An Artificial Neural Network for Prediction of Front Slope Recession in Berm Breakwaters

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ARTICLE INFO

ABSTRACT

Berm breakwaters are used as protective structures against the wave attack where larger quarry materials as armor stone is scarce, or large quarry materials are available but using berm breakwater lowers the costs considerably. In addition, wave overtopping in berm breakwaters are significantly lower than the traditional ones for equal crest level because of the wave energy dissipation on the berm.The most important design parameter of berm breakwaters is its seaward berm recession which has to be well estimated. In this paper a method has been developed to estimate the front slope recession of berm breakwaters using artificial neural networks with high accuracy. Four different available data-sets from four experimental tests are used to cover wide range of sea states and structural parameters. The network is trained and validated against this database of 1039 data. Comparisons is made between the ANN model and recent empirical formulae to show the preference of new ANN model.

1. Introduction

Unlike the conventional rock armored breakwaters, berm breakwaters have a large porous berm at their seaward side which can be reshaped during the wave attack to a stable S-shaped form. PIANC (2003) report "State-of the-Art of Designing and Constructing Berm Breakwaters" provided proper descriptions about the design and construction of berm breakwaters. In the design of berm breakwaters finding the appropriate berm width is undoubtedly associated with well estimation of its seaward berm recession. Figure 1 shows the cross sectional of initial and reshaped profile, together with the recession parameter in a berm breakwater. Estimating the optimized berm width results in more economical design.
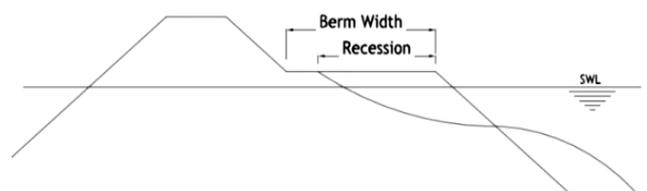

Figure 1.schematic of the berm breakwater section and the recession parameter

A number of researchers propounded methods for calculating the berm recession. There are some numerical methods proposed by Van der Meer (1992), Van Gent (1995) and Archetti and Lamberti (1996). Besides, there are some empirical formulas. For instance, Hall and Kao (1991) presented a formula considering the effect of rounded stones fraction in the armor, and stone gradation on the reshaping of berm breakwaters. Tørum (1998) proposed a formula based on the results of a small model test on different projects which have been carried out in different laboratories as a function of stability number (H_0T_0). A more complete variation of Tørum (1998) formula, including water depth and stone gradation was presented by Tørum et al. (2003). Sigurdarson et al. (2007) suggested a simple formula as a function of stability number (H_0T_0) for multilayer berm breakwaters, based on Tørum (1998) dataset. Lykke Andersen and Burcharth (2009) put forward a semi-empirical recession formula which was at the continuance of Lykke Andersen (2006) researches on his numerous model tests carried out on homogeneous berm breakwaters. Sigurdarson and Van der Meer (2011) showed that the main parameter that describes the recession, Rec, is the stability number $Hs/\Delta Dn50$. Moghim et al. (2011) presented a simple formula, as a function of modified stability number ($H_0T_0^{0.5}$) which was proposed based on their experiments. Fundamental to the Shekari (2013) experiments, Shekari and Shafieefar (2013) presented an empirical

formula, which has been ameliorated by Shafieefar and Shekari (2014). Sadat Hosseini (2013) presented a recession formula, employing M5' machine learning approach on the amalgamation of Moghim (2011) and Shekari (2013) datasets. Van Gent (2013) performed physical model tests in a wave flume at Deltares, Delft. His tests were focused distinctively on the upper and lower slope of the berm elevation. In Van Gent (2013) studies, the impact of the slope angle (1:2 and 1:4), berm width, berm level, and also the wave steepness has been investigated. He proposed a recession formula based on the damage parameter and the berm elevation with respect to the water level. Moghim and Alizadeh (2014) presented a new berm recession formula based on the proportionality of the maximum wave momentum flux at the toe of the structure and the berm recession. Van der Meer and Sigurdarson (2016) presented a book as a guidance on design and construction of berm breakwaters as the result of their cooperation, both in the scientific as well as the practical field.

Most of these studies ended to different formulas which show dissimilarities in recession parameter approximation. The aim of this study is to find a more comprehensive algorithm, alternative to the foregoing empirical formulas, aim at minimizing the berm recession estimation error, using artificial neural networks.

2. Description of database and parameters involved

The Recession database which is used for constructing the ANN includes a total of 1039 data which are obtained from the experiments carried out by Lykke Andersen (2006) (474 data points), Motalebi (2010) (120 data points), Moghim (2011) (113 data points) and Shekari (2013) (332 data points).

Lykke Andersen (2006) model tests were performed at Aalborg University. The main part of Moghim (2011) experiments has been carried out in the Shore Protection Division of Soil Conservation and Watershed Management Research Institute (SCWMRI) wave flume that is equipped with a DHI irregular wave generation system. Motalebi (2010) and Shekari (2013) carried out their tests in the wave channel at the Hydraulic Laboratory of Civil and Environmental Engineering department of Tarbiat Modares University.

Ranges of non-dimensional parameters, used in ANN set-up, for these four model tests are presented in Table 1.

Table 1. Ranges of main non-dimensional parameters for each set of data

Parameter		Range			
		Lykke Andersen (2006)	Motalebi (2010)	Moghim (2011)	Shekari (2013)
Stability number	H_0	1.35 to 4.86	1.87 to 4.23	1.53 to 4.03	1.57 to 3.87
Non-dimensional mean wave period	T_0	19.9 to 39.6	20.7 to 27.3	24 to 37.4	15.6 to 29.3
Non-dimensional water depth at the toe of the structure	d/D_{n50}	8.8 to 22.3	8.0 to 16.5	11.8 to 16.5	8.0 to 16.5
Non-dimensional berm width	B/D_{n50}	7.7 to 33.0	8.0 to 17.6	23.5 to 23.5	12.0 to 26.5
Non-dimensional berm elevation above SWL	h_b/D_{n50}	-6.1 to 2.0	0.0 to 4.6	0.9 to 4.4	0.4 to 4.12
Number of incident waves	N	3000 to 3000	3000 to 3000	500 to 6000	500 to 6000
Gradation factor	f_g	1.35 to 1.45	1.82 to 1.82	1.5 to 1.5	1.5 to 3.32
Wave steepness	S_{om}	0.0149 to 0.0638	0.0313 to 0.0511	0.0130 to 0.0724	0.019 to 0.122

3. Artificial Neural Network Modeling and Results

3.1. General

Artificial Neural networks (ANN) are a group of machine learning approaches which can be used for a variety of data mining tasks in order to model and solve the problems in technical and scientific fields. Multi Layer Perceptron networks are type of neural networks which are set up in some layers within each of these, there are one or more neurons as processing units. When the network layers connect to each other in one direction only, the network is called a standard multi-layer feed-forward neural network. The network consists of a topology graph of neurons. The first layer, which is called the input layer, consists of a number of neurons equal to the number of input parameters. The last layer is called the output layer which made up of a number of neurons equal to the number of output parameters to be predicted. The inputs and outputs are weighed by weights and shifted by bias factor specific to each neuron. There are hidden layers between the input and output layers consists of neurons, each of which computes a function of the inputs carried on the in-edges and sends the weighted sum of the outputs of the preceding layer on its out-edges. This output then is used as an input for the next layer neurons. For the output layer often a linear activation function is used (Haykin, 1994) and the final prediction of the neural

network is provided by the neurons of the output layer.

3.2. The Model Architecture

The architecture of the model has been achieved through an algorithm, which is explained as follow. The general solution algorithm is that, when the error criterion, which is in here the root mean squared error ("RMSE", Eq. (1)), of the ANN becomes less than that of the previous network, which is built prior to the present network, that ANN will be chosen as the best network.

$$RMSE = \sqrt{\sum_i^N \left[\left(\text{Re}\, c / D_{n50} \right)_{obs,i} - \left(\text{Re}\, c / D_{n50} \right)_{ANN,i} \right]^2} \quad (2)$$

In Eq. (1), indices obs and ANN refer to the experimental and predicted data by ANN model, respectfully. Index i denotes the i-th data and N is the number of data in training set or testing set.

Therefore, the whole dataset is split into training and testing set. At first, the training data is applied to train the network. The RMSE is calculated and the weights and bias are acquired. Then, a new distribution of the data is selected. In other words, if 20% of the data are selected as the testing data, the dataset is divided into 5 partitions, in which, 1 partition is assigned for testing and 4 others for training. At each step, a new distribution which consists of 20 percent of data is selected. This changes in selection, not only includes the selected partition, but, also the members of the partitioned set can be Changed. The initial weight and bias of the new network is set equal to those of the accepted network. This new network is trained with the new distribution of data. The new network is accepted if it's RMSE error is less than the previous one, as mentioned before. Otherwise, the previous selected network remain as the benchmark and again, this process is repeated with the new distribution of the data. Any changes in data distribution allows the network to be trained and tested with the lowest error, regardless of how the data have been chosen. Hence, with this method, the finally chosen network has the minimum errors. History of change in network's weights and bias could be efficacious in finding the best network with the minimum RMSE. In other words, some networks may temporarily increase the network error, but in upcoming steps, the network error could be less than the initial state. It could be said that, redirecting the decline in weights, can increase the likelihood of encountering an absolute minimum in network error. Thus, in this research, in the process of finding the best network, this feature is included that the networks, which have not fewer errors in comparison to their previous one, could be accepted (redirect to an absolute minimum) by determining a certain probability of occurrence in the process.

Avoiding to be trapped in local minimum of the network error, makes it rational to let the network to examine some other paths toward the other minimum of the network error. To carry out this idea, despite of the main procedure, some networks within a pre-determined range are accepted.

In order to identify the optimum number of hidden neurons in ANN model in the process of training and testing according to the above algorithm, an analysis of the network performance variability was carried out. Figure 2 shows the variation in RMSE value with increasing number of hidden neurons.
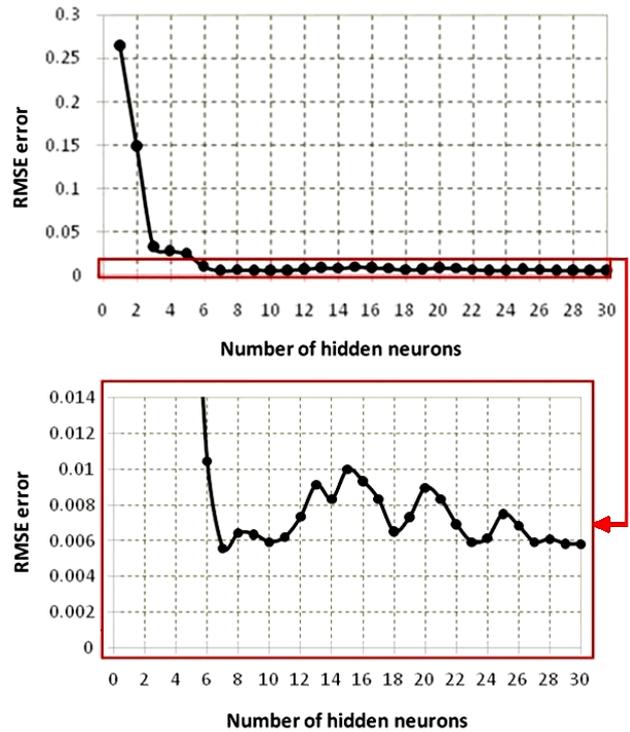

Figure 2. Mean RMSE value as functions of the number of hidden neurons in ANN simulation processes (The diagram on the right shows fluctuations of RMSE with more precision in Y-axis)

It can be observed that the RMSE stabilizes around the average value of 0.007 for a number of training–testing processes with number of neurons greater than 5. The optimum value of RMSE obtained when training–testing processes held with 7 hidden neurons.

Based on the process explained above, the ANN model is built with the following fundamental characteristics:

- Multilayer network, based on a "feed-forward back-propagation" learning algorithm;
- Static network (absence of delays and feedbacks);
- Structure and layers: the input vector with 7 elements, 1 hidden layer with 7 hidden neurons and 1 output neuron, the non-dimensional recession parameter;

- Hidden neurons transfer function: hyperbolic tangent sigmoid transfer function;
- Output neuron transfer function: linear transfer function;
- Data structures: the arrays of data can be provided to the network as "concurrent vectors", *i.e.* rows of a matrix in a random order; as long as a neural network is static, the way the arrays are provided to the ANN (i.e. subsequent or concurrent way) has no relevance for the simulation while for the training phase it is very important since the connections weights are updated accordingly; in fact, connections weights may be updated either at the end of each training epoch or within each epoch for each new test;
- Training style: "batch training", connections weights and biases are updated at the end of each training epoch, just once the ANN has read all the input data;
- Training algorithm: Levenberg–Marquardt algorithm;
- Learning algorithm: momentum gradient descent back-propagation algorithm.

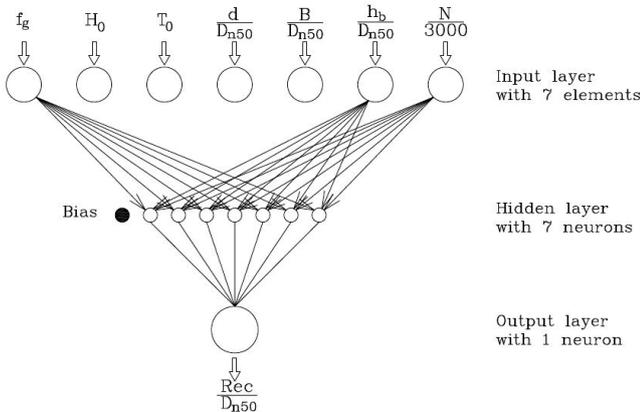In Figure 3 the logic layout of ANN configuration is schematized.

Figure 3. Logic layout of the ANN configuration

3.3. Input Parameters

The input parameters, should include a synthesis of sea, such as wave height, wave period, water depth at the toe of the structure and storm duration; and also the structural characteristics of the breakwater itself including armor stone size, berm elevation from still water level, initial berm width and seaward slope of the initial profile. The choice of the parameters was initially based on the previous simplest non-dimensional parameters in researches on prediction of reshaping parameters in berm breakwaters. Besides, Table 2 illustrates these seven non-dimensional parameters. Note that in Table 2, $\Delta= \rho_s / \rho_w - 1$, which is the relative buoyant density; ρ_s is the density of stone and ρ_w is the density of water.

Table 2. Range of non-dimensional parameters used as the *input* parameters in ANN.

dimensionless parameter	min	max	mean
f_g	1.35	3.32	1.56
$H_0=H_s/\Delta D_{n50}$	1.35	4.86	2.93
$T_0= T_m (g/D_{n50})^{0.5}$	15.6	39.6	25.74
d/D_{n50}	8.0	22.33	14.93
B/D_{n50}	7.73	33.0	19.38
h_b/D_{n50}	-6.1	4.6	1.81
$N/3000$	0.167	2.0	0.994

3.4. Weights and Biases

The main products of the trained ANN are its weights and bias elements, which allow using the network as a predictive model. These elements can be matrixes, vectors or scalars which contain the values attributed to the connections among neurons by the model itself during the training process. The weight matrixes are illustrated in Table 3.

Table 3. Weight matrixes of the connections

IW{1,1}, size: 7×7

10.051	1.444	0.53	-4.973	123.936	-117.21	7.439
35.054	2.016	0.227	3.098	13.415	-14.671	8.206
1272.168	291.355	-289.95	327.002	187.891	-231.64	519.529
44.48	-1.429	-0.081	21.886	0.111	12.015	-16.419
0.09	0.355	0.115	0.217	0.012	0.081	-0.008
415.141	-278.55	68.195	-273.74	24.88	-11.678	49.442
-413.753	-266.75	16.62	-297.63	-545.46	-416.32	242.343

LW{1,1}, size: 1×7

0.223	-0.201	0.032	-0.128	2.305	0.029	0.059

B{1,1}, size: 7×1

-36.213	22.984	967.763	15.749	0.014	432.731	-342.73

B{2,1}, size: 1×1

-0.1182

In this study, we have 4 elements: the matrix of "Input Weights" (IW, of dimensions 7×7) to connect input parameters to hidden neurons, the matrix of "Layer Weights" (LW, a single row of dimensions 1×7) which connects hidden neurons to the output neuron, the bias vector (7×1) for hidden layer and the bias scalar (1×1) for the output layer. 64 weights (7×7+1×7+7×1+1×1) associated to connections are employed overall. It is important to note that, before entering into training, the network normalizes the input elements and the output, according to the corresponding minimum and maximum values.

3.5. Performance of the model

In order to investigate the performance of the new ANN model, the observed non-dimensional recession (Rec/D_{n50} observed) is illustrated versus the predicted non-dimensional recession ($Rec/D_{n5}0$ predicted) in Figure 4.
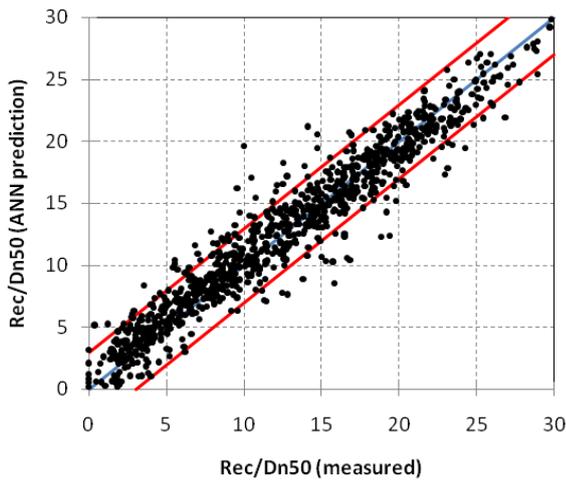
Figure 4. Observations versus ANN predictions for Rec/D_{n50} parameter

It is evident from Figure 4 that, the predictions of the ANN model are reasonably accurate in all the range of dataset. The central line stands for the perfect correspondence among predicted and experimental values and the external lines represent the 90 percent confidence boundaries. This indicative 90% confidence band indicates that there are few data points for which the ANN predictions are a factor 10 (or more) larger/smaller than the corresponding observations. Also, it is obvious from Figure 4 that, there is a good degree of symmetry provided by the ANN model. This is also apparent from Figure 5, which represents the error frequency distribution histogram.
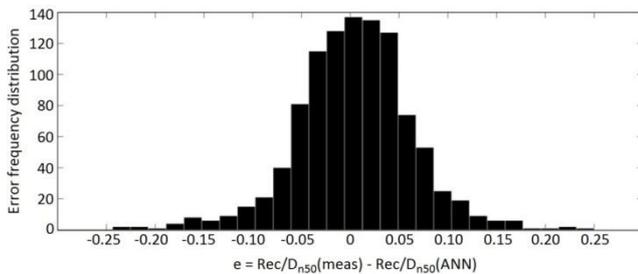
Figure 5. The error (Difference e = Rec/D_{n50}(measured) - Rec/D_{n50}(ANN prediction)) frequency distribution histogram

In order to make a quantitative estimate of the ANN model accuracy, the correlation of coefficients (R^2), the above-mentioned RMSE and the refined index of model performance (d_r) given by Willmott et al. (2012), compared to the old version of "WI" represented by Willmott (1981), are calculated. The value of R^2 is 0.93 and the RMSE value is 0.055, which shows that, the average magnitude of the forecast errors are rigorously low. The value of 0.91 for dr, which is a reformulation of Willmott's index of agreement (WI), denotes that the model-estimated deviations about average values of observed data are strong estimates of the observed deviations.

4. Comparison among the new ANN model and recent empirical formulas

The aim of the present section is to provide a comparison among ANN performance and traditional prediction formulae.

Table 4 reports the quantitative results of these simulations in terms of R^2, RMSE and d_r values. The ANN shows more accurate predictions in comparison to the other formulas.

Table 4. Statistical indices (R2, RMSE and dr values) for the ANN model versus the other formulas

Models	R^2	RMSE	d_r
Hall and Kao (1991)	0.71	6.47	0.53
Tørum et al. (2003)	0.72	7.49	0.27
Sigurdarson et al. (2007)	0.76	5.24	0.55
Lykke Andersen and Burcharth (2009)	0.86	3.81	0.73
Moghim et al. (2011)	0.81	3.14	0.76
Shekari and Shafieefar (2013)	0.79	7.51	0.39
Sadat Hosseini (2013)	0.88	2.07	0.84
Shafieefar and Shekari (2014)	0.82	3.38	0.71
Moghim and Alizadeh (2014)	0.87	2.53	0.83
ANN (This research)	0.93	0.006	0.91

According to the Table 4, The results from the new ANN model, give much less error than the closed form formulas given by the other researchers. So it is possible to predict the berm recession by using the ANN model more accurate than the formulas.

Figure 6 to 14 present comparisons between the distribution of predicted non-dimensional recession versus corresponding measured values from previous works with the ANN model.
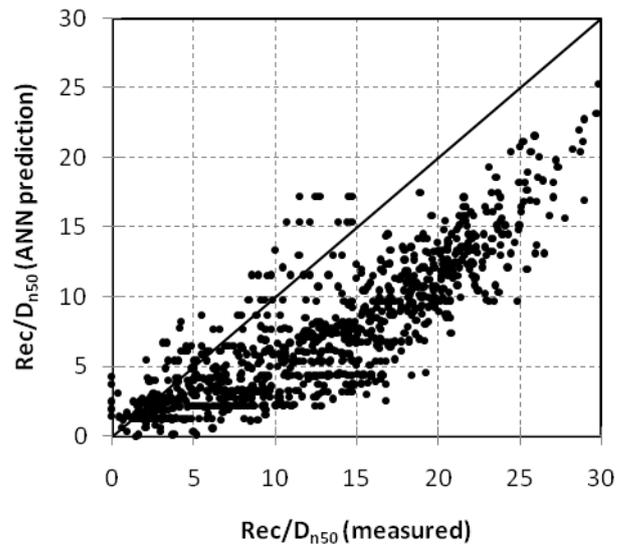

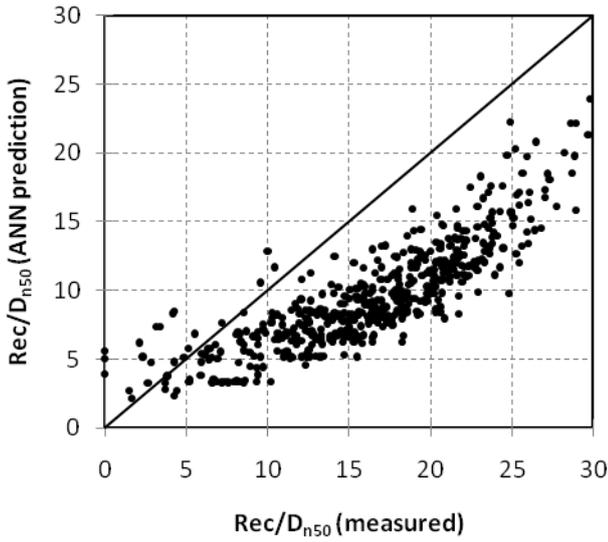**Figure 6. Observations versus predictions by Hall and Kao (1991) for Rec/D_{n50} parameter**

Figure 7. Observations versus predictions by Tørum et al. (2003) for *Rec/D*n50 parameter
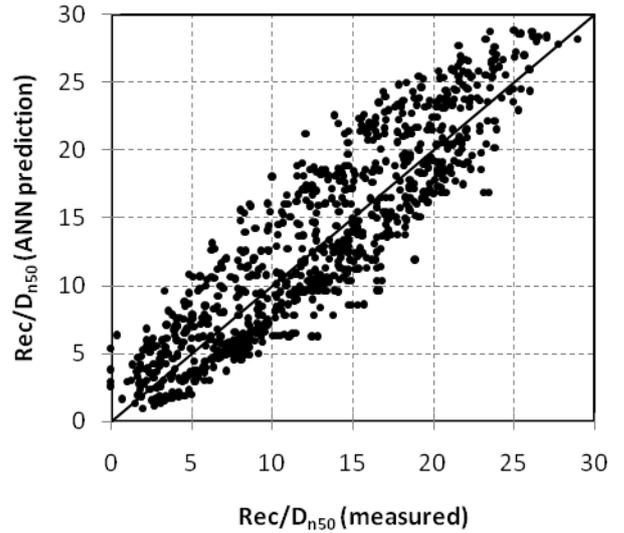
Figure 10. Observations versus predictions by Moghim et al. (2011) for *Rec/D*n50 parameter
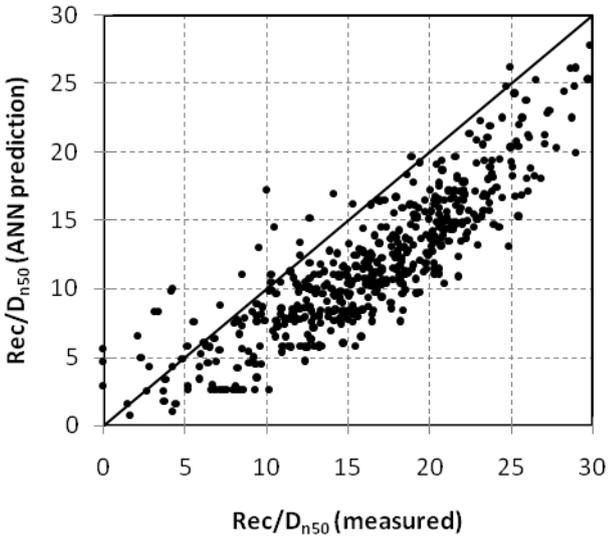
Figure 8. Observations versus predictions by Sigurdarson et al. (2007) for *Rec/D*n50 parameter
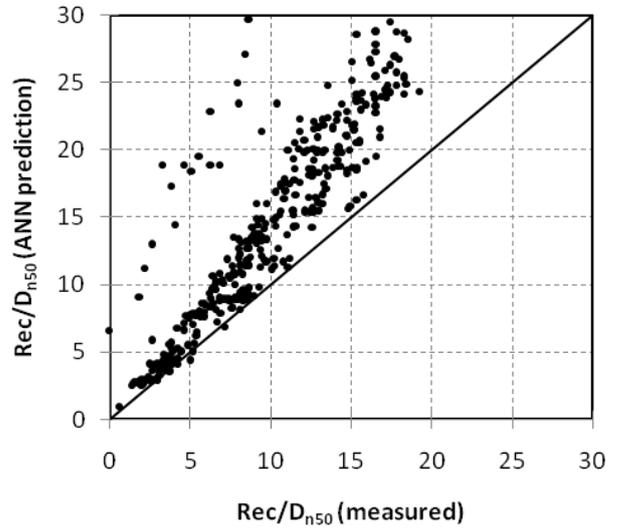
Figure 11. Observations versus predictions by Shekari and Shafieefar (2013) for *Rec/D*n50 parameter
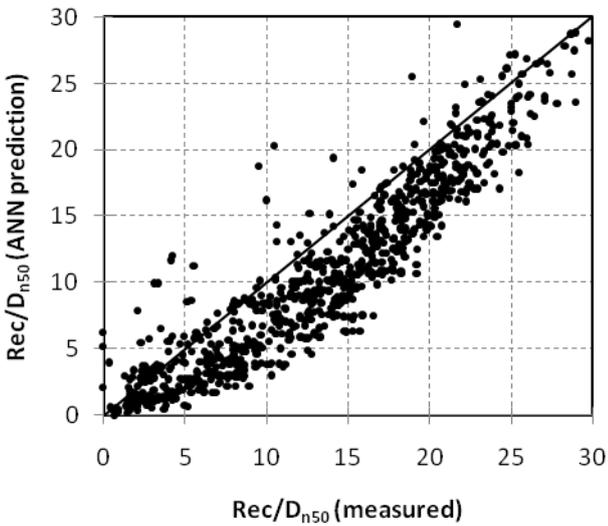
Figure 9. Observations versus predictions by Lykke Andersen and Burchart (2009) for *Rec/D*n50 parameter
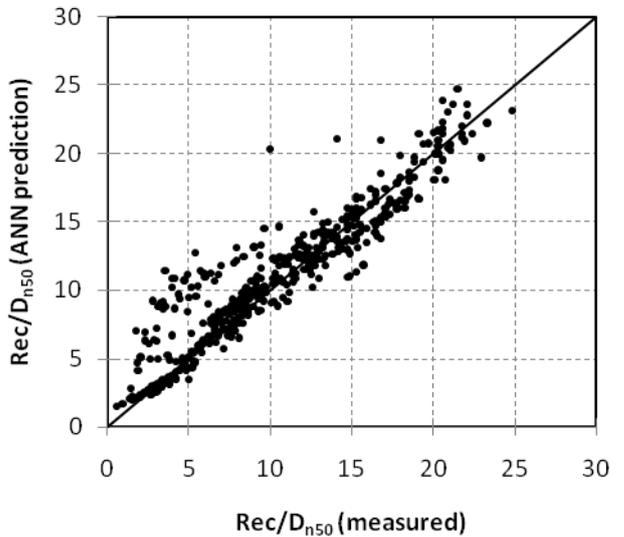
Figure 12. Observations versus predictions by Sadat Hosseini (2013) for *Rec/D*n50 parameter
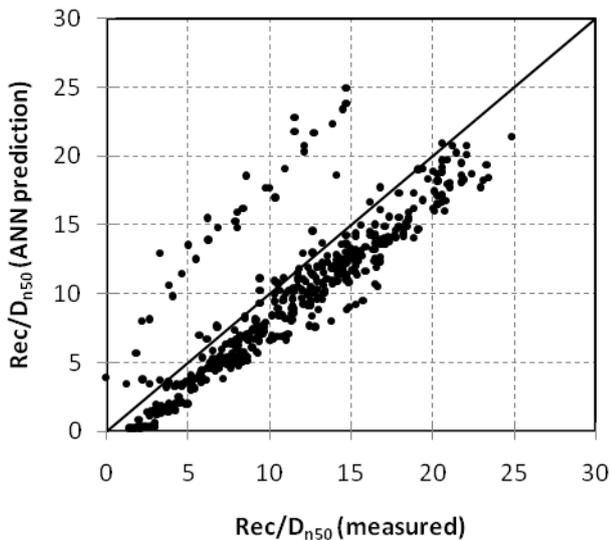
Figure 13. Observations versus predictions by Shafieefar and Shekari (2014) for *Rec/D_{n50}* parameter
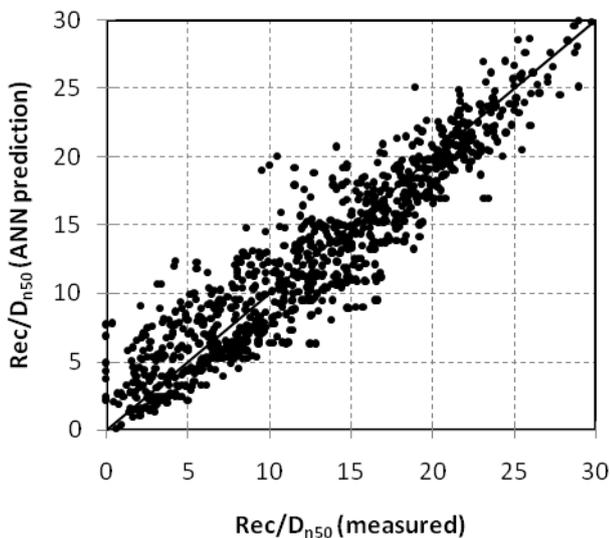

Figure 14. Observations versus predictions by Moghim and Alizadeh (2014) for *Rec/D_{n50}* parameter

5. Summary and Conclusions

A neural network based prediction method has been developed for the estimation of the seaward berm recession in berm breakwaters. A strong technique based on the reduction of the networks' RMSE which are built on the split and redistributed data have been applied to reach to the optimum ANN. The presented results show that Neural Networks can successfully be used to model the relationship between the input parameters involved in berm recession and the one obtained from experimental models. The neural network model constructed herein is based on the database from experiments performed by Lykke Andersen (2006), Motalebi (2010), Moghim (2011) and Shekari (2013). It is illustrated that the agreement between the predicted and the measured berm recession is well acceptable.

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