PREDICTION OF SCOUR DEPTH AROUND PILE GROUP USING ANN

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ABSTRACT

Prediction of the scour around a group of pile in the field exposed to oscillatory waves is very important for many offshore structure and coastal engineering projects. Conventional predictive formulas for the geometric properties of scour hole, however, are not able to provide sufficiently accurate results. In this paper the ANNs approach is used to predict the scour depth around pile group using dimensionless groups of parameters, namely, Reynolds number Re, Keulegan Carpenter number Kc, Shields parameter θ, and, densimetric Froude number Ns. The results show that a three-layer normal feed-forward multilayer perceptron with quick propagation (QP) learning rule can predict the scour depth successfully.

Key Words: ANN; Scour depth; Multilayer perceptron; Quick propagation.

1. INTRODUCTION

Piles are structures widely used in coastal and ocean engineering. Since many of these structures are located on erodible beds, the estimation of scour depth is an essential task, because failure of the bed or the toe could cause collapse of the entire structure. In order to predict the scour depth around piles, the effects of flow condition and the bed material have to be considered. The field study on scour pile group has been done by Bayram and Larson (2000). It is extremely difficult to formulate mathematical models that accurately represent the scour process and geometry of scour hole, which develop under the influence of wave and current. Thus it is a common practice to apply empirical relationships based on laboratory data for estimation of the scour around piles. Since there are numerous effective parameters, and the interaction of these parameters is highly complicated, therefore, the accuracy of the empirical relationships is very subjective and highly depends on the user's ability and knowledge. An artificial neural network, on the other hand, is an applicable and powerful tool to solve this problem. In addition, its ability to learn from examples and to generalize its learning makes it well suited to situations where the problem complexity precludes the development of empirical relationships. This technique was used to estimate the scour properties around a configuration of piles (Kambekar and Deo, 2002). Khosronejad et al. (2003) studied the scour properties around vertical pile using ANNs. They used the dimensional parameters such as wave length, water depth, wave period, maximum flow velocity and maximum shear velocity as input parameters of network.

In this paper nondimensional parameters such as pile Reynolds number, densimetric Froude number, Shields parameter and Keulegan carpenter number have been used as input parameters for designed network.

2. OVERVIEW OF ANNS

The ANN is a simplified mathematical representation of the biological neural network. It has the ability to learn from examples, recognize the various pattern of input data and to process information rapidly. A neural network is characterized by its architecture that represents the pattern of connections among nodes, its method of determining the connection weights and activation function. A typical ANN consists of number of nodes that are organized according to a particular arrangement. These nodes are generally arranged in layers, starting from the first input layer and ending at the final output layer. There can be several hidden layer, each hidden layer having one or more nodes (Jain, 2001).

Three types of the most commonly used ANNs are normal feed-forward neural network, recurrent neural network, and competitive neural network (Islam and Kothari, 2000). In this study the normal feed-forward neural network is used.

Normal feed forward neural networks are the most common among other ANNs and are widely used in function approximation and pattern classification (Islam and Kothari, 2000). The most commonly used types of normal feed-forward are the so-called multilayered perceptron *(MPL)* network and the radial basis function *(RBF)* network. In either of these two networks, the neurons are arranged in layered structure. Information passes from the input to the output side. The neurons in one layer are connected to those in the next layer. Thus, the output of a neuron in a layer is only dependent on the inputs it receives from pervious layer and the corresponding weights.

Consider a multilayered perceptron network with n inputs, an output layer with o neurons, and a hidden layer with m neurons as shown in Fig. 1. Index i is referred to the individual output layer neurons, the index j and k refer to the hidden layer neurons and the input neurons, respectively. Inputs, feed to the hidden layer neurons through weights W_{jk} and the outputs of hidden layer neurons feed to output layer neurons through weights W_{ij} . A hidden layer neuron produces as output:

$$h_j = f^{'}(s_j) = f(\sum_{k=1}^{n} W_{jk} x_k) \tag{1}$$

and an output layer neuron produces as output:

$$y_i = f^{'}(s_i^*) = f(\sum_{j=1}^{m} W_{ij} h_j) \tag{2}$$

where h_j is the output of jth neuron in hidden layer, s_j is the weighted sum of jth neuron in hidden layer, x_k is the input of kth neuron in input layer, y_i is the output of ith neuron in output layer and s_i^* is the weighted sum of ith neuron in the output layer.

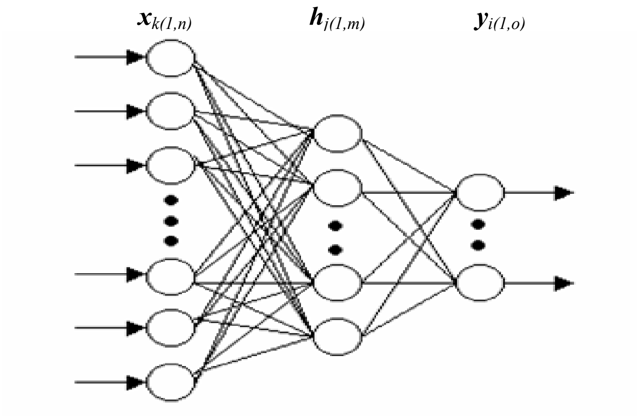

Fig. 1. Schematic of multilayer perceptron network

In this study the activation function $f^{'}$ for hidden layer is taken to be the arctangent [$f^{'}(x) = \arctan(x)$]. This non-linearity makes the mapping produced by the network nonlinear. Since the outputs s is greater than one, the linear function is selected for output layer.

3. NETWORK TRAINING ALGORITHMS

There are two types of network training, supervised and unsupervised (ASCE Task Committee, 2000-a). In supervised training algorithm, an external supervisor is needed to guide the training process, while in an unsupervised training algorithm it is not so.

In this study, supervised training algorithm has been used to update the weight matrix of ANN. The training patterns proposed by Bayram and Larson (2000) are used for this purpose. The quick-propagation *(QP)* used and it was showed that the training procedure is done well. The aim is to reduce the global error E:

$$E = \frac{1}{p}\sum_{\rho=1}^{p} E_p \qquad (3)$$

where p is total number of training patterns and E_p is error for training pattern p given by:

$$E_p = \frac{1}{2}\sum_{k=0}^{N}(y_k - t_k)^2 \qquad (4)$$

where N is total number of output neurons; y_k is network output at the kth output neuron and t_k is target output at the kth output neuron.

4. EFFECTIVE PARAMETERS ON THE SCOUR DEPTH

The significant parameters controlling the scour depth around a pile exposed to oscillatory waves are: pile diameter D, wave height H, water depth h, wave period T, maximum flow velocity U_m, maximum shear velocity U_{fm}, specific gravity of sediment s, mean diameter of sediment d, acceleration due to gravity g and kinematic viscosity of fluid ν. Thus the maximum scour depth S may be expressed as follows (see Fig. 2):

$$S = f(D, H, h, T, U_m, U_{fm}, s, d, g, \upsilon) \tag{5}$$

The maximum shear velocity U_{fm} is defined as (Sumer et al., 1992 and Herbich, 1991):

$$U_{fm} = (0.5f)^{1/2} U_m \tag{6}$$

where U_m is amplitude of the oscillatory flow velocity; f is wave friction factor. By applying dimensional analysis, the significant nondimensional parameters controlling the scour depth around a pile exposed to oscillatory waves may be identified. Thus the equilibrium maximum scour depth S normalized by the pile diameter D expressed as follows (Herbich 1991; Sumer, et al 1992 b):

$$\frac{S}{D} = f(N_{\text{Re}}, N_s, \theta, KC) \tag{7}$$

Where N_{Re} is pile Reynolds number, N_s is densimetric Froude number, θ is Shields parameter and KC is Keulegan-Carpenter number. These nondimensional numbers are defined as follows:

$$N_{\text{Re}} = \frac{U_m D}{\nu} \tag{8}$$

$$N_s = \frac{U_m}{\sqrt{g(s-1)d}} \tag{9}$$

$$\theta = \frac{U_{fm}^2}{g(s-1)d} \tag{10}$$

$$KC = \frac{U_m T}{D} \tag{11}$$

The above parameters were employed in the present study to investigate various nondimensional parameters describing the scour depth.

The data set that were used for designing the networks were the field data reported by Bayram and Larson (2000). The range of variables is summarized in Table 1. These parameters have been employed in the present study as input vectors to train the designed neural network and describe the scour depth around vertical pile. Therefore, the numbers of input layer neurons are equal to four (N_{Re}, N_s, Θ and KC) and the output neuron is *S*. The number of data is 58, out of which 48 were used for network training and 10 for testing the performance of trained network.

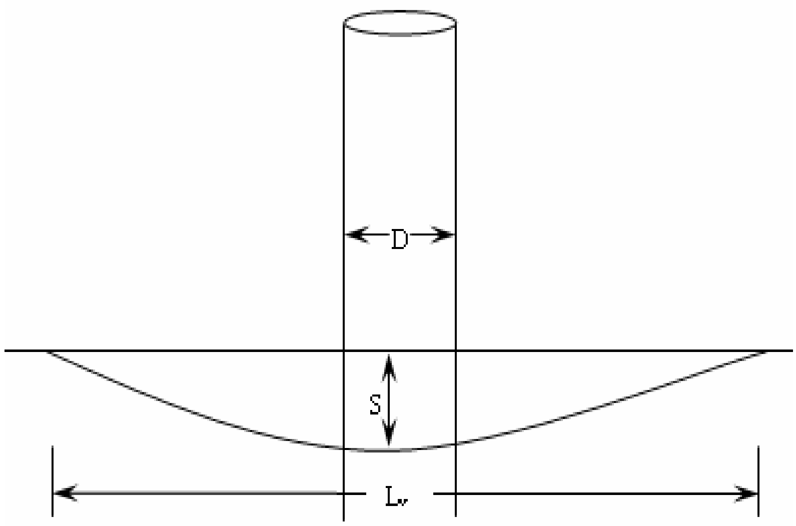

Fig. 2 Definition sketch

Table 1. Range of data set used for training and testing the Network (Bayram and Larson, 2000)

Variables	Range
Shields parameter θ	0.08-0.64
Pile Reynolds Number(N_{Re})	$3.4*10^5$-$1.1*10^6$
Densimetric Froude number (N_s)	1.2-12.5
Keulegan-Carpenter Number	7.6-22.5
Scour depth S(m)	0.42-2.1

5. DESIGNING AND TRAINING THE ANNs

This important step involves the determination of the ANN architecture and selection of a training algorithm. An optimal architecture may be considered the one yielding the best performance in term of error minimization, while retraining a simple and compact structure. A trial-and-error procedure is generally applied to decide on the optimal architecture. The number of input and output neurons is problem dependent.

In the current study, first we used two neurons at output layer and four neurons at input layer and ten or more neurons in hidden layer. In this case the network was trained with different architectures and results showed that the network can not learn accurately. The result is shown in table 2. As shown in Tables 2 the normal feed-forward architecture with quick-propagation learning rule and one hidden layer is the best choice for this case, because the network learning was obtained with the least epochs and with minimum *rms* error.

Table 2. Results of designed neural network with one neuron in output layer for relative scour depth (S/D)

Network	Learning rule	No. of neurons (1st hidden layer)	No. of epochs	Mean training error	Mean testing error
Multilayer perceptron networks	Quick-propagation (QP)	10 12 15	20000 32000 34000	0.015 0.0011 0.00012	0.51 0.014 0.008

6. THE ANNS OUTPUT RESULT VALIDATION

Similar to other modeling approaches in hydraulics, the performance of the trained ANN can be fairly evaluated by subjecting it to the new patterns that have not been seen during training process. The performance of the network can be determined by computing the error between predicted and observed values. In order to assess the networks ability, the outputs of networks for new patterns is shown in Fig. 3. As shown in Fig. 3, the trained networks could learn desired mapping successfully.

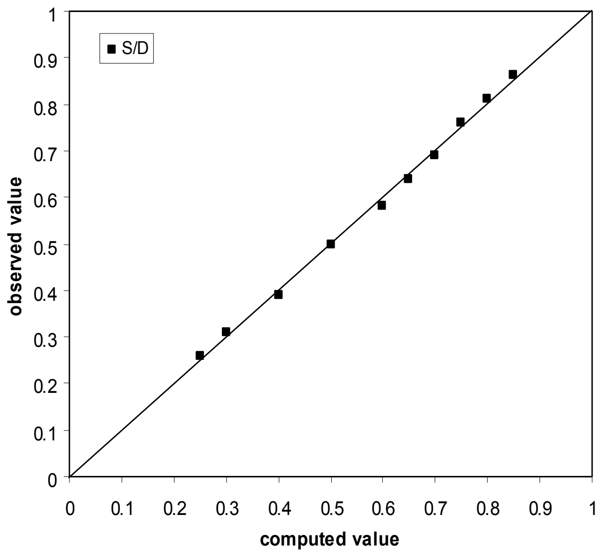

Fig. 3 Comparison of observed and computed (ANN results) nondimensional scour depth

7. CONCLUSION

The multilayer perceptron network is applied to estimate scour depth around vertical piles. It was shown that use of nondimensional parameters as input pattern produce accurate results. The designed network could learn successfully and the *rms* error was very small. The designed ANN model with normal feed-forward architecture and quick-propagation learning rule and a single hidden layer with ten neurons provide sufficiently good training and testing acuracy.

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