ARTIFICIAL NEURAL NETWORK PREDICTION OF MAXIMUM SCOUR HOLE DOWNSTREAM HYDRAULIC STRUCTURES

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ABSTRACT

The prediction of scour hole downstream a hydraulic structure 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) modeling using back-propagation learning technique was formulated to predict the maximum scour hole depth and length downstream hydraulic structure. The data used to train the ANN was obtained from a test series of physical model. The discharge, velocity, gate opening, bed material and length of apron were used as input parameters to ANN while scour hole depth and length as the output parameters. 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. An advantage of the use of ANN in the prediction of maximum scour hole depth and length that it will certainly decrease the cost and time for physical modeling and help in simulating different hydraulic conditions of the hydraulic structure.

Keywords: Hydraulic Structures, Stilling Basin, Physical Models, Scour Hole, Artificial Neural Networks

INTRODUCTION

Stilling basins are used mainly to ensure the safety of hydraulic structures against the erosive power of the issuing high velocity jet in the downstream. In order to study the stilling basins of the sluiceways that recently constructed along the Nile River, such as New Esna Barrage, New Naga Hammadi Barrage, and the future similar irrigation projects, physical models are made through hydraulic flumes which usually are two dimensional physical model, (AbddelAzim, 2005). To investigate different design of sluiceway stilling basin through obtaining suitable stilling basin that gives minimum scour downstream the apron, the best velocity distribution along the stilling basin, minimum velocity near bed, the shortest length of submerged hydraulic jump and the highest energy dissipation. The study was carried out in case of submerged hydraulic jump take place downstream the gate.

During the testing of the physical model of the New Esna Barrage, it has been observed that significant scour occurred immediately downstream the stilling basin that exceeded the expected values. This observation has been further verified during the monitoring of the structure. The same findings were repeated with the model testing of the New Naga Hammadi Barrage design. In both cases, a significant design modification has been introduced using trial and error based on expert opinions. Therefore, this problem highlights the need to develop some design criteria suitable for Nile River conditions to be used in the future applications (AbddelAzim, 2005).

Applications of ANN in the Field of Scour

Review of the applications of the ANN in different branches of Water Engineering could be found in Negm (2002). In the field of scour, very little number of studies are available in the literature. Kheireldin (1999) used the ANN to develop a prediction model to predict the maximum depth of scour around bridge abutments. It was concluded that the ANN approach performed well for one set of data (305 runs) and its performance was not satisfactory for another set of data (66 runs). Liriano and Day (2001) applied the ANN to develop a prediction model to predict the scour depth at culvert outlet. They used in addition to their own data the previously published ones as training data to the proposed ANN model. They concluded that the ANN could be used to predict the scour depth at the culvert outlet with a greater accuracy compared to the available empirical scour formulae. Negm (2002) developed ANN model to predict the length and depth of hydraulic jump while Negm et al. (2002) utilized ANN prediction model for maximum scour hole depth downstream of sudden expanding stilling basins. The present study presents a new developed ANN to predict both length and depth of the scour hole downstream hydraulic structures, case of barrage.

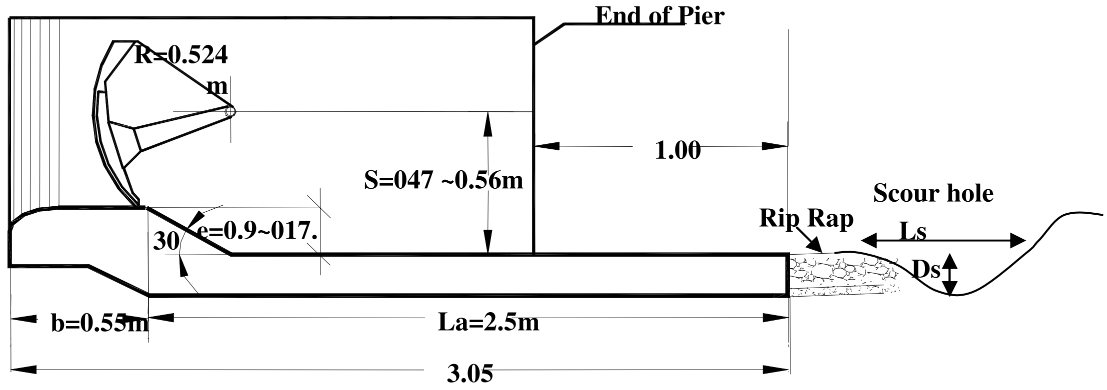

Figure 1 Stilling basin setup

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks, ANN's, as they are known today, originate from the work of McCulloch and Pitts (1943), who demonstrated the ability of interconnected "neurons" to calculate some logical functions. Hebb (1949) pointed out the importance of the synaptic connections in the learning process. Later, Rosenblatt (1958) presented the first operational model of a neural network: the ‘Perceptron’. The perceptron, built as an analogy to the visual system, was able to learn some logical functions by modifying the synaptic connections.

ANNs are massively parallel, distributed and adaptive systems, modeled on the general features of biological networks with the potential for ever improving performance through a dynamical learning process (Bavarian, 1988). Neural networks are made up of a great number of individual processing elements, the neurons, which perform simple tasks. A neuron, schematically represented in Fig. 2, is the basic building block of neural network technology which performs a nonlinear transformation of the weighted sum of the incoming inputs to produce the output of the neuron. The input to a neuron can come from other neurons or from outside the network. The nonlinear transfer function can be a threshold, sigmoid, a sine or a hyperbolic tangent function.

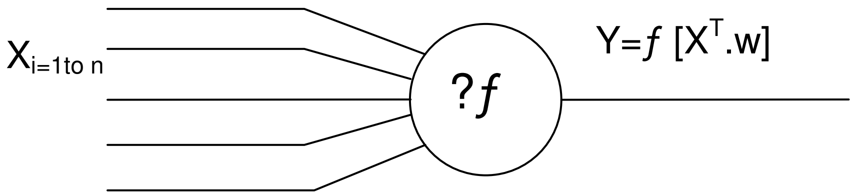

Figure 2 a Simple processing neuron

Neural networks are comprised of a great number of interconnected neurons. There exists a wide range of network architectures. The choice of the architecture depends upon the task to be performed. For the modeling of physical systems, a feed forward layered is usually used. It consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. In the present work, a three-layer feed forward network was used.

In a neural network, the knowledge lies in the interconnection weights between neuron and topology of the networks (Jones and Hoskins, 1987). Therefore, one important aspect of a neural network is the learning process whereby representative examples of the knowledge to be acquired are represented to the network so that it can integrate this knowledge within its structure. Learning implies that the processing element somehow changes its input/output behavior in response to the environment. The learning process thereby consists in determining the weight matrices that produce the best fit of the predicted outputs over the entire training data set. The basic procedure is to first set the weights between adjacent layers to random values. An input vector is then impressed on the input layer and is propagated through the network to the output layer. The difference between the computed output vector of the network and the target output vector is then adapt the weight matrices using an iterative optimization technique in order to progressively minimize the sum of squares of the errors (Hornik et al., 1989). The most versatile learning algorithm for the feed forward layered network is back-propagation (Irie and Miyanki, 1988). The back-propagation learning law is a supervised error-correction rule in which the output error, that is, the difference between the desired and the actual output is propagated back to the hidden layers. Now, if the error at the output of each layer can be determined, it is possible to apply any method which minimizes the performance index to each layer sequentially. Multi-Layer Perceptrons (MLP) are perhaps the best-known type of feed forward networks. MLP has generally three layers: an input layer, an output layer and an intermediate or hidden layer. Neurons in the input layer only act as buffers for distributing the input signal xi to neurons in the hidden layer. Each neuron *j* in the hidden layer sums up its input signals xi after weighting them with the strengths of the respective connections W_{ji} from the input layer and computes its outputs y_j as a function *f* of the sum, as:

$$y_j = f\left(\sum W_{ij} X_i\right) \tag{1}$$

Where, *f* can be a simple threshold function or a sigmoid, hyperbolic tangent or radial basis function.

The output of neurons in the output layer is computed similarly. The back-propagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change $\sum w_{ji}$ in the weight of a connection between neurons j and i as follows.

$$\Delta W_{ij} = \eta \delta_j X_i \tag{2}$$

where η is a parameter called the learning rate and δj is a factor depending on whether neuron j is an output neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(y_j^t - y_j\right) \tag{3}$$

and for hidden neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q \left(W_{qj}\delta_q\right) \tag{4}$$

In equation (3), net_j is the total weighted sum of input signals to neuron j and $y_j(t)$ is the target output of neuron j. As there are no target outputs for hidden neurons, in equation (4), the difference between the target and actual output of a hidden neuron j is replaced by the weighted sum of the δ_q terms already obtained for neurons *q* connected to the output of *j*. Thus, iteratively, beginning with the output layer, the δ_j term is computed for neurons in all layers and weight updates determined for all connections.

Back-propagation searches on the error surface by means of the gradient descent technique in order to minimize the error. It is very likely to get stuck in local minima.

Various other modifications to back-propagation to overcome this aspect of back-propagation have been proposed and the Levenberg-Marquardt modification (Hagan and Menhaj, 1994) has been found to be a very efficient algorithm in comparison with the others like Conjugate gradient algorithm or variable learning rate algorithm.

Levenberg-Marquardt works by making the assumption that the underlying function being modeled by the neural network is linear. Based on this calculation, the minimum can be determined exactly in a single step. The calculated minimum is tested, and if the error there is lower, the algorithm moves the weights to the new point. This process is repeated iteratively on each generation. Since the linear assumption is ill-founded, it can easily lead Levenberg-Marquardt to test a point that is inferior (perhaps even wildly inferior) to the current one. The clever aspect of Levenberg-Marquardt is that the determination of the new point is actually a compromise between a step in the direction of steepest descent and the above-mentioned leap. Successful steps are accepted and lead to a strengthening of the linearity assumption (which is approximately true near to a minimum). Unsuccessful steps are rejected and lead to a more cautious downhill step. Thus, Levenberg-Marquardt continuously switches its approach and can make very rapid progress.

The equations for changing the weights during training in Levenberg-Marquardt method are given as follows:

$$Modifying \Rightarrow \Delta\overrightarrow{W} = \left(J^T J + \mu I\right)^{-1} J^T \vec{e} \tag{5}$$

where J is the Jacobian matrix of the derivative of each error to each weight, μ is a scalar and e is an error vector. The Levenberg-Marquardt algorithm performs very well and its efficiency is found to be of several orders above the conventional back propagation with learning rate and momentum factor.

EXPERIMENTAL DATA COLLECTED FOR ANN TRAINING

Physical model was used to simulate one bay of the sluiceway consisting of a gated sill and two half-piers (9.5 cm thick each) symmetrically installed on both wall sides. A bras radial gate with a radius of 0.524 m is used to regulate the flow. The experiments were conducted using a 1.0 m wide, 26.0 m long and 1.20 m deep flume. The sidewalls along the entire length of the flume are made of glass with steel-frames, to allow visual investigation of the flow patterns. Different shapes of stilling basins will be used to investigate the shape that can mostly dissipate the energy of the flow downstream the radial gate.

The test setup had a horizontal apron with different elevations. The series consisted of three designs and the test series were referred to as series, where the vertical distances (e) between the sill under the gate and the apron were 0.17 m, 0.00m and 0.09 m. Also, the inclination of the apron, downstream the gate had an angle of $\alpha = 30^o$. Figure 1; show the geometric shapes of this test setup.

RESULTS OF NEURAL MODELLING

The critical step in building a robust ANN is to create an architecture, which should be as simple as possible and has a fast capacity for learning the data set. The robustness of the ANN will be the result of the complex interactions between its topology and the learning scheme. The choice of the input variables is the key to insure complete description of the systems, whereas the qualities as well as the number of the training observations have a tremendous impact on both the reliability and performance of the ANN. Determining the size of the layers is also an important issue. One of the most used approaches is the constructive method, which is used to determine the topology of the network during the training phase as an integral part of the learning algorithm. The common strategy of the constructive methods is to start with a small network, train the network until the performance criterion has been reached, add a new node and continue until a 'global' performance in terms of error criterion has reached an acceptable level. The final architecture of neural net used in the analysis is shown in Fig. 3.

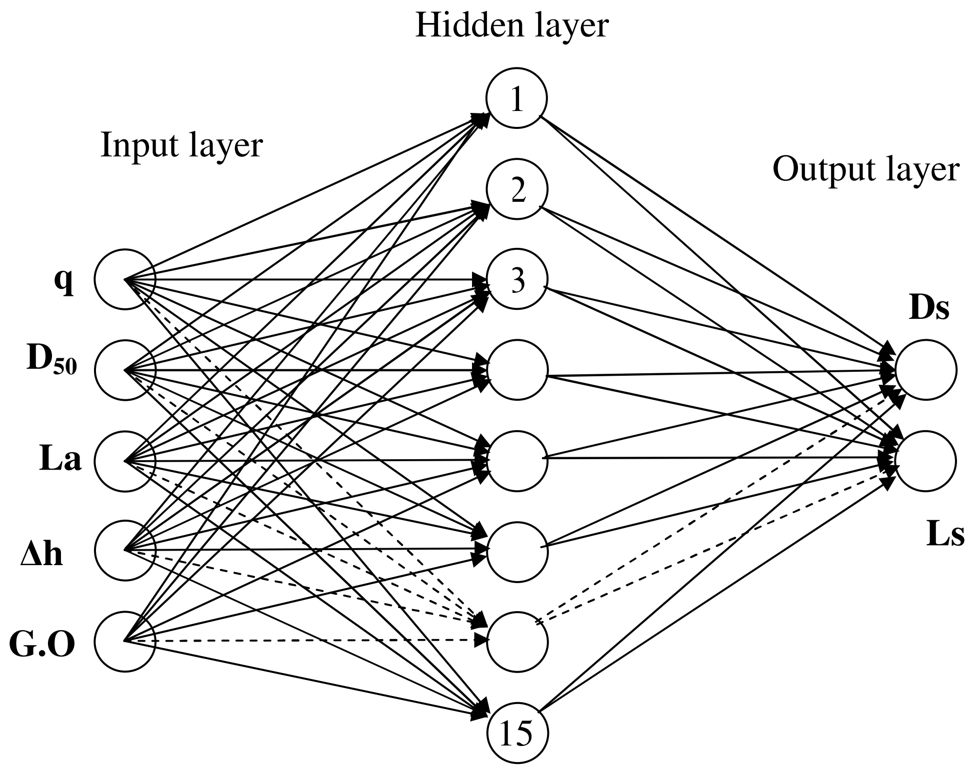

Figure 3 Back-Propagation Algorithm

Input parameters include discharge (q), head difference (Δh), apron length (La), downstream bed material (D_{50}) or riprap while the output target parameters were the depth and length of downstream scour hole as D_s and L_s respectively. Input data collected from physical model were used for training. Two third of the data were utilized for training while the rest of the data were for verification purpose. Figure 4 shows the comparison between the measured maximum scour hole depth and ANN estimated one. The plot shows a good prediction through the R^2 which equal to 0.98.

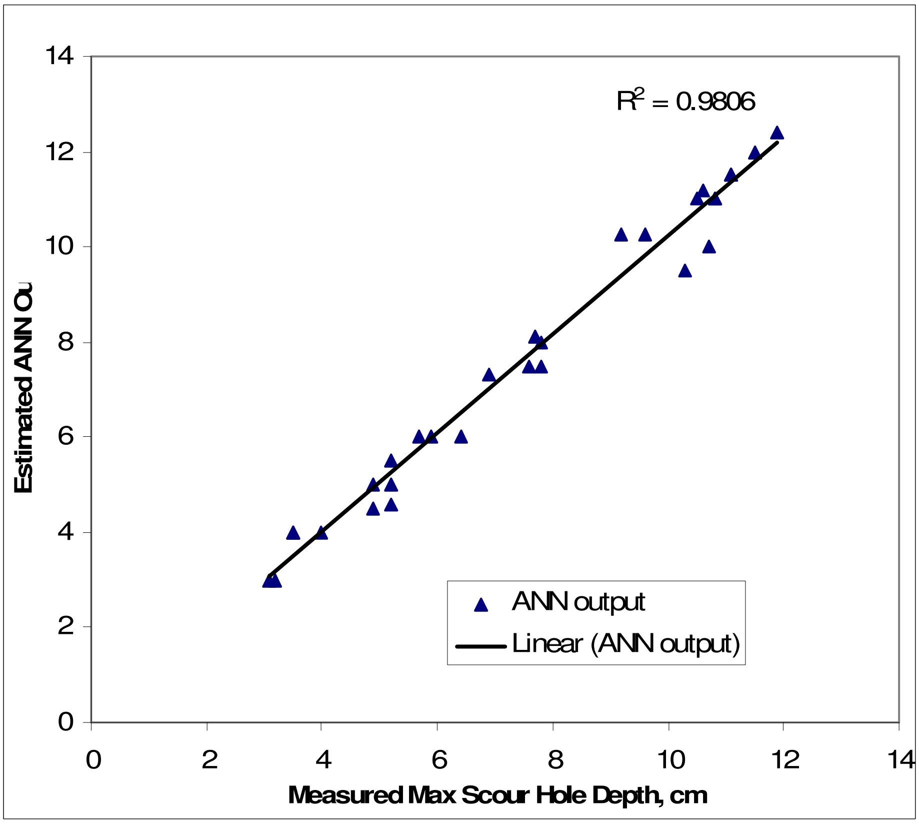

Figure 4 Comparison between measured max scour depths and estimated one via ANN

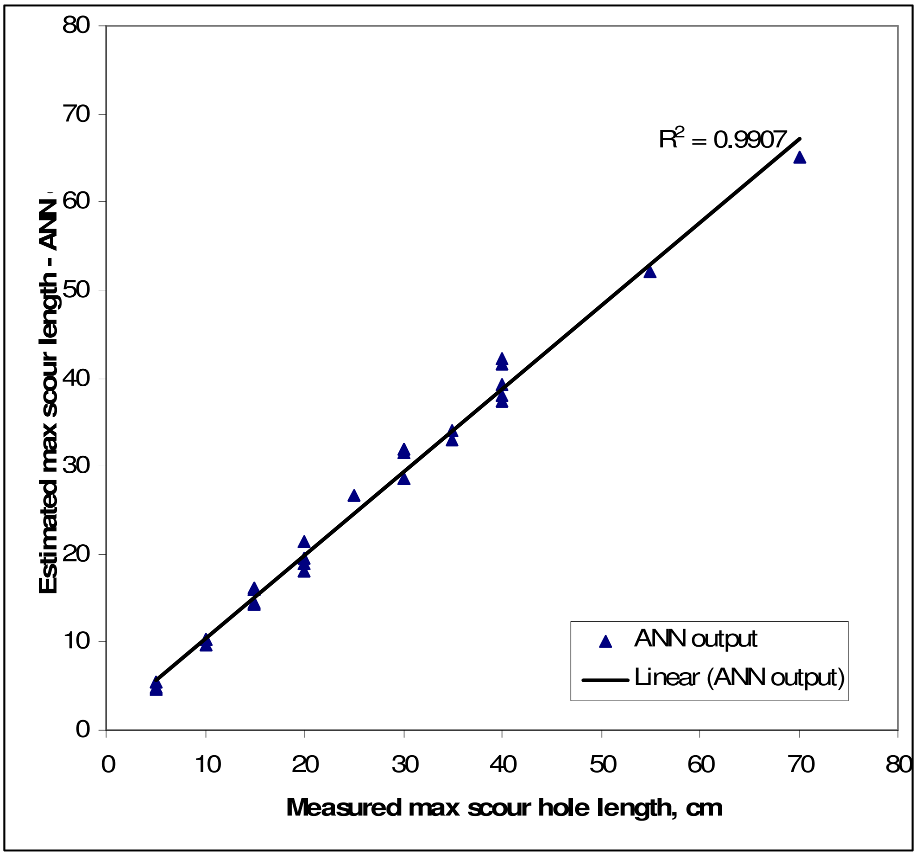

Figure 5 Comparison between measured max scour lengths and estimated one via ANN

Figure 5 shows the comparison between the measured maximum scour hole length and ANN estimated one. The plot shows a good prediction through the R^2 which is equal to 0.99.

A sensitivity analysis was done through eliminating one of the parameters and use there parameters as only available input data and estimate the scour hole depth and length. Through this process, it is found that R^2 was decreased due to missing on of the input data set. The lower value for R^2 represents the high sensitive parameter while the less value for representing the less sensitive one, which was found to be in the sequence with discharge, head difference, bed material or riprap, apron length respectively as the high sensitive to the less one.

CONCLUSIONS

The results presented in this paper have clearly shown that the neural network methodology can be used efficiently to predict the scour hole depth and length. The main advantage of neural networks is to remove the burden of finding an appropriate model structure or to find a useful regression equation. The network showed excellent learning performance and achieved good generalization.

ANN prediction for maximum scour hole for depth and length decreases the cost and time for performing physical models but will not replace it.

Sensitivity analysis with the trained neural net or during training could provide valuable additional information on the relative influence of various parameters.

The scour hole depth and length downstream hydraulic structure have been found to increase continuously with discharge, head difference, bed material or riprap, apron length, respectively.

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