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PREDICTION OF WAVE OVERTOPPING DISCHARGES AT COASTAL STRUCTURES USING ARTIFICIAL NEURAL NETWORKS AND SUPPORT VECTOR MACHINE TECHNIQUES

Abdullah H. Alshahri[1] and Moussa S. Elbisy*[2]

[1]Civil Engineering Department, College of Engineering, Taif University, Saudi Arabia
[2]Civil Engineering Dept., College of Engineering and Islamic Architecture, Umm Al_Qura University, Makkah, Saudi Arabia.

*Corresponding Author, Received: 26 June 2022, Revised: 15 Sept. 2022, Accepted: 10 Oct. 2022

ABSTRACT: The management of coastal zones as a whole affects social and economic life and includes safeguards against extreme waves and floods. The accurate estimation of wave overtopping at coastal structures is therefore crucial to adequately protect people and infrastructure in these regions. This study employed artificial neural network-based (ANN) approaches with different algorithms, such as multilayer perceptron (MPNN), and general regression (GRNN), and support vector machine (SVM) for estimating the wave overtopping discharge at rubble mound structures featuring a straight slope. This study makes use of the new EurOtop database as its data source. Six distinct parameters (*MSE*, *MAE*, *RMSE*, *SI*, *Ef* and *R*) were utilized to assess the predictive performance of each model. Regarding the prediction of the wave overtopping discharge, the GRNNN produced exceptionally precise results. The *SI* of the GRNN was lower than that of the MPNN, and SVM by 600.11%, and 65.72%, respectively. In addition, the GRFNN model outperformed the other models in terms of efficiency. The E_f of the GRNN was higher than those of the MPNN, and SVM by 82.6%, and 3.0%, respectively.

Keywords: Wave overtopping, Prediction, Artificial neural networks, Support vector machine, Coastal structures, safety.

1. INTRODUCTION

To safeguard coastal areas from storm waves and high-water levels caused by storm surges, coastal structures like seawalls are designed and constructed. To ensure the safety of people and property on and behind the structures, the overtopping rates must be lower than the permissible rate in both normal operating and extreme conditions [1]. Therefore, it is crucial to accurately predict the rate of wave overtopping when designing and evaluating the safety of structures. Additionally, the existing coastal defense structures are more susceptible to overtopping due to climate change effects like sea level rise and its impacts on wave climate [2].

Wave overtopping is influenced by a variety of parameters. Analytical methods based on somewhat simplified expressions of the processes do not always provide accurate predictions because overtopping is a complex random process. Indeed, wave overtopping has been the subject of a number of studies and projects, the majority of which were experimental in nature [3], resulting in the development of several empirical prediction formulae and artificial neural networks [4].

To predict wave overtopping, numerous tools, including empirical formulas, soft computing techniques (SCT), and numerical models, are utilized: The empirical formulas provide a quick and simple way to obtain an initial estimate of the mean wave overtopping discharge. Numerical modeling frequently necessitates unaffordable computational efforts and numerical methods have their limits. Soft computing models, on the other hand, provide near-instantaneous predictions, offer a good balance of accuracy and speed, and allow for the inclusion of numerous governing parameters. Soft computing methods are widely used in the field of coastal engineering due to their effectiveness in knowledge processing, prediction, and forecasting.

Wedge *et al.* [5] predicted wave topping discharge using multilayer perceptron networks (MPNN) and radial basis function networks (RBFNN). They discovered that the RBFNN significantly outperforms the MPNN and the curve-fitting (parametric regression) regime and approaches the accuracy of custom numerical simulations. Based on the CLASH database, Van Gent *et al.* [6] predicted wave overtopping discharges using MPNN with three layers. The number of hidden neurons that should be used is 20. Verhaeghe *et al.* [7] have developed an additional model utilizing the same data (2008). They predict wave overtopping using a 2-phase neural (MPNN) method. The quantifier is refined using the bootstrap technique. They discovered the optimal neural quantifier architecture (13 input parameters, 25 neurons in hidden layer, and 1 output parameter). The results demonstrate that the combined classifier–quantifier result is demonstrably superior to the quantifier result alone. Based on the CLASH database, The MPNN was used by Zanuttigh *et al.* [8] to predict wave overtopping discharge, wave transmission coefficient, and wave reflection coefficient. They discovered that the proposed MPNN model accurately predicts all three parameters. Zanuttigh *et al.* [9] predict wave overtopping using MPNN. The optimized NN's accuracy is demonstrated by predicting new data and datasets. Molines and Medina[10] compared different overtopping estimators and discovered that the CLASH NN performed better than other estimators. Formentin *et al.* [11] utilize MPNN to predict wave overtopping discharge. These MPNN models are trained using an expanded version of the CLASH database. The MPNN was trained using the Levenberg-Marquardt training algorithm. Bieman *et al*. [12] utilized gradient boosting decision trees to forecast average wave overtopping discharges. This model is trained with the CLASH database of wave overtopping.

The goal of this work is to provide coastal designers with a robust and accurate SCT model able to represent wave overtopping discharges for a wide range of coastal structure types under a variety of wave conditions. This study evaluates the accuracy of SCT utilizing the ANN approach, which employs various algorithms (Multilayer Perceptron, and General Regression), and a support vector machine with a redial bias function (SVM), for wave overtopping discharge prediction of rubble mound structures lacking a berm with a straight slope.

The rest of this paper is organized as follows: section 2 describes the training database for SCT models. Section 2 introduces the SCT methods utilized in this study. Section 3 demonstrates the results and discusses them. In Section 4 the main conclusions drawn from this paper are finally stated.

2. MATERIALS AND METHODS

2.1 Data

This study made use of the new EurOtop database, which contains 17,942 tests, approximately 10,000 schematized global tests on wave overtopping discharge (q) were included in the original CLASH database [3]. The study used 4401 tests for rubble mound structures lacking a berm with a straight slope. The schematization of the structure “rubble mound structure without a berm “straight slope” investigated in this study is shown in Fig. 1. The statistics of the key parameters are shown in Table 1.

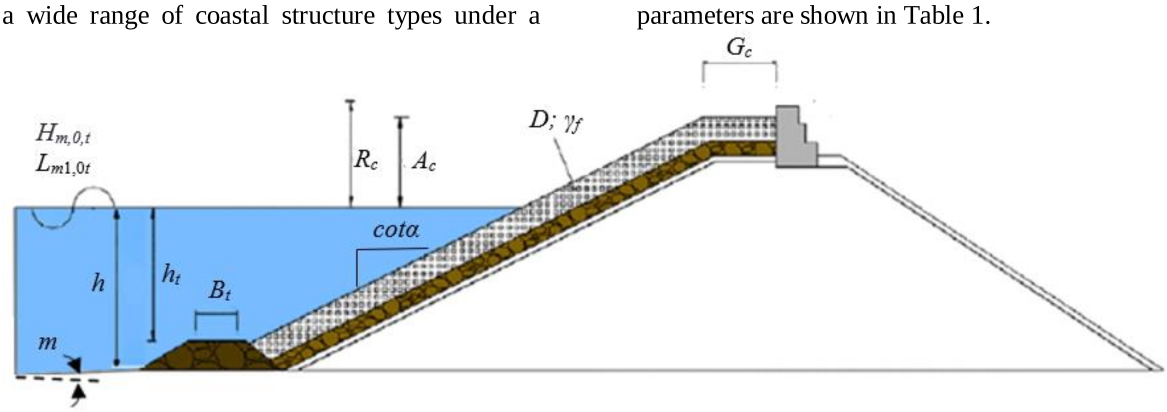

Fig. 1 Schematization of the rubble mound structure.

2.2 Methods for Wave Overtopping Discharge Prediction

The objective of soft computing is to find precise approximations that provide a robust, computationally efficient, and cost-effective solution while conserving computational time. Most of these techniques are primarily inspired by biological phenomena and social behavior patterns.

ANNs are the most popular method of soft computing. The MPNN, and GRNN algorithms are utilized in this study.

There are three layers in the MPNN: an input layer, at least one hidden layer, and an output layer (Fig. 2). The input, hidden, and output layers are connected by a simple relationship.

$$y_j = f \sum_{i=1}^{n} |xw + b|_i \tag{1}$$

where,

w: the weight.
b: the biases,
f: the operating function,
x: the i^{th} input of an ANN,
y: the j^{th} output of an ANN, and

n: the number of inputs.

The GRNN is made up of four layers: input, hidden, pattern, summation, and output (Fig. 3). The pattern layer's weights connect the first and second layers, with each unit representing a training input pattern and the output being a distance measure between the input and the stored patterns. Each unit of the pattern layer is connected to two neurons in the summation layer by the weights of the summation layer. Each of these neurons calculates a weighted sum of the previous layer's output. The weights correspond to the neuronal connections. The output value is transmitted by the output layer neuron. The predicted value (y) for an unknown input vector x as a function of the regression model.

$$y = \frac{\sum_{i=1}^{n} W_i e^{[-D(x,x_i)]}}{\sum_{i=1}^{n} e^{[-D(x,x_i)]}} \tag{2}$$

where,

x: the input vector,

x_i: the i^{th} case vector,

W_i: the weight that connects the pattern layer's i^{th} neuron to the summation layer,

n: an input vector's number of training patterns, and

D: the Gaussian function.

Vapnik invented the SVM technique (1995) [13]. Initially, the SVM model was created to solve pattern recognition issues. SVMs are machine-learning techniques that are based on the structural risk minimization principle, which is a method of lowering the upper bound risk function associated with generalization performance.

The support vector machine regression function can be written as follows:

$$f(x) = \sum_i^l y_i(\partial_i - \partial_i^*)K(x_i, x) + b \tag{3}$$

Table 1 Statistics of parameters for rubble mound structure without a berm.

Parameter	Unit	Definition	N	Min.	Max.	Mean	Std Dev
m	[-]	Foreshore slope, 1: m	4401	6	1000	499.27066	467.88465
β	[°]	Angle of wave attack	4401	0	80	3.827312	11.73031
h	[m]	Water depth at the structure toe	4401	0.029	5.01	0.463422	0.4120342
$H_{m,0,t}$	[m]	Significant wave height at the structure toe.	4401	0.017	1.48	0.1272778	0.0790924
h_t	[m]	Toe submergence	4401	0.029	5.01	0.442901	0.4164261
B_t	[m]	Toe width	4401	0	0.8	0.0519061	0.1181859
$cot\alpha$	[-]	Cotangent of the structure with a horizontal	4401	0	7	2.358368	1.201393
γ_f	[-]	Roughness factor	4401	0.38	1	0.7116471	0.2764768
D	[m]	Average size of the structure elements in the run-up/down area	4401	0	0.1	0.025248	0.0263332
R_c	[m]	Crest height with respect to SWL	4401	0	2.5	0.1689386	0.1565094
A_c	[m]	(Armor) crest freeboard without crown wall	4401	-0.03	2.5	0.1620663	0.1578372
G_c	[m]	Crest width or promenade width	4401	0	0.94	0.1187116	0.1490705
q	[m^3/s per m]	Wave overtopping discharge	4401	0.000001	0.0256	0.0008461	0.0022807

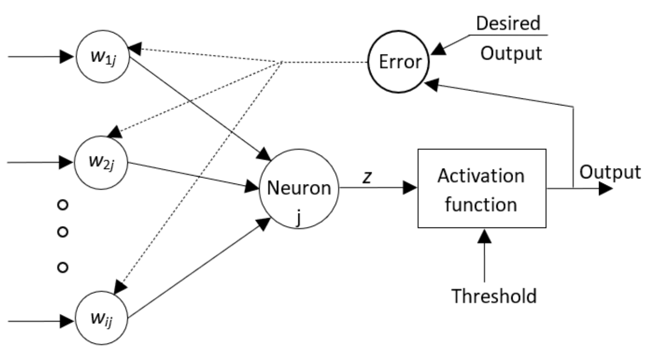

Fig.2: Neuron weight adjustments.

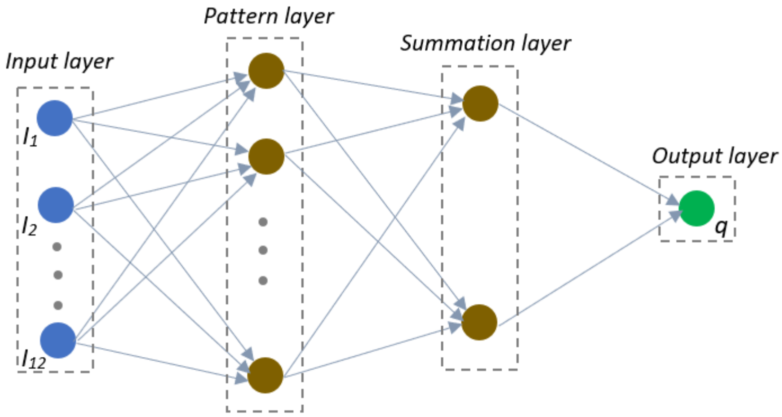

Fig. 3 Schematic diagram of a GRNN.

Table 2 Model parameters of the SCT models used for the training and testing.

Models	Parameters
MPNN	- Training method: conjugate gradient algorithm. - Transfer function: sigmoid for the hidden layer and linear for the output layer. - Architecture: 12; 20; 1 - Validation method: cross-validation and number of cross-validation folds = 10.
GRNN	- Training method: conjugate gradient algorithm. - Kernel function: Gaussian; sigma (σ) = 0.0001:10 - Validation method: Leave-one-out.
SVM	- Type of SVM model: Epsilon-SVR - Kernel function: Radial Basis Function (RBF) - Free parameters of kernel function: ε = 0.001, C = 0.1, γ = 50, P = 0.0001 - Validation method cross-validation and number of cross-validation folds = 10.

Where $K(x_i, x) = \phi(x_i)\phi(x)$ is called the kernel function, l represents the total number of data patterns, and ∂_i, and ∂_i^* are Lagrangian multipliers. Using the kernels, all necessary computation can be undertaken directly in the input space without calculating the explicit map $\phi(x)$.

Radial basis function (RBF) $K(x_i, x) = e^{(-\|x_i - x\|^2/2\delta^2)}$ is the kernel function used in this study, where δ^2 is the kernel parameter.

The coast constant C, the radius of the insensitive tube ε, and the kernel parameters are the SVM's most influential parameters. The significance of parameters C and ε is interpretable. The parameter C determines whether the approximation function is smooth or flat.

3. RESULTS AND DISCUSSION

A given amount of data processing is required before the input of the training patterns into the network.

Altogether, the non-dimensional parameters have been finally chosen as elements of the input vector (m, β, $h/L_{m-1,0,t}$, $H_{m,0,t}$ / $L_{m-1,0,t}$, h_t / $L_{m-1,0,t}$, B_t/ $L_{m-1,0,t}$, $Cot\alpha$, γ_f, D /$H_{m,0,t}$, R_c / $H_{m,0,t}$, A_c / $H_{m,0,t}$, and G_c / $L_{m-1,0,t}$). The CF and RF are only used for weighting the different records in the training data set with a weight factor (WF). The weighting formula from Van Gent et al. (2007) is used: WF = (4 − RF) (4 − CF). This way, the most reliable and least complex data has the highest weight factor. This also means that the data records with either unreliable (RF = 4) or very complex data (CF = 4) are not included in the training data set. The output was wave over topping discharge.

Evaluation of predictive performance is essential for determining the quality of soft computing models. The mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error ($MAPE$), root mean square error ($RMSE$), Scatter index (SI), correlation coefficient (R), and coefficient of performance were all used to evaluate the performance of soft computing models in this study (E_f). The formulas for these indices are as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Qp_i - Qo_i)^2 \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|q_{pi} - q_{oi}\right| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(q_{pi} - q_{oi}\right)^2} \quad (6)$$

$$SI = \frac{RMSE}{\overline{Qo}} \quad (7)$$

$$R = \frac{\sum_{i=1}^{N}(q_{pi}-\overline{q_p})(q_{oi}-\overline{q_o})}{\sqrt{\sum_{i=1}^{N}(q_{pi}-\overline{q_p})^2 \sum_{i=1}^{N}(q_{oi}-\overline{q_o})^2}} \quad (8)$$

$$E_f = \left[\sum_{i=1}^{n}(q_{oi} - \overline{q_o})^2 \; - \; \sum_{i=1}^{n}(q_{pi} - q_{oi})^2\right] / \left[\sum_{i=1}^{n}(q_{oi} - \overline{q_o})^2\right] \quad (9)$$

where:

q_{oi}: the observed value.
q_{pi}: the predicted value.
N: the number of observations.
$\overline{q_o}$: the mean value of the observations, and
$\overline{q_p}$: the mean value of the predictions.

Training (or learning) and testing are two distinct procedures needed for creating the various SCT models. The training subset, which is used to determine the ideal model parameters, and the validation subset are two subsets of the training data. After the models have been trained, a testing procedure is carried out to determine how well they can generalize the knowledge they have learned in previously unexplored cases. For model training, nearly 70% of the total data were randomly selected, and the remaining 30% were used for model testing. The various models are given MATLAB codes.

A genetic algorithm (GA) was used for the MPNN to modify the MPNN's optimum sizes. The hidden layer network with 20 neurons is discovered to form a stable and ideal network and yield the best results in this study. The MPNN model's training parameters are displayed in Table 2. For the predicted wave overtopping, MSE = 0.000004, MAE = 0.00103, $RMSE$ = 0.00209, SI = 2.475, E_f = 0.157, R = 0.414, and maximum error = 0.02457 were obtained. The relationships between the wave overtopping by the MPNN's actual and predicted values are shown in Fig. 4.

The training parameters of the GRNN model are shown in Table 2. The data revealed that MSE = 0.0000001, MAE = 0.00014, $RMSE$ = 0.0003, SI = 0.353, E_f = 0.983, R = 0.991, and maximum error 0.00255 for the predicted wave overtopping discharge when the GRNN model was used. The predicted values were fairly close to the corresponding actual measurements values based on the experimental results. The scatter plot of the wave overtopping values measured and predicted by the GRNN is shown in Fig. 5.

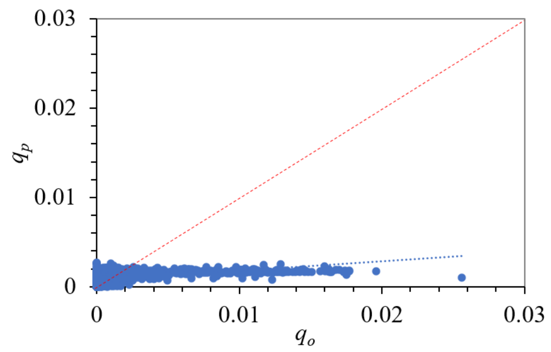

Fig. 4 Scatter plot of the measured and predicted values of wave overtopping for the MPNN.

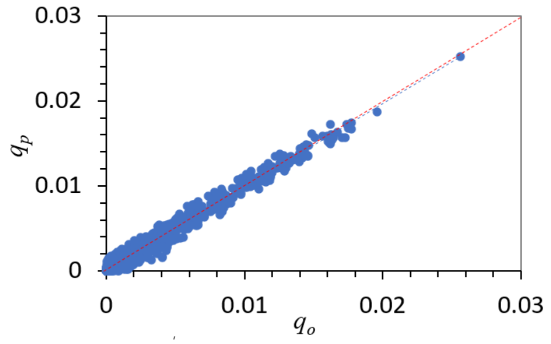

Fig. 5 Scatter plot of the measured and predicted values of wave overtopping for the GRNN.

To design an effective model, the values of the essential parameters in the SVM must be chosen carefully in advance. A SVM grid and pattern searches were used in this study to determine the optimal values of the SVM parameters ($\boldsymbol{\varepsilon}$, C, $\boldsymbol{\gamma}$, and P. The adjusted parameters with minimum validation error are selected as the most appropriate. Next, the optimal parameters are used to train the SVM model. The selected parameter values for the SVM model were shown in Table 2.

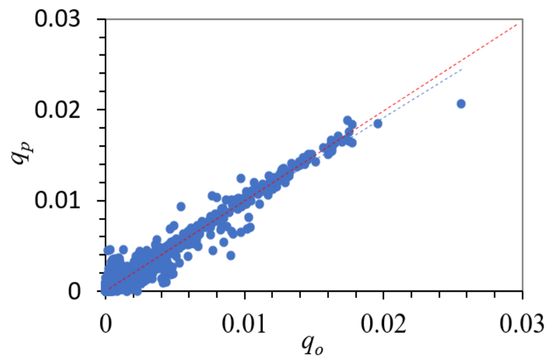

Fig. 6 Scatter plot of the measured and predicted values of wave overtopping for the SVM model.

The scatter plot of wave overtopping discharge using the SVM model is shown in Fig. 6. The results showed that the maximum error was 0.00511, *MSE* was 0.0000002, *MAE* was 0.00034, *RMSE* was 0.00049, and *SI* was 0.5845. Also obtained were *R* and E_f values of 0.981 and 0.953.

3.1 Comparison between the ANN and SVM Methods

In this section, the prediction abilities of the ANN (MPNN and GRNN) and SVM methods were compared. In terms of *MSE*, *MAE*, *RMSE*, *SI*, *Ef*, and *R* values, the GRNN model exhibited the best prediction performance, followed by the SVM model in second place. The results showed that the GRNN model predicted wave overtopping discharge more accurately than the other models. In addition, the results demonstrated that the GRNN model reduced the overall error and accurately estimated the wave overtopping discharge.

The MPNN model had the poorest predictive capabilities, implying that it is unable to accurately approximate the wave overtopping discharge. The outcomes validated the high precision of the GRNN and SVM models.

The GRNN produced a *SI* that was 600.11 %, and 65.72 % less than the MPNN, and SVM, respectively (Fig. 7). In terms of E_f, the GRNN was 82.6%, and 3.0% more accurate than the MPNN, and SVM, respectively (Fig. 7).

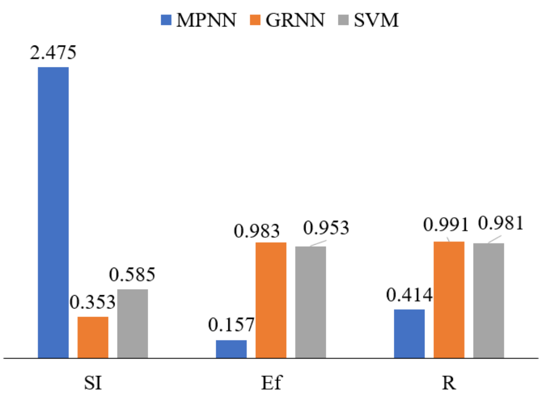

Fig. 7 Comparison of ANN and SVM models.

4. CONCLUSION

The majority of coastal structures are designed to prevent flooding or limit wave overtopping. Climate change's ongoing effects, such as sea level rise and increased storm intensity and frequency, present new challenges for risk-based design of these structures. The ability to accurately estimate overtopping discharges, as well as the characteristics of the overtopping flow over structures, is critical for determining and ensuring the safety of people, activities, and goods, or at the very least limiting their exposure.

ANN and SVM models were used to predict the wave over topping discharge. Each model's predictive performance was evaluated using six different parameters (*MSE*, *MAE*, *RMSE*, *SI*, *Ef* and *R*).

The EurOtop database (4401 data) was used to train and validate the ANN and SVM models for the rubble mound structure without berm (straight slope).

Regarding the prediction of the wave overtopping discharge, the GRNN produced exceptionally precise results. 600.11 %, and 65.72 % less than the MPNN, and SVM, respectively, was the SI of the GRNN. In addition, the GRNN model had a higher efficiency than the other models. GRNN had an E_f that was 82.6 %, and 3.0 % greater than MPNN, and SVM, respectively. According to the results, the GRNN model significantly reduced the overall error and accurately estimated the wave overtopping discharge. This demonstrates the GRNN's superior accuracy and precision in comparison to other models. The results of this study indicate that the GRNN model is a promising alternative to MPNN for forecasting wave overtopping discharge.

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