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Estimation of current-induced scour depth around pile groups using neural network and adaptive neuro-fuzzy inference system

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ABSTRACT

The process of local scour around bridge piers is fundamentally complex due to the three-dimensional flow patterns interacting with bed materials. For geotechnical and economical reasons, multiple pile bridge piers have become more and more popular in bridge design. Although many studies have been carried out to develop relationships for the maximum scour depth at pile groups under clear-water scour condition, existing methods do not always produce reasonable results for scour predictions. It is partly due to the complexity of the phenomenon involved and partly because of limitations of the traditional analytical tool of statistical regression. This paper addresses the latter part and presents an alternative to the regression in the form of artificial neural networks, ANNs, and adaptive neuro-fuzzy inference system, ANFIS. Two ANNs model, feed forward back propagation, FFBP, and radial basis function, RBF, were utilized to predict the depth of the scour hole. Two combinations of input data were used for network training; the first input combination contains six-dimensional variables, which are flow depth, mean velocity, critical flow velocity, grain mean diameter, pile diameter, distance between the piles (gap), besides the number of piles normal to the flow and the number of piles in-line with flow, while the second combination contains seven non-dimensional parameters which is a composition of dimensional parameters. The training and testing experimental data on local scour at pile groups are selected from several precious references. Networks' results have been compared with the results of empirical methods that are already considered in this study. Numerical tests indicate that FFBP-NN model provides a better prediction than the other models. Also a sensitivity analysis showed that the pile diameter in dimensional variables and ratio of pile spacing to pile diameter in non-dimensional parameters are the most significant parameters on scour depth.

1. Introduction

An accurate prediction of maximum scour depth around bridge foundations is necessary for their safe design. Bridge foundations on deep alluvial riverbeds are commonly constructed on group of piles. Generally, this is considered a safe way to avoid any scouring problems. However, scour prediction is still necessary for this kind of foundation. Piles may or may not be designed to withstand a certain exposure to the flow; after the local scour has developed, piles may interface with the pier and affect the flow and scouring. Moreover, general scour can produce a permanent bed lowering. In the simplest case, pile groups are caped above the water surface and only the pile groups obstruct the flow field. The scour mechanisms for pile groups are much more complex, and design of local scour depths more difficult to predict. Numerous empirical formulae have been presented to estimate equilibrium scour depth at pile groups under clear water conditions [1,8,19]. The main problem with these formulas is that the existing equations are based on dimensional analysis and data correlation of laboratory experiments which do not always produce reasonable results for field conditions or even for laboratory conditions. Hence, they mostly give conservative results and overestimate the scour depth [1,19]. This is because the conventional analysis of data cannot include the correct influences of the set of influential parameters on scour depth. Recognizing these difficulties and the importance of improving prediction capabilities, it is quite effective to explore and refine new methods for improving traditional physical-based analysis.

Recently, using artificial intelligence in modelling complex subjects in civil engineering has introduced as a proper method.

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Artificial neural networks (ANN) are essentially semi-parametric regression estimators, as they can approximate virtually any function up to an arbitrary degree of accuracy [11]. An important benefit of using ANN approach in system modelling could be cited that there is no need to have a well-defined physical relationship for converting an input to an output and the network has the ability to make a affiliation between input and output data. The ANN then adapts itself to reproduce the desired output (target values), when presented with training sample input. The usage of neural networks has provided many promising results in the field of hydrologic, water resource and hydraulic simulation [3,7,12,16].

Fuzzy-rule based approach has very recently attention in modelling. First introduced by Zadeh (1965), fuzzy logic and fuzzy set theory are employed to describe human thinking and reasoning in a mathematical framework. A combination of neural network concept and fuzzy logic could lead to the neuro-fuzzy networks. Nowadays, researches could be witnesses of application of a fuzzy logic approach in different branches of civil engineering [2,27] and also similar works related to scour depth estimation [14,25].

Few works could be introduced on the subject of using ANN and neuro-fuzzy network in estimating scour depth around bridge piers [5,6] and using these technical modelling for estimation pile group scour is scarce. Kambekar and Deo used the ANN model for predicting scour depth as well as scour width for a group of pile supporting a pier exposed to the oscillatory waves [15]. Also, Bateni and Jeng [4], applied a similar work using a neuro-fuzzy model.

In this paper, two types of neural networks, feed forward back propagation and radial basis function accompanied by an adaptive neuro-fuzzy inference system, were applied to existing experimental data for local scour depth at pile groups under steady, clear-water scour conditions in uniform sediments. The major objective of this paper is to investigate the potential of ANNs and neuro-fuzzy systems in simulating and predicting scour depth around pile groups and to assess its performance relative to some present techniques. The underlying principle and a brief view on ANNs and neuro-fuzzy architecture are also attended.

2. Methods

In this section, three models including feed forward back propagation and radial basis function neural networks, adaptive neuro-fuzzy inference system besides the learning algorithm for ANFIS are introduced and discussed separately.

2.1. Feed forward back propagation neural network (FFBP)

Feed forward back propagation algorithm could be mentioned as a sub-set of multi-layer perceptron neural networks. The topology of FFBP ANNs consists of a set of neurons connected by links in a number of layers. The basic configuration usually consists of an input layer, a hidden layer and an output layer. A multi layer FFBP ANN is shown in Fig. 1. The number of hidden layers establishes the complexity of the network. Designating the correct number of hidden layers and the number of nodes in each layer has been evaluated by trial and error. However, each node multiplies every input by its interconnection (synaptic) weights and then adds the sum of the products to a bios number, and then passes the sum through a transfer function to generate the results. The transfer function which is usually a sigmoid function can be presented as the following relation:

$$y_i = f\left(\sum w_{ij}x_i + b_i\right) = \frac{1}{1 + e^{-(\sum w_{ij}x_i + b_i)}} \tag{1}$$

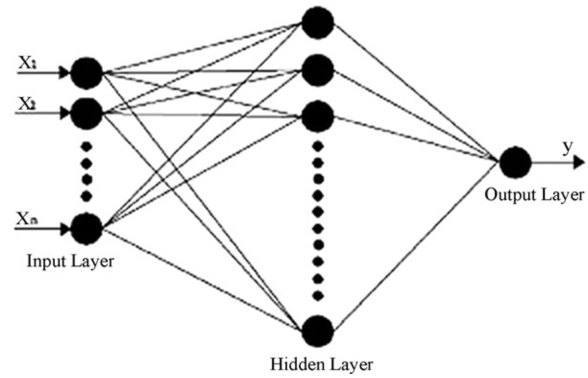

Fig. 1. Configuration of a feed forward neural network [11].

where w_{ij} is the weight of the connection joining the jth neuron in a layer to the ith neuron in the previous layer and x_i is the value of ith neuron in the previous layer. Under the aegis of this function, the output y_j from the jth neuron in a layer could be calculated.

After comparing the obtained results with the target values, the errors would be calculated and by using the back propagation algorithm the entire weights would be corrected. This process will be continued until either errors are less than a specified value or the number of training epochs reaches the favourite repetition. At this stage, ANN is considered as trained [2,11,12].

2.2. Radial basis function neural network (RBF)

The RBF network ranks among the most popular tools for function approximation. An important property of RBF neural networks is that a high-dimensional-space nonlinear-problem can be easily broken down through a set of combination of radial basis functions, besides they are the beneficiary of the ability to be quickly trained [7]. Fig. 2 shows a schematic diagram of a general RBF network. The input layer is composed of n input nodes. The hidden layer consists of j locally tuned units and each unit has a radial basis function acting like a hidden node. The hidden node output $z_j(x)$ calculates the closeness of the input and projects the distance to an activation function. The activation function of jth hidden node used in this study is the Gaussian function given by

$$z_j(x) = \exp\left(-\frac{||x-\mu_j||^2}{2\sigma_j^2}\right) \tag{2}$$

where x is known as input vector; μ_j is the centre of the radial basis function for hidden node j; $||x-\mu_j||$ denotes the Euclidean distance between the centre of the radial basis function and input; and σ_j is a parameter for controlling the smoothness properties of the radial basis functions. The third layer of the network is the output layer with L nodes that are fully interconnected to each hidden node. The output of the network is the sum of the linear weighted $z_j(x)$

$$y_l = \sum_{j=0}^{J} w_{lj} z_j(x) \tag{3}$$

$$z_0(x) = 1 \tag{4}$$

where y_l is the lth component of the output layer; w_{ij} is the synaptic weight between the lth node of hidden layer and the lth node of output layer. Eq. (4) denotes the constant, w_{l0}, in the regression equation (3).