



WAVE TRANSMISSION PREDICTION OF MULTILAYER FLOATING BREAKWATER USING NEURAL NETWORK

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Abstract: In the present study, an artificial neural network method has been applied for wave transmission prediction of multilayer floating breakwater. Two neural network models are constructed based on the parameters which influence the wave transmission of floating breakwater. Training and testing of the network models are carried out for different hidden nodes and epochs. The results of network models are compared with the measured values. It is observed that the correlation (above 90%) between predicted wave transmission values by the network models and measured values are in good agreement.

Keywords: Artificial neural networks; wave transmission; multilayer floating breakwater; transfer function.

INTRODUCTION

The environmental stress on the coastal zone is rapidly growing and there is a need to protect the coastal environment. The development of structures to provide protection against the destructive forces of the sea waves and to withstand the action of waves has been the constant challenge to the coastal engineers. The coastal defense works such as seawalls, groins, offshore breakwaters, artificial nourishments have been tried to overcome the problem of erosion. Some of them have been successful while some others have failed to perform the job assigned to them. In the last two decades, floating breakwaters (McCartney, 1985; Mani, 1991; Murali and Mani, 1997; Sannasiraj et al, 1998; Sundar et al, 2003) have generated a great interest in the field of coastal engineering, as floating breakwaters are less expensive compared to conventional type breakwaters. In addition, they have several desirable characteristics such as, comparatively small capital cost, adoption to varying harbour shapes and sizes, short construction time and freedom from silting and scouring. Floating breakwaters could also be utilized to meet location changes, extent of protection required or seasonal demand. They can be used as a temporary protection for offshore activities in hostile environment during construction, drilling works, salvage operation etc. In order to design a floating breakwater, it is necessary to study the motion characteristics of the structure. Hence, a study on wave transmission of the floating breakwater would provide a proper

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Configuration of the Structure.

There is a great volume of published work dealing with floating breakwaters (Harris and Webber, 1968; Homma et al, 1964; Kennedy and Marsalek, 1968; Harms, 1979; Bishop, 1982; Leach, McDougal and Solitt, 1985), but it is noticed that there is a lack of a simple mathematical model for these structures for predicting breakwater characteristics on its performance and upon the transmission coefficient. Number of studies have been carried out considering a floating breakwater with a simple form and adopted some assumptions common in hydrodynamics which shows less improvement. The stability and reliability analyses of coastal structures such as rubble mound breakwaters using neural networks have been carried out (Mase et al, 1995; Kim and Park, 2005). Similarly in this paper we have applied neural network to predict the wave transmission of the floating breakwater.

WAVE TRANSMISSION OF FLOATING BREAKWATER

Floating breakwaters are based on the concept of either reflecting the wave energy or dissipating wave energy by induced turbulent motion. In recent times, many types of floating breakwater models have been tested and some have been constructed and their prototype performances have been assessed. Floating breakwaters can be subdivided into four general categories: Box, Pontoon, Mat and Tethered float. The prime factor in the construction of the floating breakwaters is to make the width of the breakwater (in the direction of wave propagation) greater than one half the wavelengths and preferably as wide as the incident wavelength; else, the breakwater rides over the top of the wave without attenuating it. Also to be effective, the floating breakwater must be moored in place with both leeward and windward ties; otherwise it would sag off and ride over the incident wave. Pontoon and Box type of floating breakwaters belong to the first category in which the wave attenuation is achieved by reflecting the wave energy. Mat and Tethered belong to the second category in which wave energy dissipation is mainly due to drag from the resultant float in motion.

The development of floating breakwaters by various investigations has been influenced by certain important features; large masses, large moment of inertia, and the combinations of two or more of the concept of large effective mass or moment of inertia. Most of the literature indicates that the parameter “relative width” influences greatly the wave attenuation characteristics of the breakwater.

Experimental Floating Breakwater

The details of the floating pipe breakwater used by the Department of Applied Mechanics, NITK Surathkal, India are shown in Figure-1 (Deepak, 2006; Hegde et al, 2007; Jagadisha, 2007). The breakwater comprises of the rigid PVC pipes. The pipes are placed parallel to each other with certain spacing between them in each layer and the adjacent layers are oriented at right angles to each other so as to form a interlacing. Hence, longitudinal pipes are placed along the direction of propagation of waves. Transverse pipes are placed and tied perpendicular to longitudinal pipes. The length of the longitudinal pipes defines the width of the breakwater. It is felt that with proper number of layers, spacing of pipes and relative breakwater width, it is possible to achieve a considerable and effective attenuation of waves. Figure-1 shows a pictorial representation of model in plan and section.

Wave transmission prediction of multilayer floating breakwater using neural network

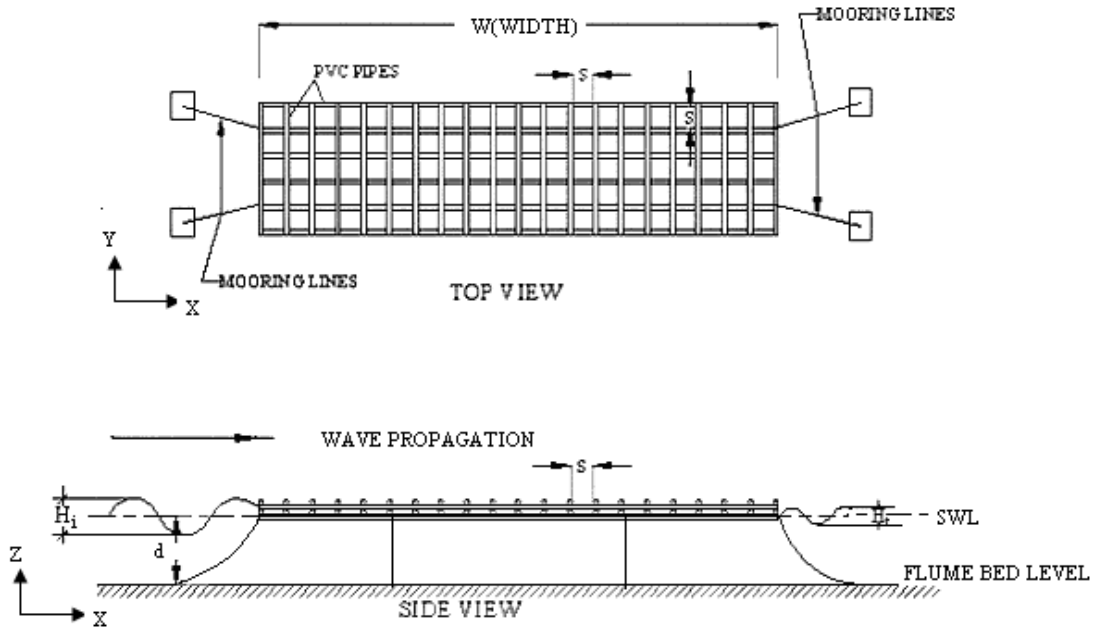


Fig.1. Floating breakwater model setup

The experimental wave transmission data on multilayer floating breakwater was generated using wave flume at National Institute of Technology Karnataka, Surathkal, India (Deepak, 2006; Jagadisha, 2007; Hegde et al, 2007). The wave transmission of floating breakwater was estimated for 5 layer PVC pipes with S/D (spacing to diameter ratio) of 2, 3, 4 and 5; pipe diameter of 3.2 cm; incident wave height (H_i) of 3, 6, 9, 12, 15 and 18 cm; wave period of 1.2, 1.4, 1.6, 1.8, 2.0 and 2.2 s; water depth (d) of 50, 45 and 40 cm, relative breakwater width (W/L) from 0.40 to 2.65. These experimental data are divided into two sets for training and testing the network models as shown in Table-1.

Table 1. Data used for training and testing the network models

S/D ratio	Data for training	Data for testing	Total data
2	609	203	812
3	576	233	809
4	366	143	509
5	581	234	815
Combined total	2132	813	2945

NEURAL NETWORK

Artificial neural network (ANN) is an information-processing paradigm that is inspired by the way of biological nervous system, such as brain process information. ANN is composed of large number of highly connected processing element (neurons) working in unison to solve a specific problem. The network learns through examples, so it requires good examples to train properly and further a trained network model can be used for prediction purpose.

In order to allow the network to learn both non-linear and linear relationships between input nodes and output nodes, multiple-layer neural networks are often used. Among many neural network architectures, the three layers feed forward error backpropagation neural network (BNN) is the most commonly used representing the input nodes as first layer, hidden nodes as second layer and output nodes as third layer.

The back-propagation is a supervised learning technique used for training the neural network. It is most useful for feed forward networks. The back propagation needs to know the correct output for any input parameters. The number of input nodes depends upon the complexity of the problem and the parameters which influence the output parameters.

The input parameters that influence the wave transmission (K_t) of floating breakwater such as spacing of pipes relative to pipe diameter (S/D), breakwater width relative to wave length (W/L), incident wave relative to water depth (H_i/d), incident wave relative to wave length (H_i/L) are considered. Based on above input parameters, two ANN models are constructed to predict the transmission coefficient of floating breakwater as shown in Table-2.

Table 2. ANN models with input parameters

Model	Input Parameters
ANN1	$W/L, H_i/d, H_i/L$
ANN2	$S/D, W/L, H_i/d, H_i/L$

The main objective of BNN technique is to train the model such that the result outputs are nearer to the desired values. Therefore, the error between network output and desired value is minimum.

Mathematically, the feed forward artificial neural network is expressed as

$$Z_k(x) = \sum_{j=1}^m W_{kj} * T_r(y) + b_{ko} \quad (1)$$

$$Y_j = \sum_{i=1}^n W_{ji} * x_i + b_{ji} \quad (2)$$

Where x is input values from 1 to n , W_{ji} are the weights between input layer and hidden layer nodes and W_{kj} are the weights between hidden layer and output layer nodes. b_{ji} and b_{ko} are bias values at hidden and output layer respectively. m is the number of hidden layer nodes and $T_r(y)$ is transfer function. This transfer function allows a non-linear conversion of summed inputs.

A non-linear transfer function is applied between input nodes and hidden nodes. In the present study *Tansig* is used as transfer function, which is expressed as

$$T_r(y) = \left[\frac{2}{1 + \exp(-2 \times y)} - 1 \right] \quad (3)$$

y is the summation of input values with weights and biases. The transfer function improves the network generalisation capabilities and speeds up the convergence of the learning process. The bias values for both hidden layer and output layer get adjusted for each time of iterations. The weights between hidden and output layers are calculated using updated Levenberg-Marquardt algorithm.

The linear transfer function purelin is applied between hidden layer and output layer. And the transfer function expressed as

$$\text{Purelin}(n) = n \quad (4)$$

The overall objective of training algorithm is to reduce the global error, E is defined as,

$$E = \frac{1}{P} \sum_{p=1}^P \left[\sum_{k=1}^K (\mathbf{d}_{kp} - \mathbf{o}_{kp})^2 \right] \quad (5)$$

Where; p is the total number of training patterns, \mathbf{d}_{kp} is the desired value of the k^{th} output and the p^{th} pattern, \mathbf{o}_{kp} is the actual value of the k^{th} output and p^{th} pattern. Here, Levenberg-Marquardt updated algorithm (Wilamoski et al, 2001) is used to train the network.

K_t CALCULATION BY ANN

The ANN structure is constructed for estimating wave transmission (K_t) of floating breakwater as shown in Figure-2. After training the network model, weights and biases of the network are fixed. These fixed weight and bias values are shown in Figure-2. The each input value gets multiplied with the weight and adds with bias value. The total sum is the input at each hidden node and pass through a transfer function as defined in Equation 3, and further the output from hidden node get multiplied with the weight and adds with the bias value and total sum pass through purelin as shown in Equation 4.

The wave transmission (K_t) is estimated using following formulations:

$$\text{Transfer function } F_i = \left[\frac{2}{1 + \exp(-2 \times N_i)} - 1 \right] \quad \dots i = 1 \text{ to } 5 \quad (6)$$

Where, N_i are values of hidden nodes and F_i are the transfer functions of hidden node i .

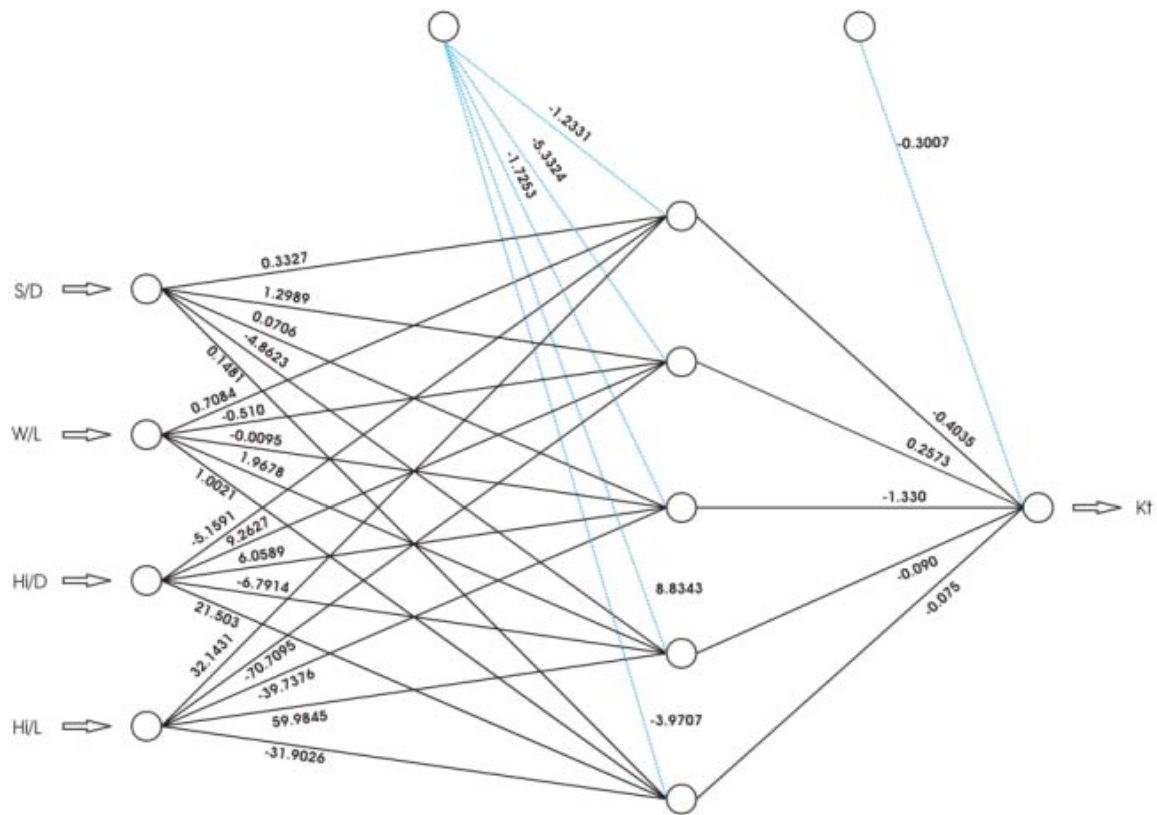


Fig.2. The ANN2 structure with weights and biases for N-4-5-1.

For ANN2 model, the trained hidden nodes and its transfer functions are

$$\begin{aligned}
 N_1 &= S/D(0.3327) + W/L(0.7084) + Hi/d(-5.1591) + Hi/L(32.1431) - 1.2331 \\
 N_2 &= S/D(1.2989) + W/L(-0.510) + Hi/d(9.2627) + Hi/L(-70.7095) - 5.3324 \\
 N_3 &= S/D(0.0706) + W/L(-0.0095) + Hi/d(6.0589) + Hi/L(-39.7376) - 1.7253 \\
 N_4 &= S/D(-4.8623) + W/L(1.9678) + Hi/d(-6.7914) + Hi/L(59.9845) + 8.8343 \\
 N_5 &= S/D(0.1481) + W/L(1.0021) + Hi/d(21.503) + Hi/L(-31.9026) - 3.9707
 \end{aligned}$$

$$\begin{aligned}
 F_1 &= (2 / (1 + \exp(-2xN_1))) - 1 \\
 F_2 &= (2 / (1 + \exp(-2xN_2))) - 1 \\
 F_3 &= (2 / (1 + \exp(-2xN_3))) - 1 \\
 F_4 &= (2 / (1 + \exp(-2xN_4))) - 1 \\
 F_5 &= (2 / (1 + \exp(-2xN_5))) - 1
 \end{aligned}$$

N_1 to N_5 and F_1 to F_5 represent summation function and transfer function at each hidden node respectively.

The K_t is computed as:

$$K_t = F_1(-0.4035) + F_2(2.2573) + F_3(-1.330) + F_4(-0.090) + F_5(-0.075) - 0.3007 \quad (7)$$

Equation 7 provides trained ANN2 model for estimating wave transmission (K_t) of floating breakwaters.

The correlation coefficient is calculated to know the how best the network predicted K_t values are matches with the measured K_t values. The straight line is drawn at an angle of 45° between the two axes to fit the data points. A high correlation is obtained when all the points lies exactly on this straight line.

The network predicted wave transmission (K_t) is calculated using Equation 7. At end of each training process Correlation Coefficient (CC) is calculated between measured (desired) K_t and predicted K_t using following equation

$$CC = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \quad (8)$$

Where, $x = X - X'$

X = network predicted K_t values

X' = mean of X

$y = Y - Y'$

Y = measured K_t values.

Y' = mean of Y .

RESULTS AND DISCUSSION

In neural network technique training of the network plays a very important role and it mainly depends upon updated algorithms to be chosen to train the network.

The ANN modeling of wave transmission of floating breakwater is carried out for 5 layer pipes with S/D (spacing to diameter ratio) of 2, 3, 4 and 5. The input parameters of ANN1 model are W/L , H_i/d and H_i/L . An optimal S/D can be chosen from ANN1 modeling. To study over a range of spacing of pipes (S/D) on K_t , an input parameter, S/D is added to form ANN2 model.

After training and testing of both network models, CCs are calculated between desired output and network output using Equation 8.

In the present study, updated algorithms such as Levenberg-Marquardt algorithm (LM) is used to train the two network models with 100 and 200 epochs (Wilamoski, et al, 2001). The trained and tested ANN1 model's correlation coefficients (CC) and mean square error (MSE) of K_t for different S/D values are shown in Tables 3 to 6. This shows that the CC increases with S/D . The trained and tested ANN2 model's correlation coefficients of K_t are shown in Tables-7. The final trained and tested results (CCs) of two network models are shown in Table-8 and Figures 3 to 6.

It is observed that the correlation coefficients obtained are above 0.90. A high correlation coefficient is obtained at epoch equal to 200 with hidden nodes equal to 4 for ANN1 model (CCtrain=0.9672, CCtest=0.9649) and hidden nodes equal to 5 for ANN2 model (CCtrain=0.9537, CCtest=0.9488). Since all S/D values are considered in ANN2 model, CCs are in general less than that for ANN1 model with spacing ratio (S/D) of 5. The highest CC is obtained for ANN1 model (N-3-4-200) with spacing ratio of 5.

Table 3. Correlation coefficient of K_t for ANN1 model with S/D=2

Hidden Nodes	CCtrain	CCtest	MSEtrain	Epochs
2	0.9377	0.9312	0.00342	100
3	0.9449	0.9400	0.00303	100
4	0.9495	0.9426	0.00279	100
2	0.9376	0.9302	0.00342	200
3	0.9488	0.9430	0.00282	200
4	0.9552	0.9504	0.00248	200

Table 4. Correlation coefficient of K_t for ANN1 model with S/D=3

Hidden Nodes	CCtrain	CCtest	MSEtrain	Epochs
2	0.9310	0.9205	0.00230703	100
3	0.9382	0.9260	0.00207239	100
4	0.9419	0.9328	0.0019508	100
2	0.9263	0.9126	0.0024562	200
3	0.9469	0.9368	0.00178878	200
4	0.9506	0.9404	0.00166577	200

Table 5. Correlation coefficient of K_t for ANN1 model with S/D=4

Hidden Nodes	CCtrain	CCtest	MSEtrain	Epochs
2	0.9490	0.9447	0.00164663	100
3	0.9620	0.9562	0.00122984	100
4	0.9647	0.9563	0.00114397	100
2	0.9551	0.9534	0.00144801	200
3	0.9619	0.9569	0.00123356	200
4	0.9642	0.9601	0.0011579	200

Table 6. Correlation coefficient of K_t for ANN1 model with S/D=5

Hidden Nodes	CCtrain	CCtest	MSEtrain	Epochs
2	0.939	0.937	0.00286544	100
3	0.9508	0.9488	0.00232692	100
4	0.9654	0.9642	0.00164658	100
2	0.9401	0.9369	0.00281679	200
3	0.9586	0.9567	0.00196222	200
4	0.9672	0.9649	0.00156346	200

Table 7. Correlation coefficient of K_t for ANN2 model

Hidden Nodes	CCtrain	CCtest	MSEtrain	Epochs
2	0.9102	0.9003	0.00444906	100
3	0.9353	0.9286	0.00325118	100
4	0.9467	0.9414	0.00269082	100
5	0.9508	0.9473	0.00248828	100
2	0.9294	0.9237	0.00353477	200
3	0.9372	0.9345	0.00315484	200
4	0.9453	0.9421	0.00276019	200
5	0.9537	0.9488	0.00234973	200

Table 8. Correlation Coefficients of K_t for two network models

Model	Network (Input nodes - Hidden nodes - Epochs)	CCtrain	CCtest
ANN1	3-4-200	0.9672	0.9649
ANN2	4-5-200	0.9537	0.9488

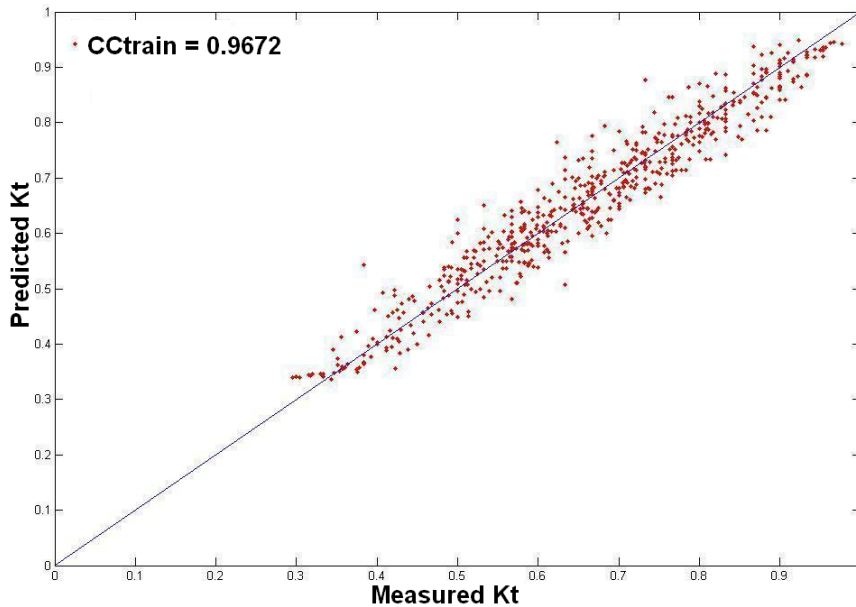


Fig. 3. Trained correlation between predicted and measured K_t for ANN1 model with $S/D=5$.

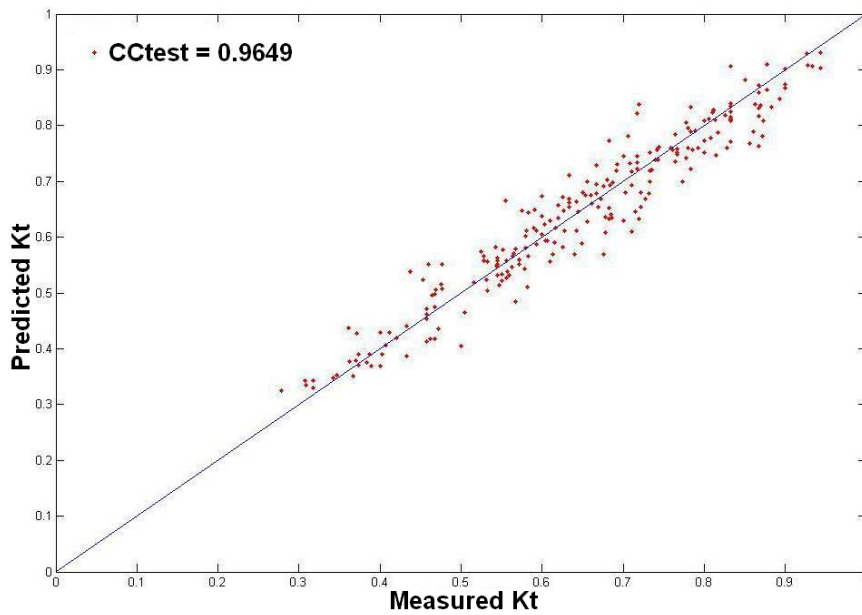


Fig. 4. Test correlation between predicted and measured K_t for ANN1 model with $S/D=5$.

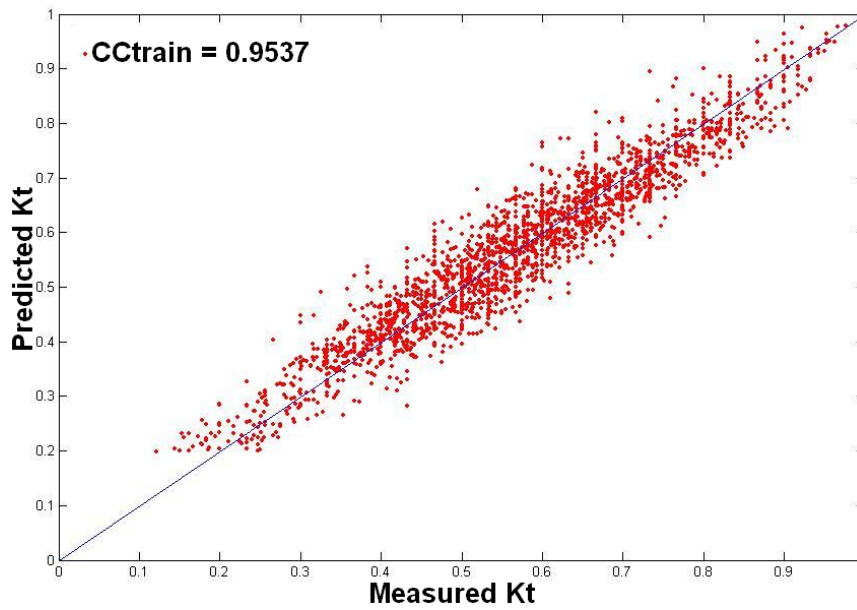


Fig. 5. Trained correlation between predicted and measured K_t for ANN2 model.

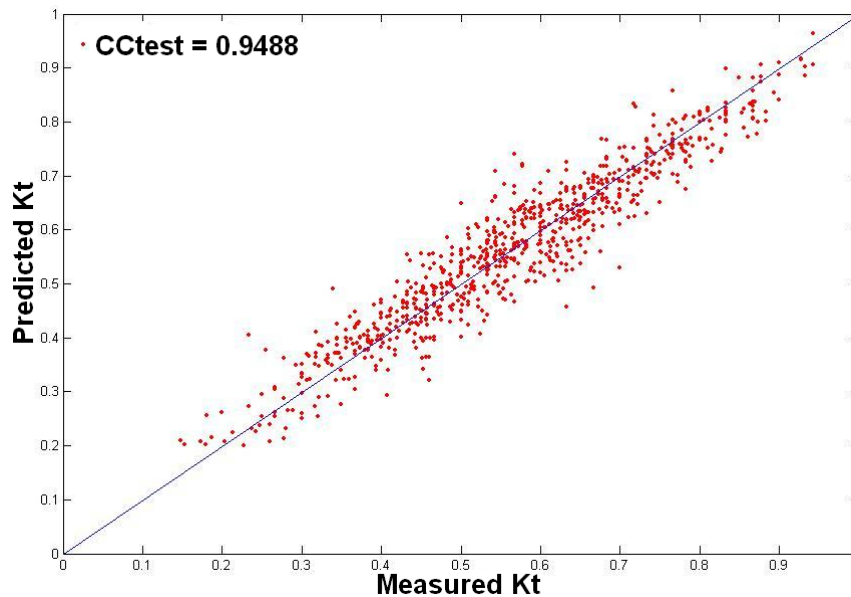


Fig.6. Test correlation between predicted and measured K_t for ANN2 model.

CONCLUSIONS

Based on the present study the following conclusions are drawn:

In neural network technique, selecting a proper network algorithm plays very important role. In this study, the artificial neural network model with Levenberg-Marquardt updated algorithm is used to predict the wave transmission of floating breakwater. The ANN models are trained upto 200 epochs. This study shows that the correlation coefficient of wave transmission coefficient increases with pipe spacing ratio. The highest train and test CCs of K_t for ANN1 model with $S/D=5$ are 0.9672 and 0.9649 respectively. This shows an improvement of predicted K_t for higher pipe spacing ratio.

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