# Wave Run-up Prediction on Antifer Armor Using Neural Network Method

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The certainly goal of this study is to present the better way from terms of cost and experimenting duration, instead using experimental ways for investigates the wave run-up (Ru) over rubble-mound breakwater and examines the effect of placement pattern of Antifer units on the amount of wave run-up. In order to, it is suggested utilizing the Artificial Neural Networks (ANNs). For the sake of comparison, the proposed modeling is put into contrast by the ones obtained via other approaches in the literature. The Multi-Layer Perceptron (MLP) is selected as the artificial neural network exerted in this study. In the designed neural network, the numbers of inputs and outputs are selected as four and one, respectively. Additionally, the number of neurons in the single hidden layer of the network are appointed by trial and error. The Mean Square Error (MSE) of the training and correlating data set are investigated so that, seven hidden neurons is selected. This study has presented the regression equations and MSE for the results obtained by ANN are compared with other models. In conclusion, the regular placement would have offered to other placement patterns for the reason that its less MSE obtained by ANN.

*Keywords: Wave run-up, Breakwater, Antifer, Armor, Artificial Neural Network, Multi-layer Perceptron, MSE.*

## INTRODUCTION

Wave run-up is one of the main physical processes which are taken into account in the design of rubble mound breakwater covered by armor units. The wave run-up on rubble mound breakwaters have been investigated by many researchers.In previous studies, many researchers have explored the wave run-up on breakwaters through laboratory experiments which are inappropriate in terms of cost and experimenting duration. Some of investigations were mainly concentrated on the wave run-up on various kinds of armor as well as Antifer, Tetrapod, Accropod, Xblock and Cube [1], and Yagci and Kapdasli have offered alternative placement technique for antifer units [2]
Synolakis has verified variation of wave run-up for breaking and non-breaking solitary waves [3]. Also, Hughes has re-examined exiting wave run up data for regular, irregular and solitary waves on smooth and impermeable plane [12].

Bakhtyar et al. have indicated which a main benefit of neural networks are recognizing the relations in system thus, the neural networks are modern technique for solving complicated problems. In addition, they have presented an appropriate prognostication method for wave run-up on each armor unit with using neural network [4].

Between 1976 and 1978, the researches on the design of armor have showed that blocks with simple shape did not protect sufficiently the stability of the armor layer, thus the scientists have carried out on the blocks grooved on four sides. These grooved cubes, Antifer-blocks called [5, 6]. Among other works important documents were “wave run-up’’ Battjes (1971) [7], van der meer (1992) [8], Van de Walle (2003) [9], Shanker et al. (2003) [10], Hughes (2004) [12], , Dentale et al. (2012) (2013) [14, 15], Najafi-Jilani et al. (2014) [16], Altomare et al. (2014) [17], Crespo Alejandro [18], and Dong-Soo et al. (2014) [19]. Furthermore, some of investigations have used SPH model to simulate wave run-up [18, 19].

In the present study, by utilizing the Artificial Neural Networks (ANNs), the objective of the investigation is to determine the importance of a placement pattern of Antifer units and its effect over the amount of wave run-up. The results can be obtained which reduces the computational time and the experiment costs. For the sake of comparison, the proposed modeling is put into contrast by the ones obtained via other approaches in the literature.

In the other hand, for the validation of conclusions, the wave run-up on virtual breakwater (armor in Antifer) were compared with some practical formulae and some laboratory tests. It will be presented based on the complete experiments of Najafi-Jilani and Monshizadeh [11]. The result of this approach are fantastic due to having at least errors (calculated MSE), at present, however this numerical approach can be used instead of to innovate the new formulae or to obtain some laboratory tests.

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## DATABASE

In the present work, practical results of Najafi Jilani and Monshizadeh [11] in hydro-environmental laboratory of the Water Research Institute in Iran have been utilized. They have designed a wave flume which was concluded the virtual breakwater at end of the flume and regular waves were made by wave maker. This flume was 2.5 m high, 1 m wide and 25 m long (fig 1).

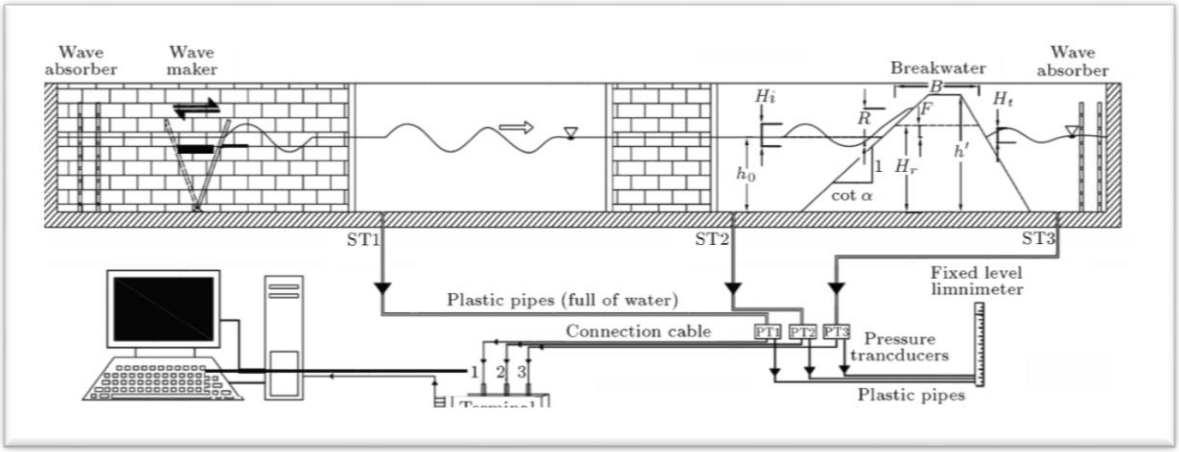


**Figure 1. Experimental set-up in the laboratory tests of Jilani's experiments [11].**

The some of certain variables were considered as the main variable parameters in the experiments. These variables were as follows: the placement patterns of antifer units, the front slope angle of the rubble-mound breakwater (cot $\alpha$), the incident wave height ($H_i$), incident wave period (T) and mean water depth ($h_0$).

**Table 1. The range of parameters influencing over the wave run-up in the samples of Jilani [11].**

| Variables | Range | dimension |
|---|---|---|
| Placement Patterns | Regular, Irregular A & B | [-] |
| Slope of breakwater (cot $\alpha$) | 1, 1.5, 2, 2.5 | [-] |
| wave height ($H_i$) | 8, 12, 16, 20 | [cm] |
| wave period (T) | 0.0017 | [s] |
| water depth ($h_0$) | 80 | [cm] |

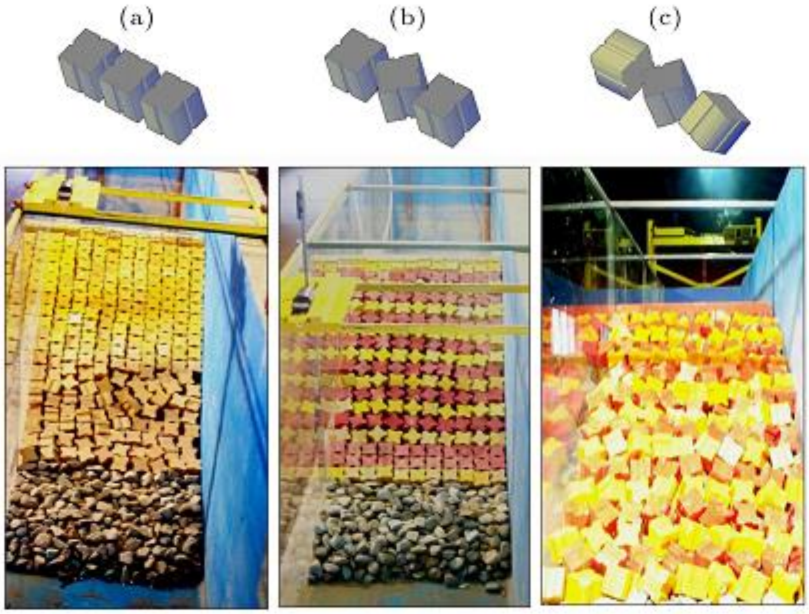


**Figure 2. Various placement of the Antifer units; (a) Regular, (b) Irregular-Type A, and (c) Irregular Type B, were used in Jilani's experiments.**

They [11] have offered the outcome of laboratory tests, then have estimated the wave run-up on the slopes covered by Antifer blocks in regular and irregular placement patterns:

$$\frac{R}{h_0} = K_p \left(\frac{\pi}{2\alpha}\right)^{0.18} \left(\frac{H_i}{h_0}\right)^{1.23} \left(\frac{H_i}{L_i}\right)^{-0.15} \tag{1}$$

Where R is the wave run-up, $h_0$ is the still water depth, $H_i$ is incident wave height, $L_i$ is wave length and $K_p$ is a coefficient which is based on the placement pattern of antifer units that is equal to 1.25 for Regular, 1.1 for Irregular-Type A and 0.85 for Irregular-Type B.(Figure 1)

The some of researchers have investigated over impermeable smooth bed such as Hughes [12] who have prognosticated non-breaking wave run-up as:

$$\frac{R}{h_0} = 3.84 \tan\alpha \left(\frac{M_F}{\gamma_\omega {h_0}^2}\right)^{\frac{1}{2}} \tag{2}$$

Where $\gamma_\omega$ is the water density, $M_F$ is momentum flux of the incident wave. Dimensionless momentum flux was given as:

$$\left(\frac{M_F}{\gamma_\omega h_0}\right) = \frac{1}{2}\left[\left(\frac{H_i}{h_0}\right)^2 + 2\left(\frac{H_i}{h_0}\right)\right] + \frac{N^2}{2M}\left(\frac{H_i}{h_0}+1\right)\left\{\tan\left[\frac{M}{2}\left(\frac{H_i}{h_0}+1\right)\right] + \frac{1}{3}\tan^3\left[\frac{M}{2}\left(\frac{H_i}{h_0}+1\right)\right]\right\} \tag{3}$$

Where M and N are empirical coefficients which were introduced as:

$$M = 0.98\left\{\tanh\left[2.24\left(\frac{H_i}{h_0}\right)\right]\right\}^{0.44} \tag{4}$$

$$N = 0.69 \tanh\left[2.38\left(\frac{H_i}{h_0}\right)\right] \qquad (5)$$

Large distinction of researches have been behaved on wave run-up, some of empirical formulae have been flesh out with laboratory observations. Synolakis [13] has expended a particular model for the analysis of maximum run-up which its position was non-breaking wave on smooth and impermeable plane slopes, then the below function was presented:

$$\frac{R}{h_0} = 2.831\left(\frac{H_i}{h_0}\right)^{1.25} . \sqrt{\cot\alpha}. \qquad (6)$$

Furthermore, maximum run-ups have been predicted by Li & Raichlen [13]. They have denoted inconsiderable adjustment in the above equation, have appeared with:

$$\frac{R}{h_0} = 2.831(\cot\alpha)^{0.5}\left(\frac{H_i}{h_0}\right)^{1.25} + 0.293(\cot\alpha)^{1.5}\left(\frac{H_i}{h_0}\right)^{2.5} \qquad (7)$$

Conclusively, the outcomes of neural network model are evaluated, after that are compared with the regression estimates, criterion of mean squared error (MSE) normalized are used [4], that as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (8)$$

Where $y_i$ is a prognosticated value; $\hat{y}_i$ is an observable value; N is the number of observation.

## NEURAL NETWORK MODELLING

Due to the rather large amount of parameters that affect wave run-up at breakwaters it is difficult to describe the effects of all pertinent parameters. For such processes in which the interrelationship of parameters is unclear while adequate experimental data are available, Artificial Neural Network (hereafter "ANN") modelling may be a suitable alternative. ANNs are data analyses techniques widely used in artificial intelligence. This technique has been successfully used in the past for solving difficult modelling problems in a variety of technical and scientific fields [20].

ANN is an abstract simulation of a real nervous system. It can foresee diverse nonlinear relations among experimental parameters, optimization, classification, control, etc. [21].

ANN includes; input layer, hidden layer, and output layer. There are one or more processing nodes that are called 'neurons'. Each neuron in each layer takes information from the front layer through connectivity. The input of neuron includes of a weighted sum of the outputs of the front layer. A neural network consists of several interconnected neurons; each neuron is composed of independent units of computation per unit of input [21]. Output is calculated from the following equation:

$$y_k = f\left[\sum x_i w_{ij} + \beta\right] \qquad (9)$$

Where $x_i$ is the input unit, $w_{ij}$ is the network weight (from input unit $x_i$ to hidden unit $z_j$), and β is bias. The above equation ($y_k$) is activation function [16]. One of the important activation functions is bipolar sigmoid function, which is defined as:

$$f(x) = \frac{1-\exp(-x)}{1+\exp(-x)} \qquad (10)$$

Where $f(x)$ is activation function, and exp (-x) is exponential function.

The input layer include (i) neurons that code for the (i) pieces of input signal ($X_1$ ... $X_i$) of the net. The number of neurons of the hidden layer is empirically chosen by the operator. At the end, the output layer comprises K neurons for the K classes. Each relation between two neurons is associated with a weight factor; this weight is altered by successive repetition during the training of the network according to input and output data.

Figure 1 shows the diagram of a one-hidden-layered MLP network structure that where $Y_k$ is output unit, $w_{jk}$ is the network weight (from $z_j$ to $Y_k$).

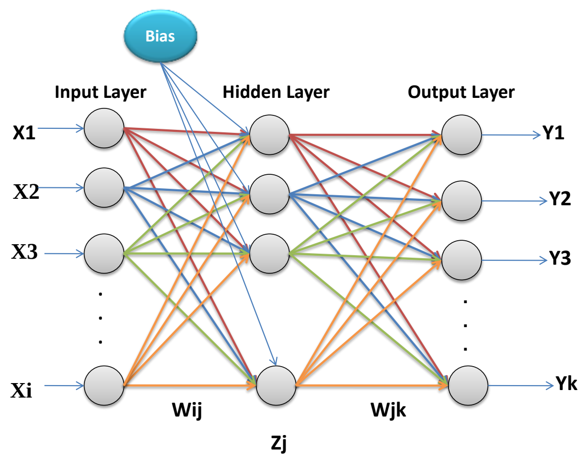


**Figure 3. MLP network structure [16].**

A multilayer neural network is trained with the Back Propagation (BP) algorithm, Multi-Layer Perceptron (MLP) network is called. The BP algorithm is to plan the process inputs to the desired outputs by minimizing the errors between the desired outputs and the calculated outputs driven from the inputs and network learning. In this study, the network will be trained Levenberg-Marqurdt backpropagation algorithm, unless there is not enough memory, in which case scaled conjugate gradient backpropagation will be used.

The data set of Jilani's experiments [11] have been exerted in this work, there are 192 data which; 70% (134 data) for training, 15% (29 data) for validation, and 15 % (29 data) to test the trained network. These data set have been chosen according to random in each cycle the trained ANN. In during to train, the data of training use to back propagation algorithm for to update network's weights. The data of validation employ for optimization algorithm and to stop training when generalization stops improving. The data of testing provide an independent measure of network performance during and after training meanwhile it's out of network training's affect.

After training, the conducting of the network has to be tested. As in explicit analysis, a first suggestion is given by the percentage of correct arrangement of the training set records. Nevertheless, the performance of the network with a test set is more related .The present investigation focuses in the advance of a neural network for estimating wave run-up. One of ways is an essential addition since the neural network method results in a tool acts for operators

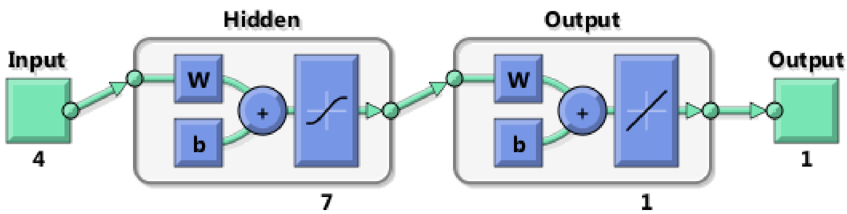


**Figure 4. Neural Network Diagram**

as a kind of black box [22]. Figure 4 is indicated this respect.

## RESULTS AND DISCUSSION

Firstly, after training, the number of hidden neurons should have chosen. As illustrated in Table 2, by increasing the number of hidden neurons, MSE of training data set decreases while MSE of validating data reduces up to seven neurons and increases from seven neurons onwards. Thus, to avoid over-fitting, the number of seven hidden neurons is chosen in the hidden layer of the neural network.

The testing data set are used to investigate the performance of ANN to be appropriate. In the other words, the main reason for utilizing the testing data are to evaluate the model validity is that after some point in the training method, over-fitting starts on the training data set.

The testing data set have got no effect on training and so provide an independent measure of network performance during and after training. The validating data set are used to measure network generalization, and to halt when generalization stops improving.

An epoch is equivalent of one cycle the complete set of training vectors. Generally, many epochs are needed for training a back propagation neural network. [15]

Figure 4 portrays the decrease of mean squared error (MSE) for the training, validating and testing data set versus training replication (Epoch). It can be seen that up to epoch 4, MSE of validation data decreases, then it does not take any other less value in the following epochs. The training process stops in epoch 4 (MSE=0.001655) in order to avoid over-fitting in training data set. The number of best epoch denotes after this epoch, changes become inconsiderable, slope of changes approximately become horizontal and weights update stop.

furthermore, after to train the model, the linear regression have obtained, then the best fitting lines for the training, validating, and test set have acquired.

Correlation is computed into what is known as the correlation coefficient, which ranges between -1 and +1. As can be seen in figure 5 the calculated correlation of training, validating and testing data are too identical that it's one of the signs of reliability of model. In this figure the predicted values of ANN model have been called "Output", the measured data set of Jilani's examination have been introduced "Target".

**Table 2. MSE of training, test and validating data set for the various hidden neurons.**

| Hidden neurons | 5 | 6 | 7 | 8 | 10 |
|---|---|---|---|---|---|
| **Training** | 0.0029 | 0.0022 | 0.0022 | 0.0015 | 0.0012 |
| **Validation** | 0.0019 | 0.0017 | 0.0016 | 0.0045 | 0.0046 |
| **Testing** | 0.0032 | 0.0016 | 0.0023 | 0.0019 | 0.0049 |
| **Epochs** | 4 | 6 | 4 | 6 | 10 |

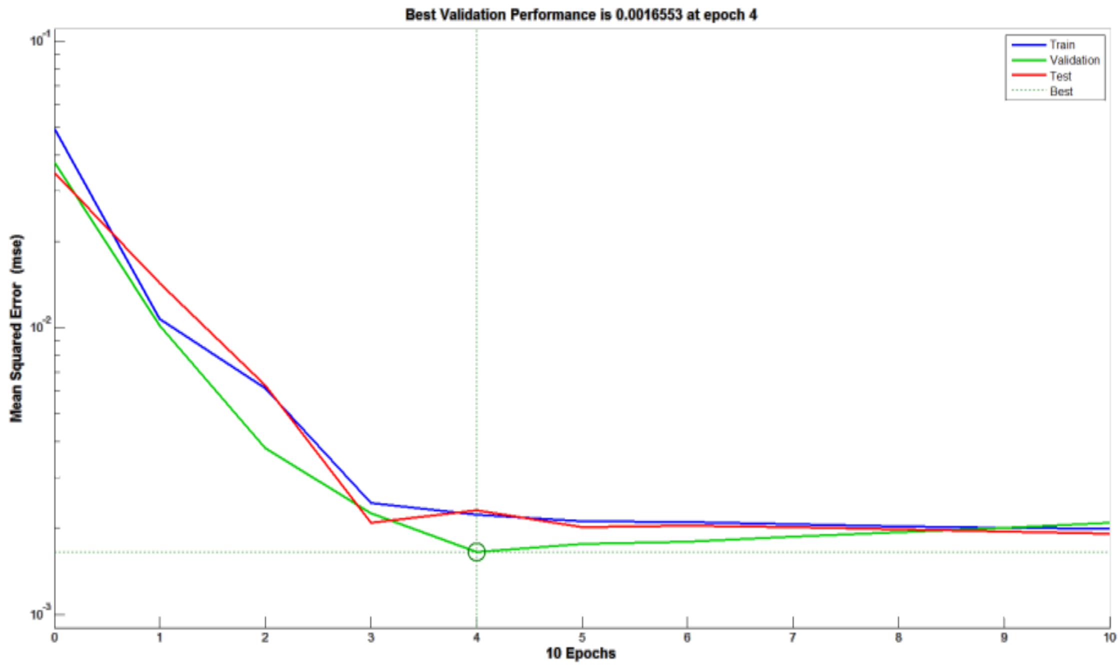


**Figure 5. The decrease of (MSE) for the training, validating and testing data set versus training replication.**

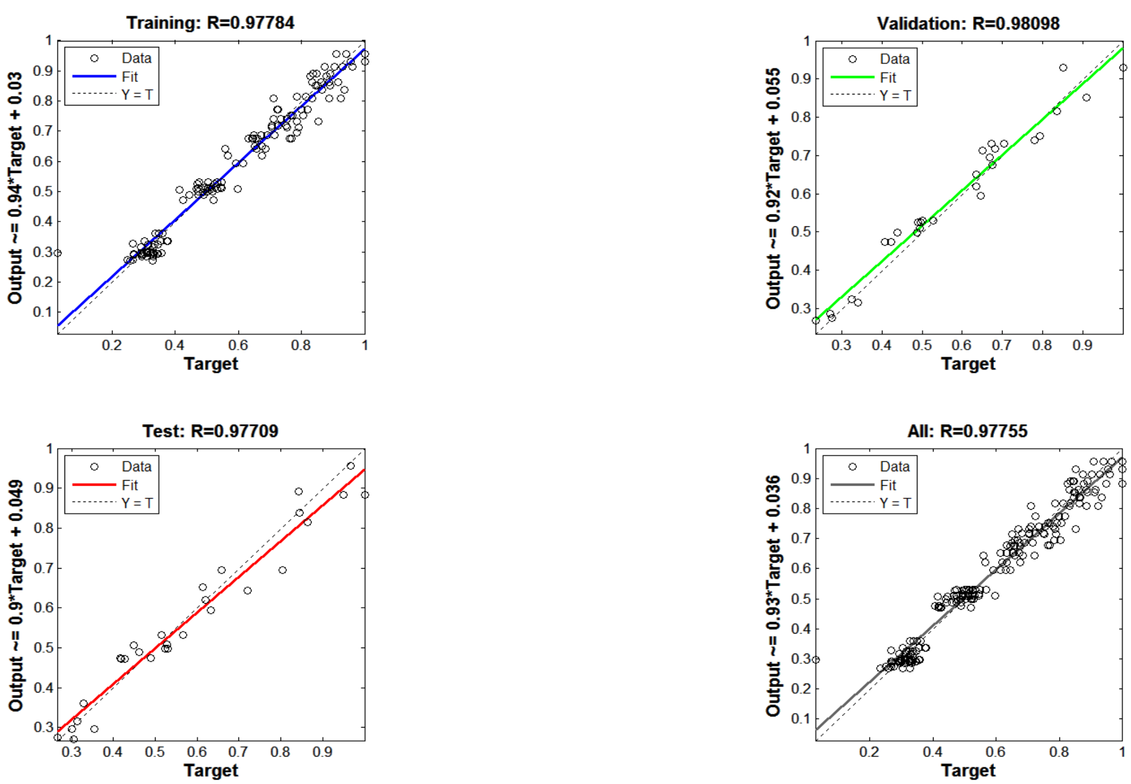


**Figure 6. The correlation between the predicted values of ANN and experimental values for validating, training and test data set.**

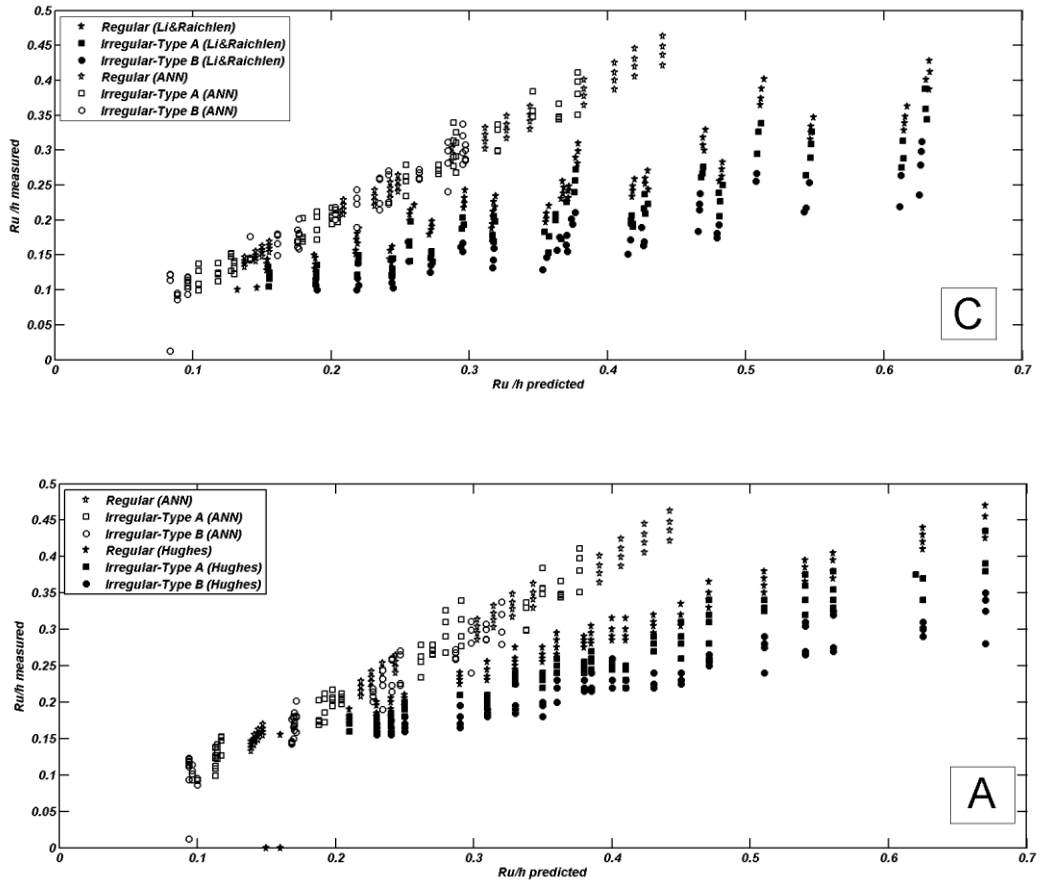


**Figure 7. The measured data versus the predicted wave run-up (Ru) in the obtained results of ANN, and experiments of (A) Hughes [12], (C) Li&Riachlen [13] over the breakwater covered by Antifer units with difference placement pattern.**

Eventually, the laboratory and experimental outcomes of Hughes [12], and Li&Riachlen [13] were used as a result of calibration of trained model (ANN). The measured data set of Jilani for wave run-ups on a breakwater front slope covered by different types of Antifer were utilized for the verification of the provided model (ANN) (figure 6). In the other words, acceptable agreement can be observed in these Figures (A, C) between predicted values and measured data set, also the reliability of the provided model, especially for Antifer units, was obtained.

As can be seen in figure 7, the best fitting lines have been obtained from models of (a) ANN, (b) Hughes [12], and (c) Li&Riachlen [13], also shows correlation of ANN data set (R=0.9844) more than other researches in the literature. Considering y=x as the ideal line, one can conclude the appropriate performance of the ANN by observing the approximately coincidence of the best-fitting line obtained for ANN outputs with the ideal line y=x.

In conclusion, the obtained correlation these researches and comparison with the ANN model in listed in Table 3, thus represent that correlation of obtained results of the ANN model is higher than other studies, So the ANN model is acceptable for to calculate wave run-up on the breakwater protected by Antifer units with difference placement pattern.

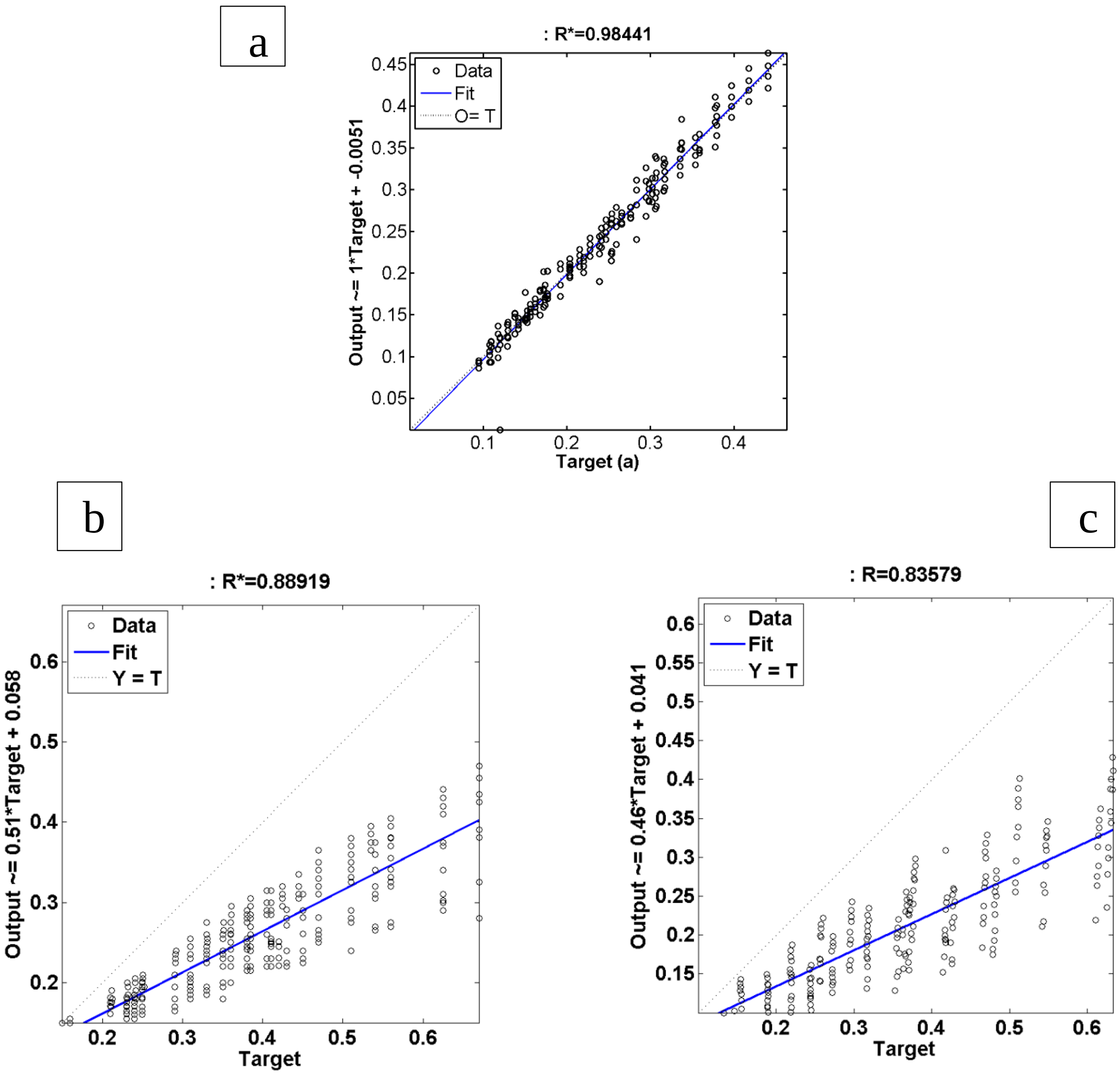


**Figure 8. The best fitting line to data for models of (a) ANN, (b) Hughes [12], and (c) Li&Riachlen [13].**

**Table 3. Comparing the obtained correlation between ANN modeling, and models of Hughes [12], and Li&Riachlen [13].**

| researches | Calculated Correlation (R) |
|---|---|
| Hughes[12] | **0.8892** |
| Li& Riachlen [13] | **0.8357** |
| ANN | **0.9844** |

Table 4 and 5 demonstrate the Regression equations and MSE for the obtained results by ANN are compared with other models in the literature. With respect to the obtained results, it can be concluded that, the regular placement should be preferred to other placement patterns due to its less MSE obtained by ANN. Moreover from the evaluation of the ANN model can be concluded that the regular placement methods behave more stable than the irregular placement.

**Table 4. The regression equations and the calculated MSE in the experiments of Hughes [12], and Li& Riachlen [13] over the breakwater covered by Antifer units with difference placement pattern.**

| | Hughes [12] | MSE | Li& Riachlen [13] | MSE |
|---|---|---|---|---|
| **Regular** | Y=0.54X+0.044 | 0.0139 | Y =0.64 X– 0.036 | 0.0202 |
| **Irregular Type A** | Y= 0.47X+0.033 | 0.0223 | Y =0.52 X– 0.054 | 0.0316 |
| **Irregular Type B** | Y= 0.37X+0.035 | 0.0398 | Y =0.38 X – 0.072 | 0.0506 |

**Table 5. The regression equations and the calculated MSE of the results of ANN, and compare with the obtained results of table 4.**

| | ANN | MSE (ANN) |
|---|---|---|
| **Regular** | Y = 0.99X+0.005 | 0.0001 |
| **Irregular Type A** | Y =0.97X+0.011 | 0.0003 |
| **Irregular Type B** | Y =0.97X+0.010 | 0.0004 |

## NOMENCLATURE

The following symbols are used in this paper:

$\alpha$ front slope angle of the breakwater (deg)

β bias

$\gamma_\omega$ water density ($MT^{-2}L^{-2}$)

$f$ function defined to related inputs and their weight in the neural network (equation 9)

$h_0$ still water depth (L)

$H_i$ incident wave height

$K_p$ empirical coefficient indicated the placement of antifer units (-) in run-up estimation (-)

$L_i$ incoming wave length (L)

M, N empirical coefficients to estimate incoming wave moment flux (equation 4 and 5)

$M_F$ moment flux of the incident wave (equation 3)

n number of observation for calculating MSE

T incoming wave period (T)

R value of correlation (-)

Ru wave run-up on the breakwater (L)

$w_{ij}$ weight in the neural network

$x_i$ input unit in the neural network

$y_i$ predicted value for calculating MSE

$\hat{y}_i$ observed value for calculating MSE

$y_k$ activation function in the neural network (equation)

$z_j$ hidden unit in the neural network

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