

Prediction of Wave Transmission using ANN for Submerged Reef of Tandem Breakwater

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ABSTRACT: A Tandem breakwater is a combination of rubble mound breakwater and a submerged reef unit at a specified distance in front of it. The concept of tandem breakwater is derived from the S shape equilibrium profile attained by a conventional rubble mound breakwater upon the action of waves on it. The detached submerged breakwater acts as a wave attenuator and reduces the wave impacts on the conventional breakwater thus minimizing the size of armor stones required for those conditions. Present study focuses on application of artificial neural networks in predicting the transmitted wave heights for a submerged reef of tandem breakwater. Artificial neural network model predictions were almost 98% in accordance with experimental results.

KEYWORDS: Tandem Breakwater, Submerged reef, Artificial Neural Network (ANN).

I. INTRODUCTION

Tandem Breakwater

Breakwaters are those structures which are built to protect ports and harbors from wave attack to maintain a calm condition, to protect river mouth from silting, to protect beaches. The breakwater can be used as a structure for both dissipating wave energy and as a facility for loading and unloading passengers and cargos. The tandem breakwater was derived from the most stable rubble mound breakwater to berm breakwater and then finally to tandem breakwater [9].

Rubble mound breakwater was found to fail near the waterline by material slumping down the slope forming a toe extension which finally stabilises as berm breakwater with S shaped profile bench. Later it was noted that we can shift the extended toe as a separate submerged breakwater to the front of main breakwater and the result is tandem breakwater.

From ancient days the breakwaters have been designed by conducting experiments on physical models (Van der Meer, 1988, 1992; Hall and Kao 1991; Subba Rao, Pramod and Rao, 2004; Subba Rao, Subrahmanya, Rao and Chandramohan, 2008) which are time consuming and costly. For minimizing both soft computing tools like Artificial Neural Network (ANN), Support Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System (ANFIS), etc can be utilized for predicting the experimental results. So these are new areas of interest which can be applied to the field of structural design and calculation there by reducing an enormous amount of time in planning and design which will in turn lead to the reduction in overall cost.

Artificial Neural Network and Its Methodology

Artificial Neural Networks are computational models naturally performing a parallel processing of information. Essentially, an ANN can be defined as a pool of simple processing units (neurons) which communicate among themselves by means of sending analogue signals. These signals travel through weighted connections between neurons. Each of these neurons accumulates the inputs it receives, producing an output according to an internal activation function. This output can serve as an input for other neurons, or can be a part of the network output.

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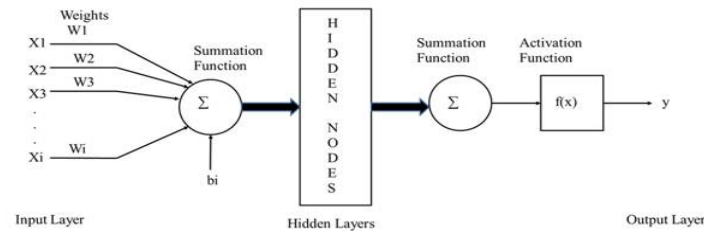


Figure 1: Traditional ANN structure

There is a set of important issues involved in the ANN design process. As a first step, the architecture of the network has to be decided. Initially, two major options are usually considered: feed forward networks and recurrent networks (additional considerations regarding the order of the ANN exist, but are out of scope). The feedforward model comprises networks, in which the connections are strictly feedforward, i.e., no neuron receives input from a neuron to which the former sends its output, even indirectly. The recurrent model defines networks in which feedback connections are allowed, thus making the dynamical properties, of capital importance. In this work, concentration is on the first and simpler model: the feedforward networks. To be precise, so-called multilayer perceptron (MLP) (Rosenblatt, 1962) are considered, in which units are structured into ordered layers, and connections are allowed only between adjacent layers in an input-to output sense. For any MLP, several parameters such as the number of layers and the number of units per layer must be defined. After having done this, the last step in the design is to adjust the weights of the network, so that it produces the desired output when the corresponding input is presented. This process is known as training the ANN or learning the network weights. Network weights comprise both the previously mentioned connection weights, as well as a bias term for each unit. The latter can be viewed as the weight of a constant saturated input that the corresponding unit always receives. As initially stated, we will focus on the learning situation known as supervised training, in which a set of input/desired-output patterns is available. Thus, the ANN has to be trained to produce the desired output according to these examples..

The present study employs a standard back propagation algorithm for training, and the number of hidden neurons is optimized by a trial and error procedure. In these networks, there is an input layer consisting of nodes that simply accept the input values and successive layers of nodes that are neurons as depicted in Figure 1. The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers. The activation function $T_{r(y)}$ is given as

$$T_{r(y)} = \left(\frac{1}{1 + e^{-2y}} - 1 \right) n$$

$$y = \sum_{i=1}^n W_i X_i + b_i$$

Where, X_i is input value from 1 to n and W_i are the weights between input layer and hidden layer nodes and y is output. The backpropagation algorithm (BP) (Rumelhart, 1986) is a classical domain-dependent technique for supervised training. It works by measuring the output error, calculating the gradient of this error, and adjusting the ANN weights (and biases) in the descending gradient direction. Hence, BP is a gradient-descent local search procedure (expected to stagnate in local optima in complex landscapes). First, we define the squared error of the ANN for a set of patterns:

$$E = \frac{1}{P} \sum_{p=1}^P \sum_{k=1}^k (P_{kp} - O_{kp})^2$$

Where, p is the total number of training patterns, P_{kp} is the desired value of the k^{th} output and the p^{th} pattern, O_{kp} is the actual value of the k^{th} output and p^{th} pattern. The actual value of the previous expression depends on the weights of the network. The basic BP algorithm (without momentum in our case) calculates the gradient of E (for all the patterns in our case) and updates the weights by moving them along the gradient-descendent direction. This can be summarized with the expression $\Delta W = -\eta \Delta E$, where the parameter $\eta > 0$ is the learning rate that controls the learning speed.

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Hybridization can also be done to modify the algorithm, refers to the inclusion of problem-dependent knowledge in a general search template. We can distinguish two kinds of hybridization: strong and weak hybridization. In the first one, the knowledge is included using specific operators or representations. In the latter, several algorithms are combined somehow. In this last case, an algorithm can be used to improve the results of another one separately or it can be used as an operator of the other.

II. EVALUATION CRITERIA

The statistical tools such as equation 1, 2, 3 and 4 are Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Scatter Index (SI) and Correlation Coefficient (CC) respectively, were used to check the accuracy of the predicted values with the experimental data sets. The prediction will be considered good when RMSE, SI are minimum while NSE and CC are maximum.

Consider O_{pi} and P_{pi} as the observed and predicted values, $\overline{O_{pi}}$ and $\overline{P_{pi}}$ as the average of observed and predicted values number of observations is N, then, RMSE is calculated using the formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=0}^N (P_{pi} - O_{pi})^2}$$

NSE is calculated using the formula:

$$NSE = 1 - \frac{\sum_{i=1}^N (P_{pi} - O_{pi})^2}{\sum_{i=1}^N (O_{pi} - \overline{O_{pi}})^2}$$

SI is calculated using the formula:

$$SI = \frac{\sqrt{\frac{1}{N} \sum_{i=0}^N (P_{pi} - O_{pi})^2}}{\overline{O_{pi}}}$$

CC is calculated using the formula:

$$CC = \frac{\sum_{i=1}^N (P_{pi} - \overline{P_{pi}})(O_{pi} - \overline{O_{pi}})}{\sqrt{\sum_{i=1}^N (P_{pi} - \overline{P_{pi}})^2} \sqrt{\sum_{i=1}^N (O_{pi} - \overline{O_{pi}})^2}}$$

Data Collection:

Experimental work on Tandem breakwater conducted by Manu et. al., (2012) in Flume Laboratory Applied Mechanics and Hydraulics dept NITK Surathkal, India. The collected data is used in the present study, which contain data sets of length 108. The data is divided in the ratio of 70% and 30% for training and testing respectively. The data has been divided randomly into two sets for training and testing and to check the relative consistency in training and testing data, time series plots are done. Different neural network models are constructed by varying number of hidden layer neurons and for the inputs of f/H_i , X/d , b/d , H_i/gt_2 and H_t as output.

III. RESULTS AND DISCUSSIONS

Four neural network models are constructed using four inputs neurons and 1 output neuron by varying number of hidden neurons. Levenburg-Marquadt algorithm has been used to train all the network models. The network learns at every iteration and the weights and biases will be reassigned for every training of the network. The network parameters are saved for every run of model so that the same network with the biases and weights can be used to predict the output for any other data. The variation of CC, RMSE, SI and NSE as calculated by using the formulae mentioned above for all the models is tabulated in Table 1.

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ANN models →	4-1-1		4-2-1		4-3-1		4-4-1	
Statistical Parameter ↓	Train	Test	Train	Test	Train	Test	Train	Test
RMSE	0.171	0.200	0.069	0.078	0.038	0.044	0.030	0.054
CC	0.647	0.432	0.951	0.937	0.986	0.981	0.990	0.970
SI	0.397	0.428	0.161	0.166	0.087	0.093	0.072	0.115
NSE	0.419	0.181	0.904	0.876	0.972	0.961	0.981	0.940

Table 1: Details of results obtained from ANN models with different number of neuron

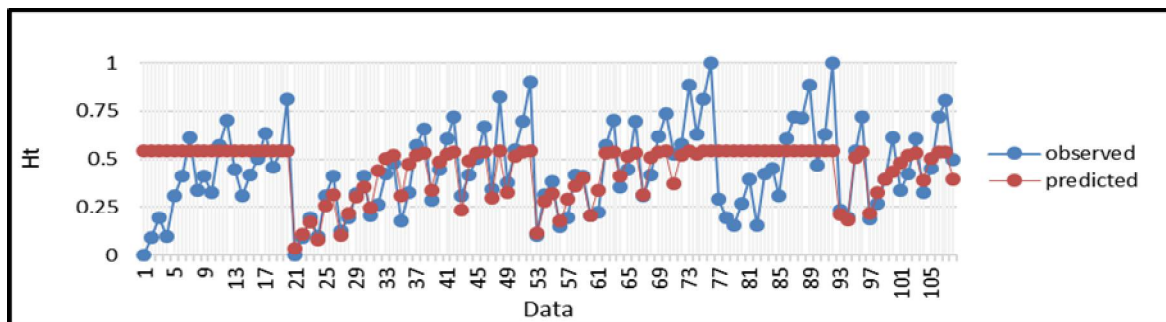


Figure 2: Shows predicted and observed data of wave transmission for ANN 4-1-1

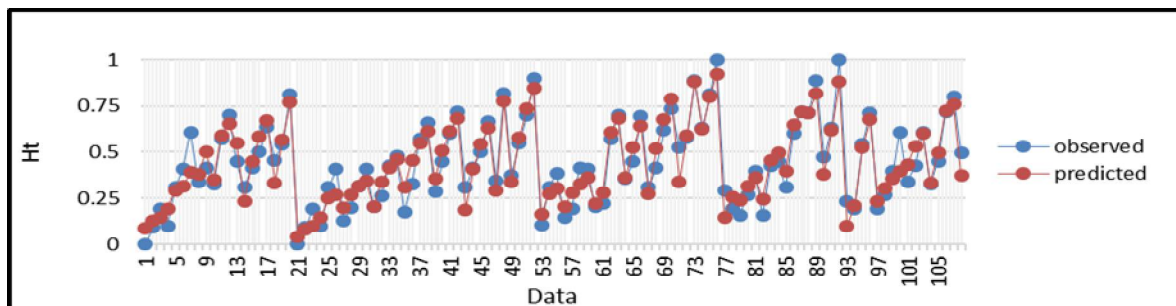


Figure 3: Shows predicted and observed data of wave transmission for ANN 4-2-1

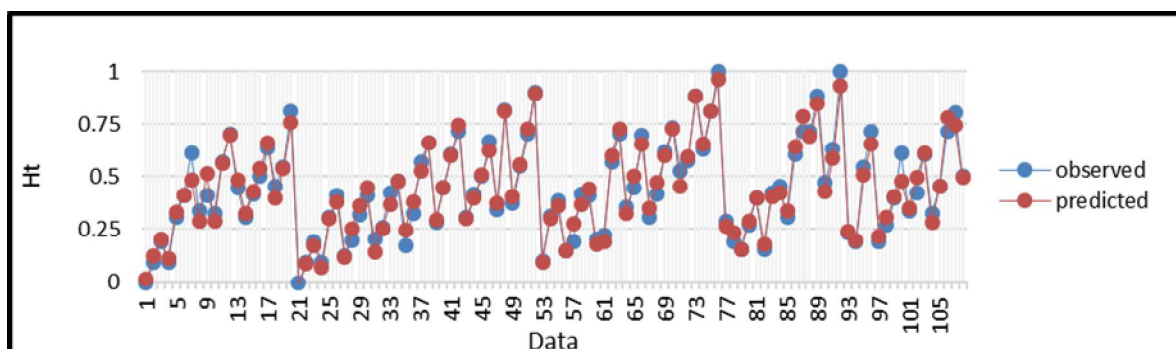


Figure 4: Shows predicted and observed data of wave transmission for ANN 4-3-1

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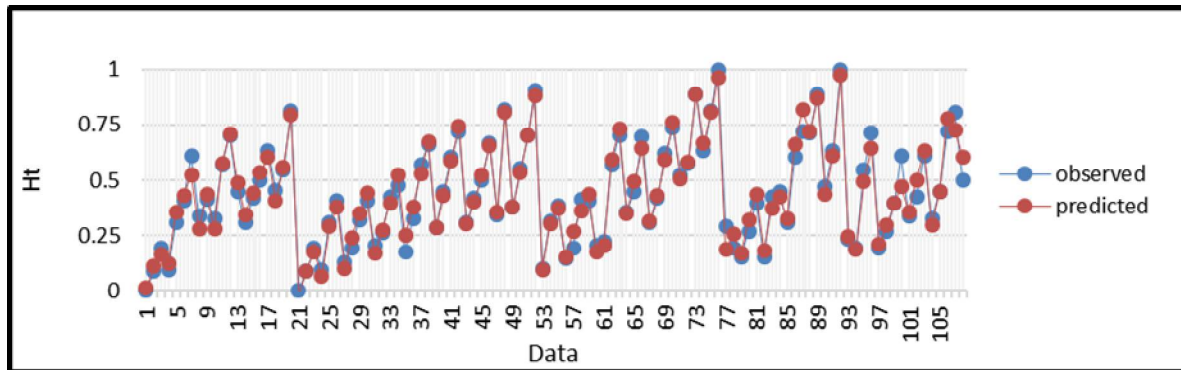


Figure 5: Shows predicted and observed data of wave transmission for ANN 4-3-1

Figures 2-6 shows superimposed plots of predicted and observed transmitted wave heights which gives the accuracy of the four models and it can be shown that models constructed using 3 and 4 hidden neurons predictions were as close as the observed data. Also from Table 1, ANN 4-3-1 is giving good results compared to other models where in ANN 4-4-1 is predicting slightly less accurate than ANN 4-3-1

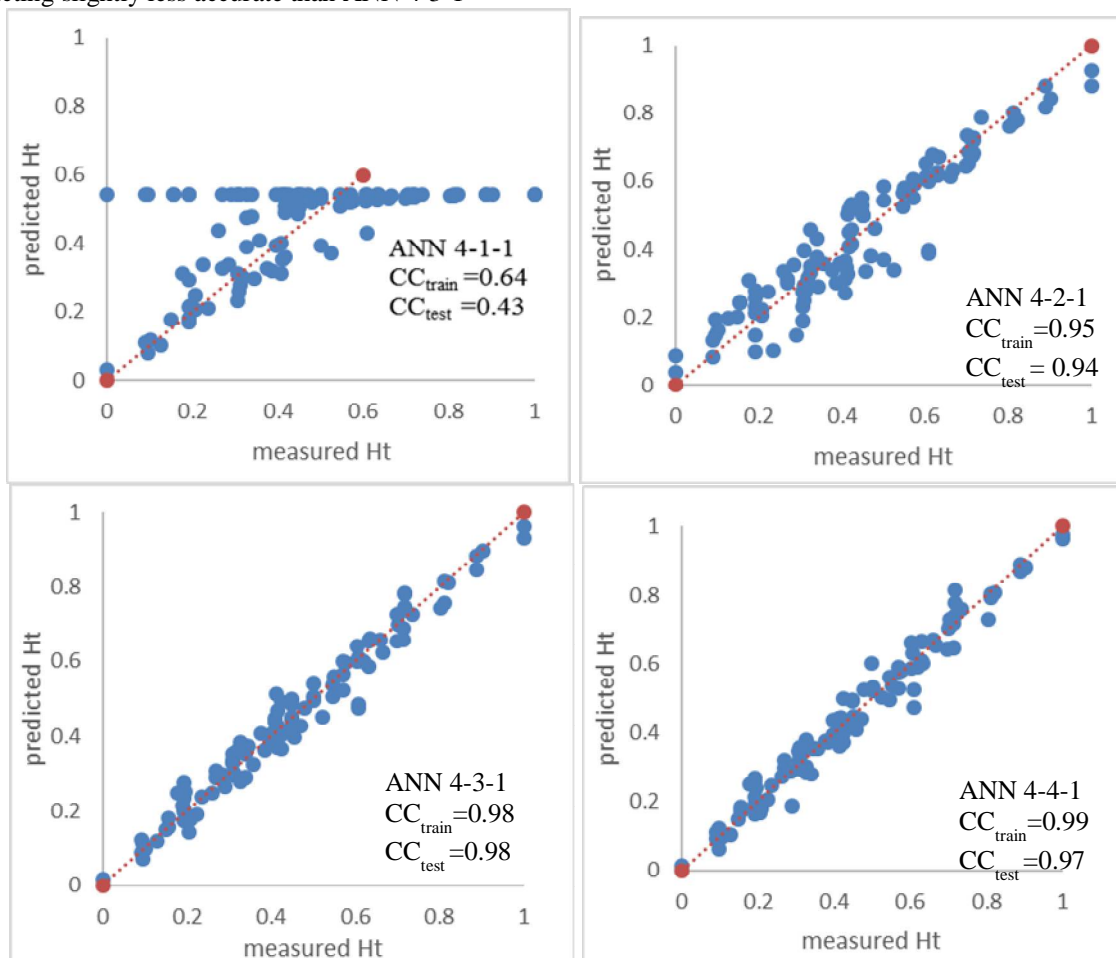


Figure 6: Shows the scatter plot for wave transmission (H_t) by different ANN models

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Figure 3 shows the scatter plots of measured and predicted transmitted wave heights for all the four configurations of ANN. It can be clearly shown from the plots that ANN 4-3-1 give better predictions and the standard deviation of predicted H_t is less from the observed H_t .

IV. CONCLUSIONS

1. The transmitted wave heights H_t are predicted using ANN for different configurations varying the hidden neurons in each network
2. Artificial Neural Networks have been proved to be a reliable tool in many fields. The present study also confirms that using Levenburg-Marquardt updated algorithm, ANN can give very good estimates of transmitted wave heights. ANN model configuration 4-3-1 and 4-4-1 give a very good estimate of H_t with a correlation coefficient of 0.98 and 0.97 for testing.

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