Artificial Neural Network Prediction Of Maximum Scour Around Brige Piers Due To Aquatic Weeds' Racks

T, Gamal[1], M. Hosny[2], T, Al_Samman[3] And N, Aboul_Atta[4]

[1]Assistant researcher; Channel Maintenance Research Institute; National Water Research Center, Egypt.
[2]Professor; National Water Research Center; Ministry of Water Resources and Irrigation; Cairo – Egypt.
[3]Professor; National Water Research Center; Ministry of Water Resources and Irrigation; Cairo – Egypt.
[4]Professor; Irrigation Design; Faculty of Engineering – Ain_Shams University; Cairo – Egypt.

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 depth around bridge piers due to installation of aquatic weeds racks. The data used to train the ANN was obtained from a test series of physical model. The discharge, velocity, Froude number and opening area percentages; unoccupied area by rack element, were used as input parameters to ANN while scour hole 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 hole depth and length that it will certainly decrease the cost and time for physical modeling and help in simulating different hydraulic conditions.

Keywords: Physical Models, Scour Depth, Artificial Neural Networks

1. INTRODUCTION

Most of the open water irrigation channels in Egypt suffer from heavy infestation of aquatic weeds especially the submerged and floating ones that cause lots of hydraulic problems for the open channels such as increasing water losses, obstructing water flow, and reducing channels water distribution efficiencies as well as threat the hydropower plants. Installations of aquatic weeds' racks are commonly used solution for saving the hydropower plants turbines and trapping floating weeds and other trashes. Such installation either use the body of bridge structure for hanging up rack structural elements or insert isolated piers to support aquatic weeds racks' own weight and resist forces exerted by trapped floating weeds and trashes. These construction methodologies may cause excessive local and contraction scour around piers, either bridge' piers or the inserted ones. The current study presented in this manuscript utilizes the ANN technique in developing a simulation and prediction models for the scour behavior around piers due to installation of racks and develops the ANN models for an experimental data as a proof of ANN technique capability for modeling such scour behavior. The experimental data used in the current study for developing the ANN models is the one reported by T.Gamal (2013) for his PhD Thesis.

2. APPLICATIONS OF ANN IN THE FIELD OF SCOUR

In the field of scour, very little number of studies is 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 and its performance was not satisfactory for another set of data. 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 depth downstream of sudden expanding stilling basins. The present study presents a new developed ANN to predict depth of the scour hole downstream hydraulic structures, case of bridge piers.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN's) as they are known today; originate from the work of McCulloch and Pitts (1943), Fig (1), 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 (l958) presented the first operational model of a neural network: The perceptron, built as an analogy to the visual system, was able to learn some logical functions by modifying the synaptic connections.

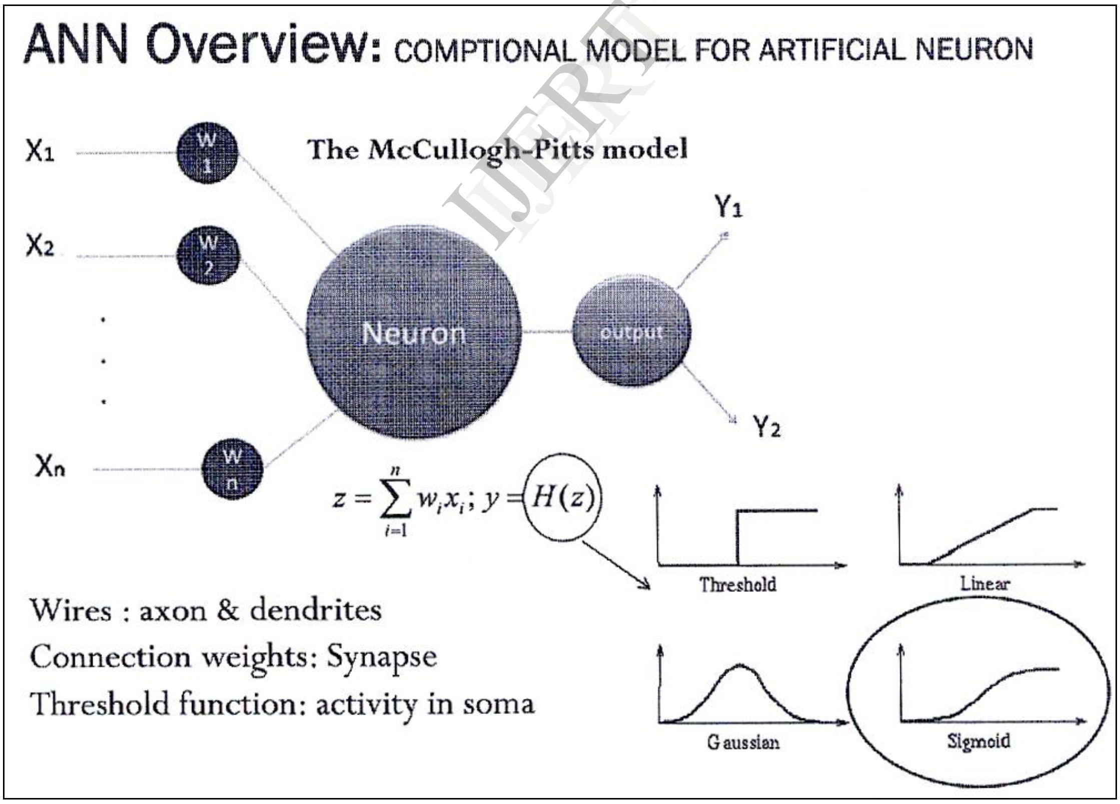


Fig (1) The McCullough-Pitts model

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 cans be a threshold, sigmoid, a sine or a hyperbolic tangent function.

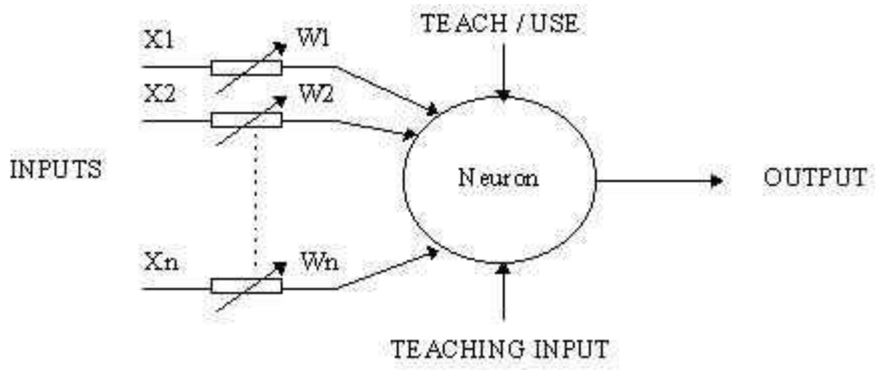


Fig (2). A simple Neuron

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. 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 he 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 x_i 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 of the sum as:

$$y_j = f(\Sigma\, W_{ji}\, X_i) \tag{1}$$

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 $\Sigma\, W_{ji}$ in the weight of a connection between neurons j and i as follows.

$$\Delta\, W_{ji} = \eta\, ó_j\, X_i \tag{2}$$

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

$$ó_j = \{\partial f/\partial_{net\, j}\}\, (y_j^2 - y_j) \tag{3}$$

And for hidden neurons

$$ó_j = \{\partial f/\partial_{net\, j}\}\, \Sigma_q\, (W_{ij}\, ó_q) \tag{4}$$

Where net_j is the total weighted sum of input signals to neuron j and y_j 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 terms already obtained for neurons q connected to the output of j. Thus. Iteratively j, beginning with the output layer, the ó 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 Fig (3). Various other modifications to back-propagation to overcome this aspect of back- propagation have been proposed and the Levenherg-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 he 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).

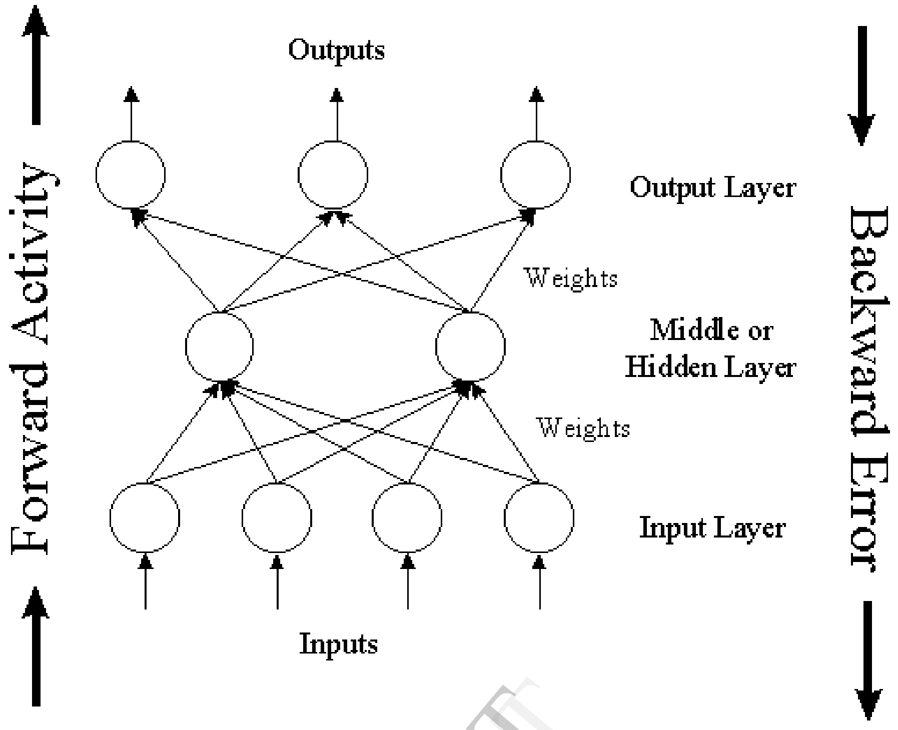


Fig (3) Back Propagation Algorithm

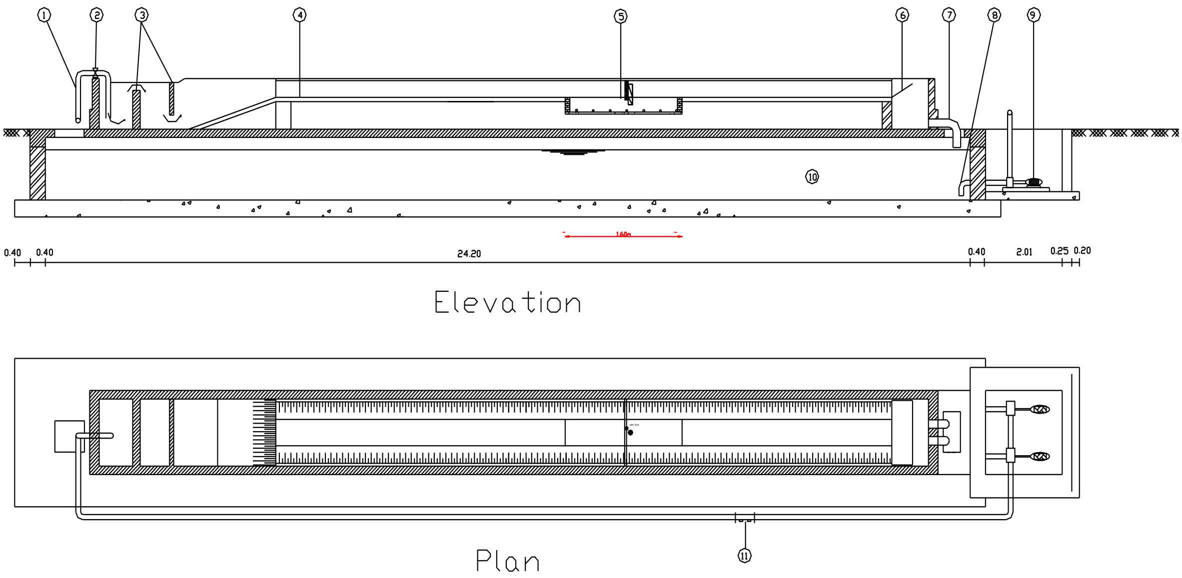
Unsuccessful steps are rejected and lead to a more cautious downhill step. Thus, Levenberg-Marquardt continuously switches its approach and can make very rapid progress. The equations for changing the weights during training in Levenberg-Marquardt method are given as follows:

$$\text{Modifying } \Delta \ddot{W} = (J^T J + \mu I)^{-1} J^T e \qquad (5)$$

Where J is the Jacobian matrix of the derivative of each error to each weight. T 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.

4. EXPERIMENTAL WORK

The experimental work performed by T.Gamal for his PhD Thesis. The work was carried out in the hydraulics laboratory of the Channel Maintenance Research Institute within the National Water Research Center, El_Kanater El_Khairiah, Egypt. The flume used in the experimental work is a reinforced concrete flume and has a total length of 22.10 m. The operating system of this flume is re-circulated through an underground reservoir, with dimensions (24.10 m long, 1.75 m wide, and 1.5 m height) to supply the flume with water. The layout of the flume and all the hydraulic structures within the experiment can be shown in Figs (4), (5).



1 5 inch diameter pipe
2 Control valve
3 Turbulence elimination
4 Horizontal bed trapezoidal flume
5 Sand Basin
6 Tilted tail gate
7 8 inch diameter drain pipe
8 5 inch diameter suction pipe
9 Group of motors and pumps
10 Under ground reservoir
11 Current flow meter

Figure (4) experimental flume and its underground reservoir

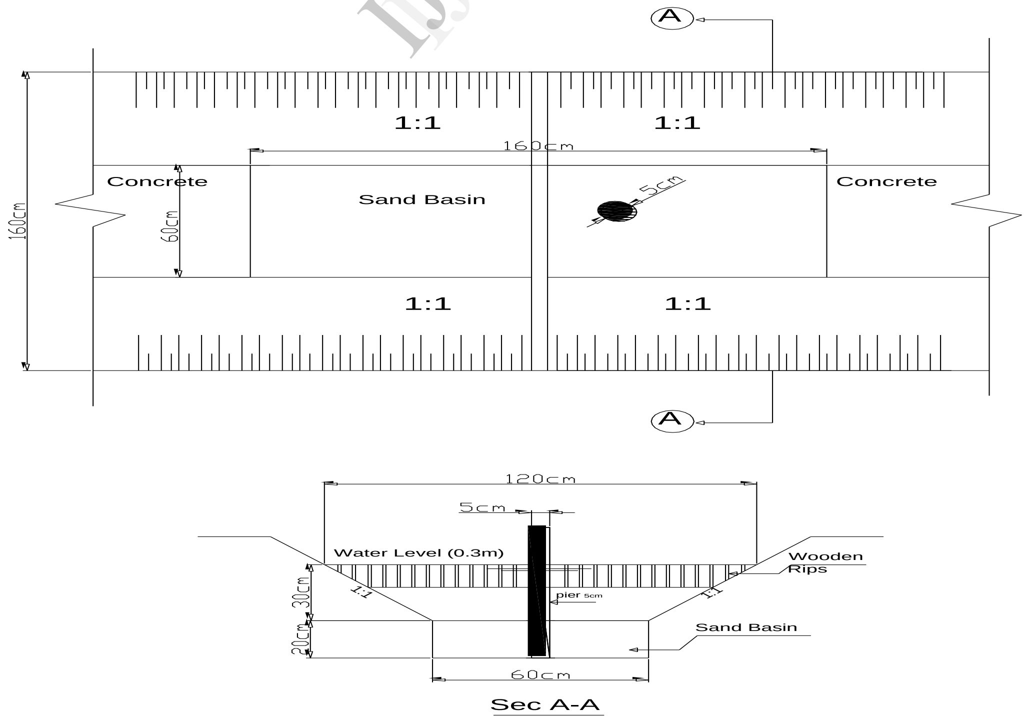


Figure (5). The flume structure and its scoured soil basin

5. SIMULATION CASES AND DATA COLLECTED FOR (ANN)

To investigate and model the scour around piers using ANN technique, the experimental work data of T.Gamal (2013) was utilized in the current study. To fully understand how the scour depth around piers can be affected by weeds' accumulation on aquatic weeds racks, five different discharges were examined for simulation cases in this study; and three various trash racks' depths (2/3, 1/2 and 1/3 of water depth from surface), as water depth kept constant at 30 cm, and for every trash rack's depth, opening areas of trash racks were varied from 10% to 90% Fig (6). Opening area percentages mentioned in table (1) area referred to total water cross section. The simulation cases are divided into three main groups based on racks' depth. The three groups simulate and model the impact of different discharges on scour depth according to various weeds' accumulation percentages and various opening areas.

Table (1), Key inputs and out puts variable for the three network simulation groups.

Groups No	Simulation Case	Variables	Input Variables		Output Variables
First Group	Rack depth = (2/3) water depth	Various Discharges & Various Blocking%	Froude Number	Opening area %	Scour depth
Second Group	Rack depth = (1/2) water depth	Various Discharges & Various Blocking%	Froude Number	Opening area %	Scour depth
Third Group	Rack depth = (1/3) water depth	Various Discharges & Various Blocking%	Froude Number	Opening area %	Scour depth

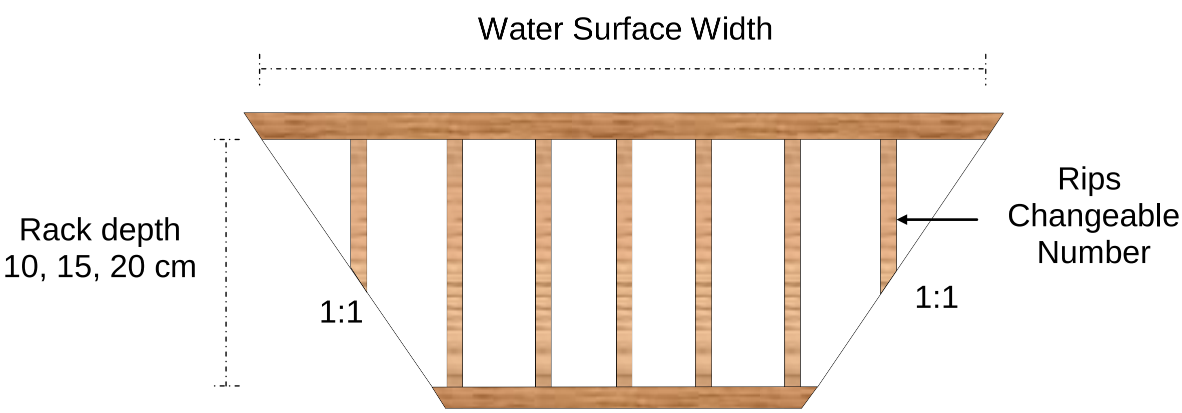


Fig (6) Weed's trash rack prototype

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. Several neural network architectures are designed and tested for each of the sub-simulated cases investigated in the current study to finally determine the best network model to simulate, very accurately, the max scour depths were based on minimizing the Root Mean Square (RMS-error). Figure (7) shows a schematic diagram for a generic neural network.

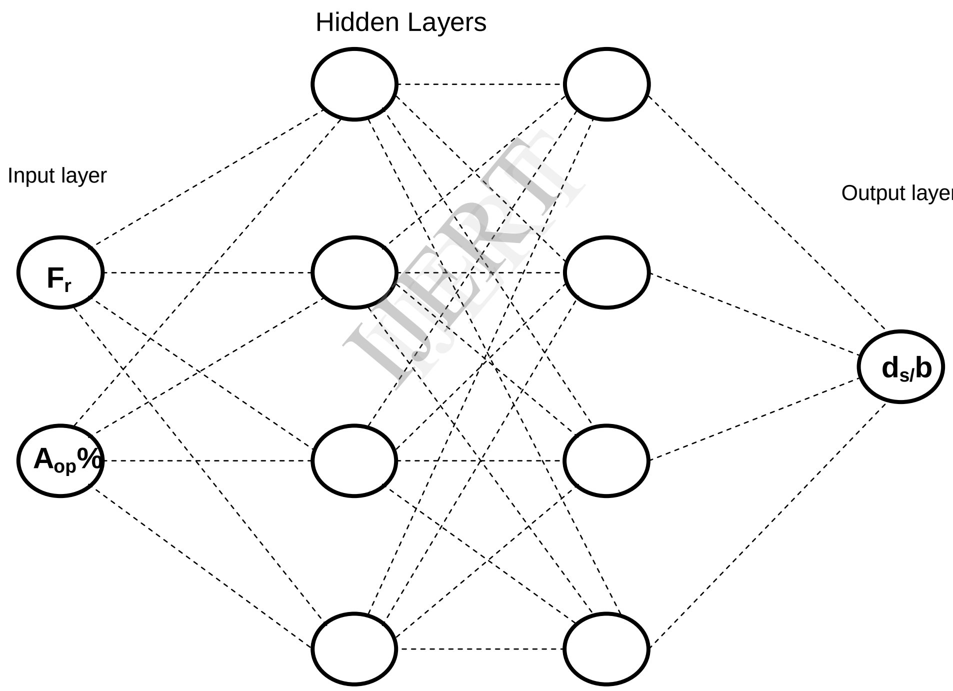


Figure (7) Schematic diagram of a generic neural network

Regarding the adopted activation function within the current developed ANN models, it is important to mention here that some of the developed models incorporated the sigmoid activation function presented in Fig (8). The choice for any activation function, in the different models' development, was based on the power of this function in simulating the real nature of the water surface profile in each case. The Sigmoid function typically has a narrow region about zero wherein the output will be roughly proportional to the input, but outside this region the Sigmoid function will limit to full inhibition or full excitation, Shin (1996). The Sigmoid function can be expressed mathematically as follows:

$$f(\chi) = 1 / (1 + e^{-\chi})$$

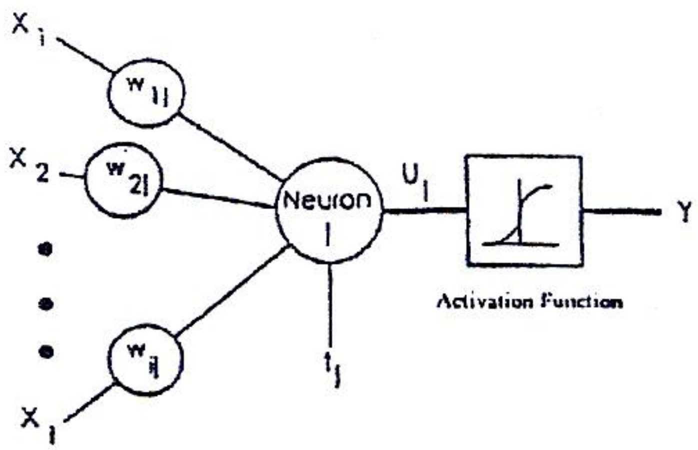


Fig (8) Typical Algorithm of Sigmoid Activation Function

On the other hand, the Hyperbolic function is shaped exactly as the sigmoid one with the same mathematical representation but it ranges from -1 to +1 rather than from 0 to 1. Thus it has the interesting property that there is inhibition near 0, but values at either extreme will be excited to full level, but in opposite sense. In addition, the hyperbolic function can be considered as a switch with an intermediate range where it can be discriminating.

The training parameters of the various network models developed in the current study for the different sub-simulation cases can be described according to their tasks as well as their values for the different developed ANN models as follows:

- Learning Rate (LR): determines the magnitude of the correction term applied to adjust each neuron's weights during training process. LR = 0.5 for all developed ANN models.

- Momentum (M): determines the "life time" of a correction term as the training process takes place. M = 0.7 for all developed ANN models.

- Training Tolerance (TRT): defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process. TRT = 0.03 for all developed ANN models.

- Testing Tolerance (TST): it is similar to Training Tolerance, but it is applied to the neural network outputs and the target values only for the test data. TST = 0.03 for all developed ANN models.

- Input Noise (IN): provides a slight random variation to each input value for every training epoch. IN 0 for all developed ANN models.

- Function Gain (FG): allows a change in the scaling or width of the selected function. FG = I for all developed ANN models.

- Scaling Margin (SM): adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst v1.4 software, Shin (1996), in preparing data for the neural network or interpreting data from the neural network. SM = 0.1 for all developed ANN models

6. RESULTS AND DISCUSSION

As described previously, several ANN models were developed for all the simulated cases investigated within the current study and their modeling designs were presented in table. The results and the prediction power of the developed ANN models in simulating scour behavior in term of depth around piers are presented in a detailed fashion in the following sections according to their simulation group.

The prediction processes results will be presented in graphs' format. However, the maximum percentage relative error between the predicted results and the actual measurements for all ANN models for flow rates for each trash racks depth operation cases are presented in table 1. It is probably worth mentioning here that this percentage relative error is computed based on Equation (6) as follows:

$$PRE = (\text{Absolute Value } (ANN\ PR — AMV) / AMV) * 100 \qquad (6)$$

Where:
PRE: Percentage Relative Error
ANN_PR: Prediction results using the developed ANN model
AMV: Actual Measured Value

Figures (9), (10) and (11) show comparison between the actual measured and predicted scour depth for collected data. It is clear from this figure that the developed ANN models were capable of predicting the scour depth around piers with maximum percentage relative error less than 9%. Since the most important result for evaluating the prediction power of the ANN technique is the percentage relative error; the following figures (12), (13) and (14) presentation will focus on showing this error values. Considering the small values for the maximum percentage relative errors, presented in these figures, It is quite clear that all ANN models developed for the current different flow discharges and racks' depth simulation cases were very successful in predicting the scour depth around piers for the specific previously mentioned discharges.

7. SUMMARY AND CONCLUSIOIN

Lots of experimental work was performed to investigate and measure the impacts of weeds existence in various accumulations at weed racks on the scour behavior around piers. On the other hand, the mathematical modeling efforts for simulating these impacts are still very limited. However, the Artificial Neural Networks (ANN) modeling approach has proven its capabilities in providing very useful information and simulating various physical phenomena. In addition, ANN has been recorded as a very powerful modeling technique and simulation process in predicting the behavior of different engineering systems .The current study was aimed towards utilizing the

ANN technique in investigating the impacts of floating aquatic weeds existence in various percentages at weed racks on scour depths around piers.

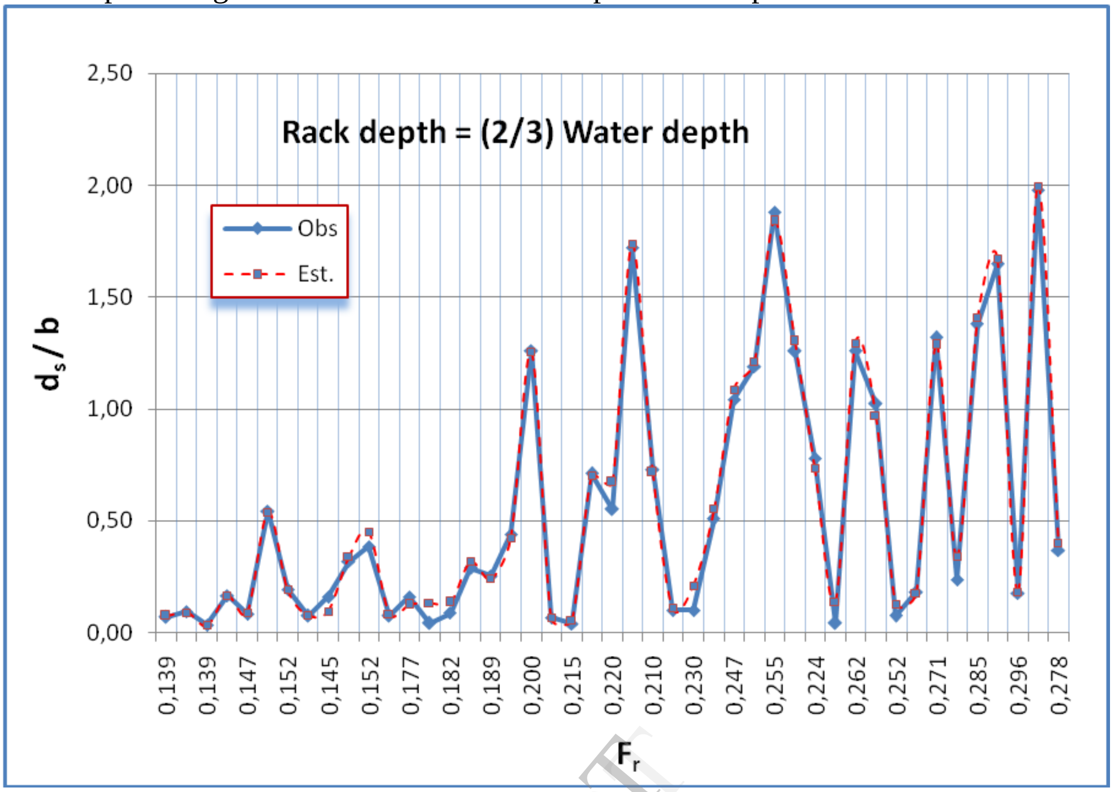


Fig (9). Comparison between measured and predicted (ANN) results of scour maximum depth, rack depth = 2/3 water depth.

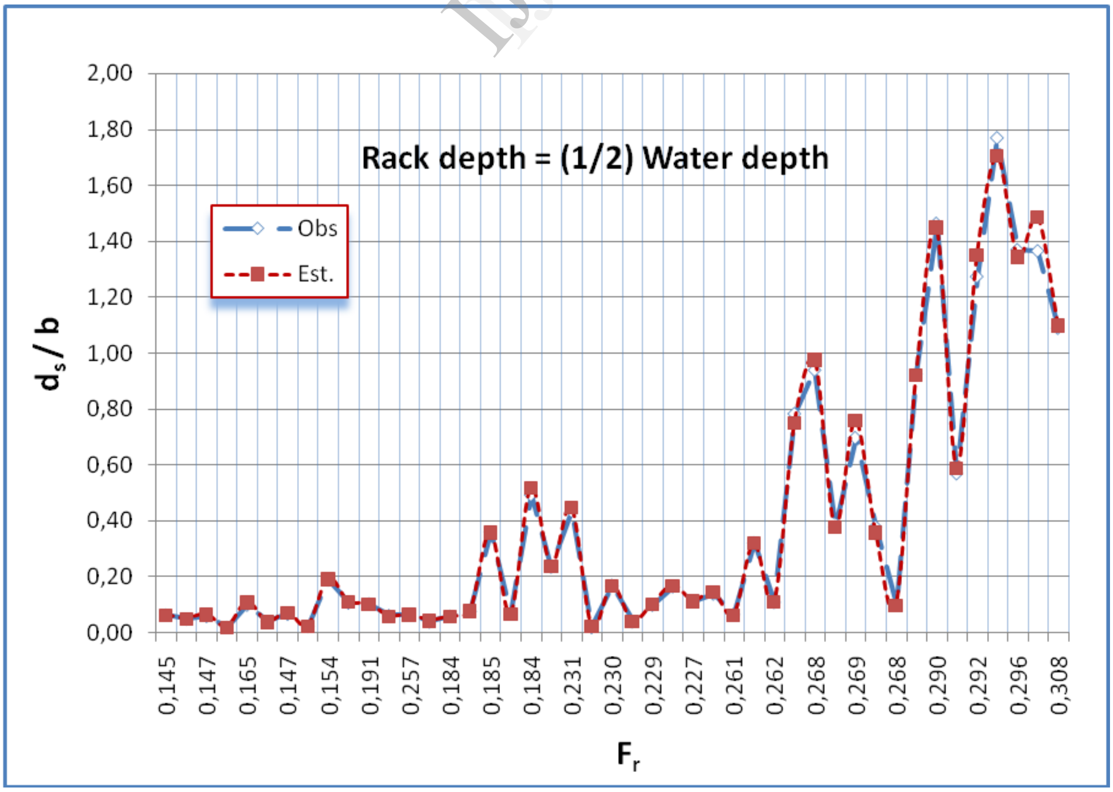


Fig (10). Comparison between measured and predicted (ANN) results of scour maximum depth, rack depth = 1/2 water depth.

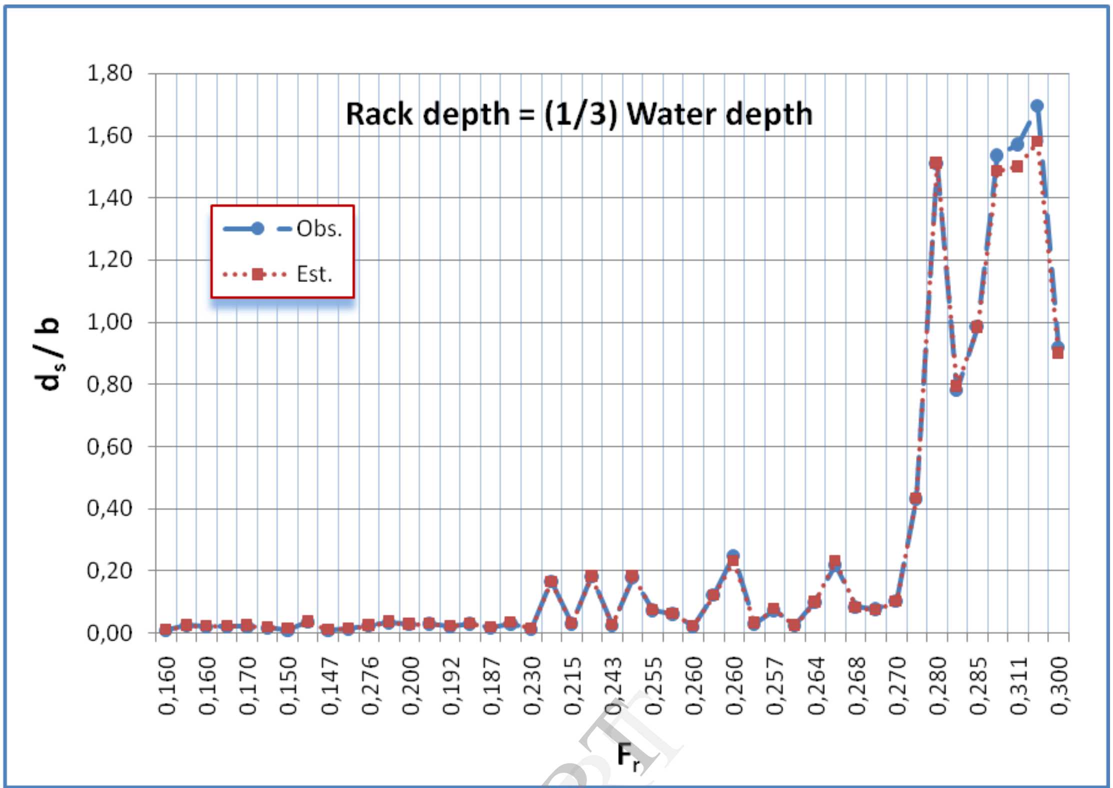
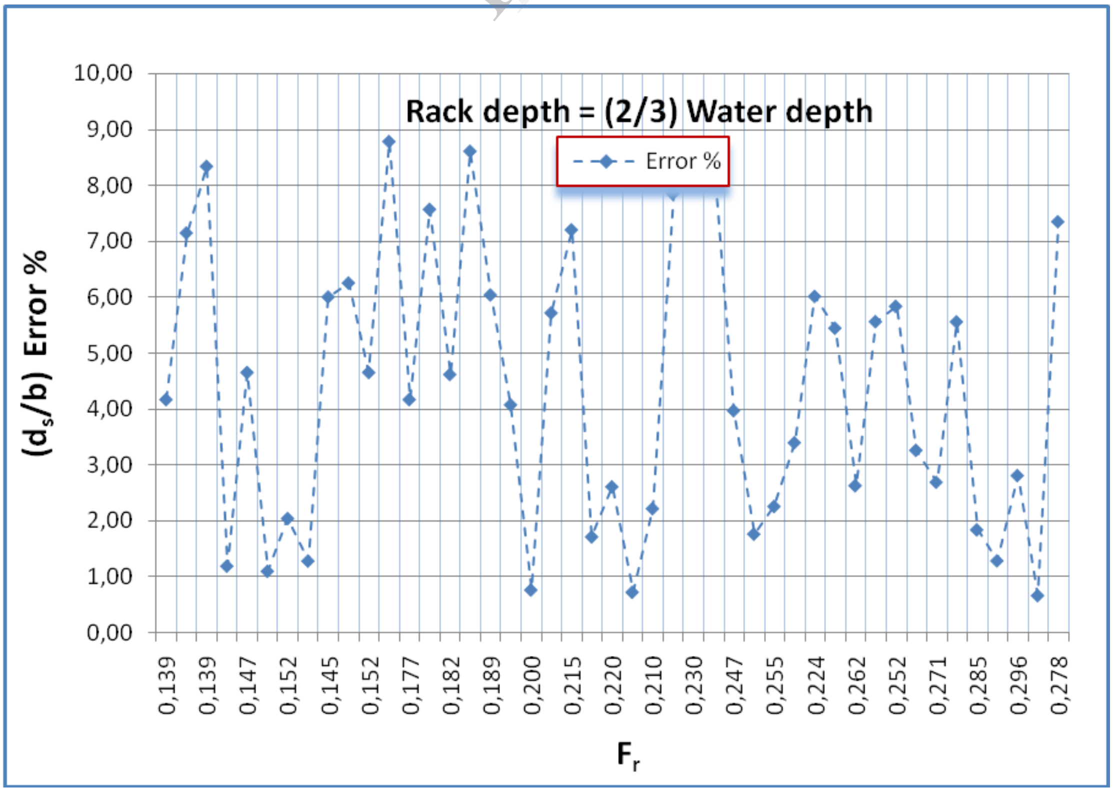
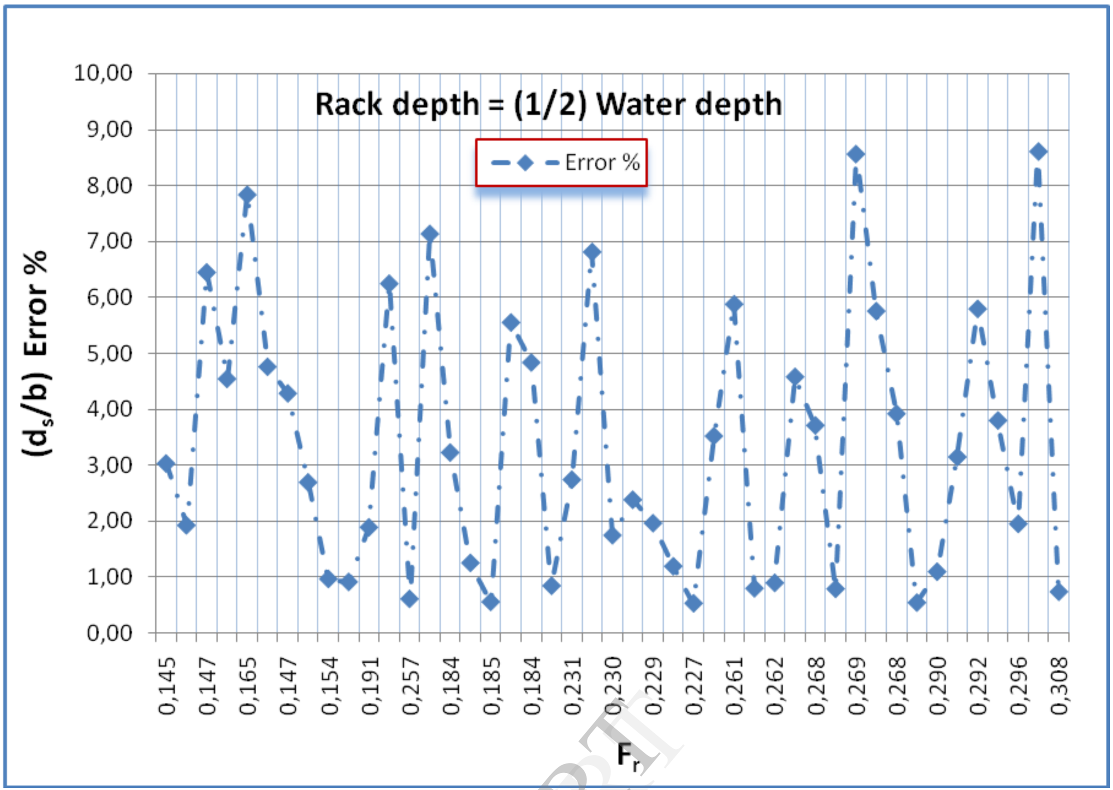


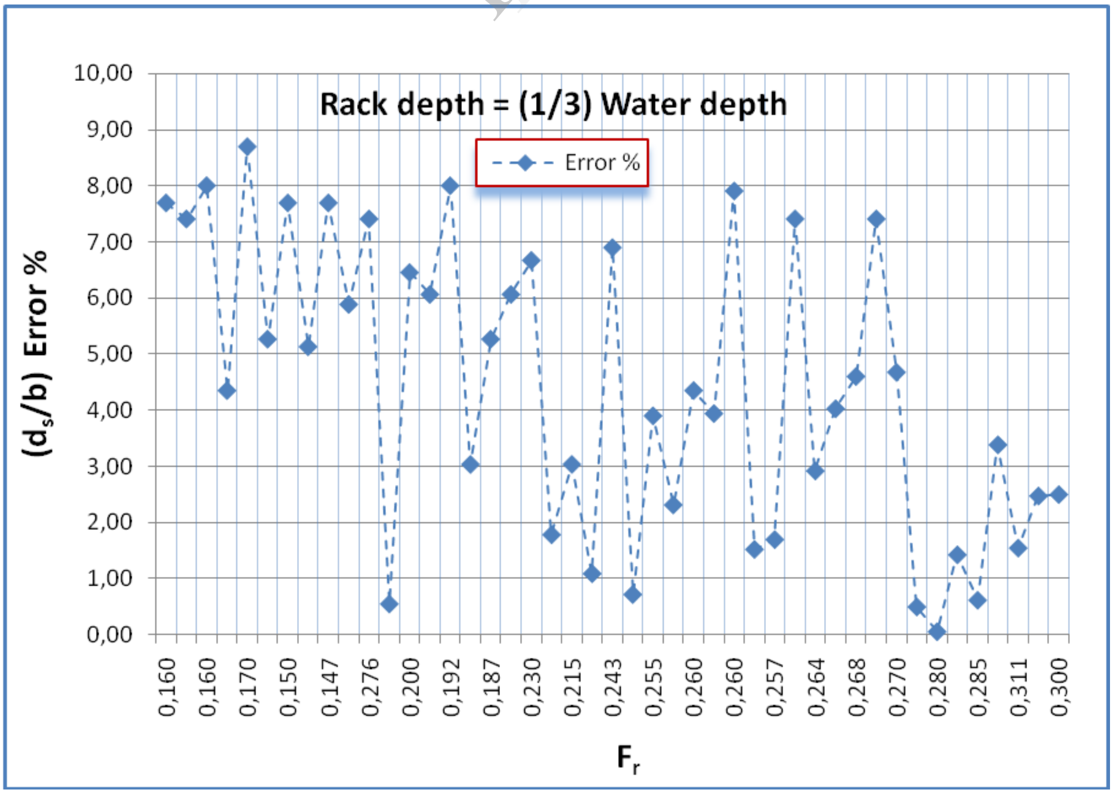
Fig (11). Comparison between measured and predicted (ANN) results of scour maximum depth, rack depth = 1/3 water depth.



Fig(12). Percentage relative error between the predicted ANN results and the actual measured data for rack depth = 2/3 water depth.



Fig(13). Percentage relative error between the predicted ANN results and the actual measured data for rack depth = 1/2 water depth.



Fig(14). Percentage relative error between the predicted ANN results and the actual measured data for rack depth = 1/3 water depth.

The current study was directed towards proving the concept of utilizing ANN technique in an experimental flume that is designed to simulate the open channels. Several ANN models were developed in the current study to predict the scour depth pattern for particular cases as different discharges and various weeds accumulations percentages. Three main simulation groups were considered in the current manuscript according to weed rack's depths.

The results of the various developed ANN models, with maximum percentage relative error less than 9% in all models, showed that ANN technique was very accurate and successful in simulating the scour behavior around piers. This conclusion is considered very encouraging for the scientific community to utilize the ANN approach in predicting the impacts of submerged aquatic weeds on the hydraulic performance of the open channels within the irrigation and drainage networks. In addition, the implementation of the ANN concepts and models is foreseen to provide the irrigation engineers with very useful information regarding the direct impacts of the aquatic weeds infestation on the hydraulic performance of open channels with almost no cost. This information is considered very essential to the distribution and design irrigation engineers.

The scour depths around piers have been found to increase continuously with discharge and trash rack blocking percentage.

The results presented in this paper have clearly shown that the neural network methodology can be used efficiently to predict the scour depth. The main advantage of neural networks is to remove the burden of finding an appropriate model structure or to find a useful regression equation. Also, ANN prediction for maximum scour depth decreases the cost and time for performing physical models tests, but will not replace it.

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