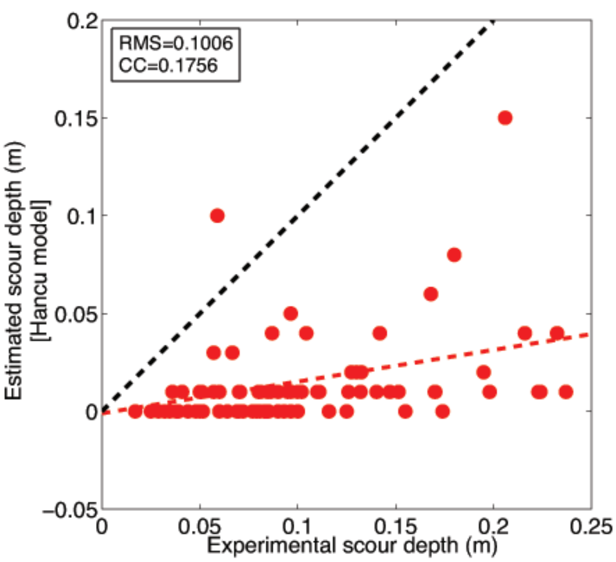

FIGURE 8: estimate for the equilibrium depth of the local scour from the Hancu model.

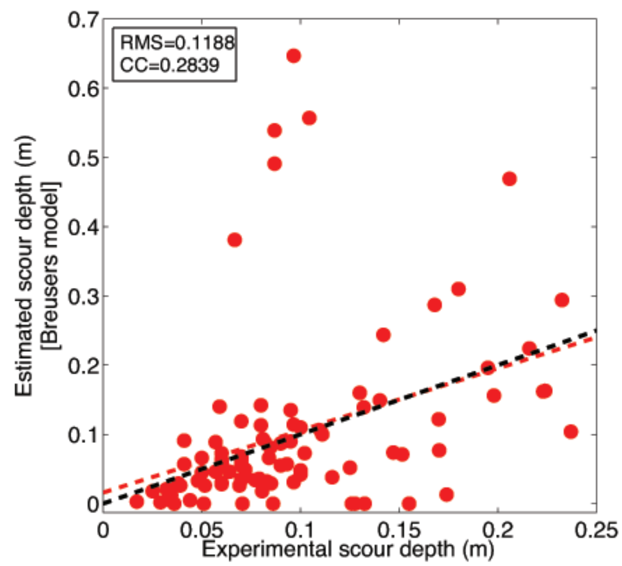

FIGURE 9: estimate for the equilibrium depth of the local scour from the Breusers model.

local scour. The performance of these models is also given in table 4 and can be compared.

TABLE 4: comparison of the estimates for the equilibrium depth of the local scour obtained from the different models.

Model	Laursen	Hancu	Breusers	neural network
RMS	0.0822	0.1006	0.1188	0.0302
CC	0.4800	0.1756	0.2839	0.8214

5 CONCLUSION

An efficient bridge design requires a proper estimate for the equilibrium depth of the local scour. Use of empirical models for such estimations can be time consuming as well as costly. These models often lead to an overestimate for the scour depth. In addition, due to the inherent complexity of the scour problem, deriving an accurate theoretical model is extremely difficult.

Artificial neural network was used to estimate the equilibrium depth of the local scour. Having observed that the neural network model offers a better performance, a combination of several different cases was also done in order to find the best number of hidden neurons and initial weights for the neural network for the cases examined.

It has been shown that the neural network estimation is more accurate in comparison with the performance results obtained from the empirical models. The data used to train the network were a combination of data obtained from several numbers of bridges. Therefore it can be expected that the developed neural network model works regardless of the local conditions governed by the river flow regime.

The efficiency of using neural networks model comparing to the classical methods to estimate the scour depth was illustrated in this study. However, the performance of the neural networks-based methods can vary depending on the choice of the network type. Adoption of different network types may improve the results.

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