Estimating Wave-Overtopping Discharges at Coastal Structures Using Multilayer Perceptron, and General Regression Neural Networks

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ABSTRACT : *Coastal zone management has significant social and economic implications, including protection against extreme waves and floods. Accurately estimating waveovertopping at coastal structures is essential for safeguarding people and infrastructure. This study utilized multilayer perceptron neural networks (MPNN) and general regression neural networks (GRNN) to predict wave overtopping discharge at coastal structures with straight slopes (without a berm). The newly developed EurOtop database was employed for this purpose. The predictive performance of each model was evaluated using six statistical metrics: MSE, MAE, RMSE, SI,* E_f*, and R. Among these models, the GRNN demonstrated the highest accuracy in predicting wave overtopping discharge.*

KEYWORDS *-Artificial neural networks, prediction, wave overtopping coastal structures, safety.*

I. INTRODUCTION

In coastal zones, assessing the risk of wave overtopping is crucial for determining the potential collapse of marine structures and flooding of protected areas. A reliable estimate of the wave overtopping rate is vital for ensuring the safety and development of coastal infrastructure. Extreme overtopping events can lead to rapid water flow over the crest, posing serious threats to infrastructure and lives. Such incidents are particularly dangerous, having led to the loss of people, vehicles, and even trains being washed into the sea.

Accurate forecasting of wave overtopping spread is essential for the design of coastal structures. Numerous techniques for forecasting the mean wave overtopping discharge (q) have been documented, classified into empirical, numerical, and machine-learning methodologies. In recent decades, machine learning methodologies have been extensively utilized for wave overtopping challenges, providing rapid and economical resolutions to intricate problems. Wedge et al. (2005) predicted the q value via MPNN and radial basis function neural networks (RBFNNs), concluding that the RBFNN surpassed both the MPNN and parametric regression techniques, producing results comparable to those from tailored numerical simulations.

The ANN model was originally created for the CLASH project [1] and subsequently introduced by EurOtop[2]. Van Gent et al. [3]further refined this model, which EurOtop endorsed for forecasting the q value. Verhaeghe et al. [4] improved prediction accuracy by creating a two-phase neural network model to classify and quantify the overtopping rate. In contrast to empirical methodologies, ANN models exhibit a deficiency in transparency and fail to offer physical insights [5].

Numerous specific ANN techniques have been developed for the estimation of the Kr, Kt, and q parameters [6]. Zanuttigh et al. [7]created an advanced ANN model for diverse coastal structures, published by EurOtop (2018), utilizing an expanded dataset from the CLASH database. Molines and Medina [8] utilized an artificial neural network to formulate an explicit wave overtopping equation for breakwaters with crown walls, attaining prediction accuracy similar to that of the CLASH-ANN. Lee [9] developed new formulas for calculating wave overtopping discharge at vertical and inclined seawalls utilizing the enlarged CLASH datasets and the group method of data handling (GMDH) algorithm. Lee and Suh[10] utilized GMDH to formulate wave overtopping equations for smooth, impermeable vertical seawalls, demonstrating GMDH's enhanced efficacy compared to empirical equations, achieving accuracy comparable to the EurOtop-ANN model.

Recently, den Bieman et al. [11] illustrated the efficacy of the XGBoost approach as a substitute for ANN models. Their results demonstrated that XGBoost substantially diminished prediction errors in comparison to the ANN created by Van Gent et al. [3]. Hosseinzadeh et al. [12] investigated the efficacy of SVM and Gaussian process regression (GPR) models in forecasting mean wave overtopping rates in uncomplicated sloped breakwaters, utilizing data from the EurOtop database. The findings indicated that both models, particularly GPR, demonstrated great accuracy.

This study assesses the precision of the multilayer perceptron neural network (MPNN), and general regression neural network (GRNN) for estimating the wave overtopping discharge of coastal structures. The study also examines the relative significance of factors that influence the accuracy of these models.

II. MATERIALS AND METHODS

A. ANN Methods

Artificial Neural Networks are optimal for intricate challenges where the interrelations among variables are poorly delineated. As data-driven models, they can discern essential inputs without requiring prior assumptions regarding variable relationships, so filling a gap in the existing literature. Artificial Neural Network models necessitate comparatively few inputs and can proficiently estimate overtopping discharge. This study utilized the MPNN and GRNN models.

The multilayer perceptron neural network (MLPNN) is a prevalent model with three completely interconnected layers: an input layer, one or more hidden layers, and an output layer. This work employed the conjugate gradient approach to train the MLPNN. Forward propagation (loss calculation) and backpropagation (derivative computation) were employed to modify the parameters, with sigmoid and linear functions acting as activation functions for the hidden and output layers, respectively.

General Regression Neural Networks (GRNNs) are feedforward networks that use a non-linear regression-based learning mechanism [13]. Introduced by Specht [14], GRNNs generalize both radial basis function neural networks and probabilistic neural networks. During GRNN training, each pattern is memorized, making it a single-pass network that does not require backpropagation. The main advantages of GRNNs are their short training time and high accuracy. They also require fewer training samples than traditional backpropagation networks, making them efficient for practical system modeling and performance comparison.

GRNNs require minimal initial parameters to learn the relationships between variables. A typical GRNN consists of four layers: input, pattern (radial basis), summation, and output (Fig. 1). Notably, the number of neurons in the pattern layer equals the number of training data points [15]. The pattern layer's output is passed to the summation layer, which includes numerator and denominator neurons. The numerator neurons calculate the weighted sum of the previous layer's outputs, while the denominator neurons perform distinct functions to finalize the output.

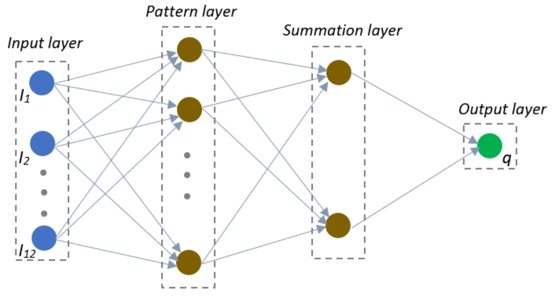


Fig.1. Schematic diagram of a GRNN.

B. Data

This study utilized the newly developed EurOtop database, which contains 17,942 tests, approximately 13,500 of which focus solely on wave overtopping. The original CLASH database included about 10,000 schematized tests on wave overtopping discharge (q), collected globally. The database features 42 parameters, including 3 output parameters (q, Kr, and Kt), 11 hydraulic parameters, 23 structural parameters, and 5 general parameters. A column labeled "core data" indicates whether a test is considered part of the “core” data, making it suitable for training neural networks.

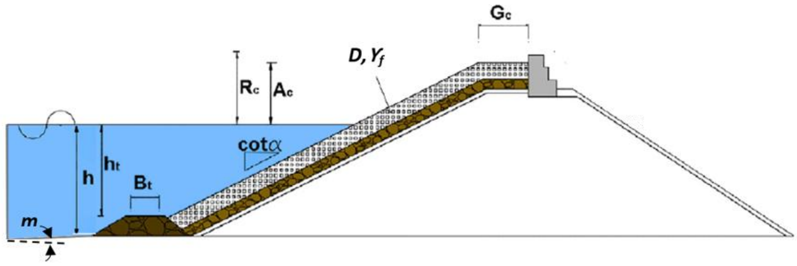


Fig. 2. Schematization of the coastal structure with straight slopes.

Table 1. Statistics of parameters for coastal structures with straight slopes.

Parameter	Unit	Type	Number	Min	Max	Mean	Std. Dev.	Upper 95% Mean	Lower 95% Mean
m	[-]	structural	4401	6	1000	499.27066	467.88465	513.09775	485.44358
β	[°]	hydraulic	4401	0	80	3.827312	11.73031	4.1739701	3.4805639
h	[m]	structural	4401	0.029	5.01	0.463422	0.4120342	0.4775985	0.4512454
$Hm,0,t$	[m]	hydraulic	4401	0.017	1.48	0.1272778	0.0790924	0.1296152	0.1249405
h_t	[m]	structural	4401	0.029	5.01	0.442901	0.4164261	0.4552073	0.4305946
B_t	[m]	structural	4401	0	0.8	0.0519061	0.1181859	0.0553988	0.0484135
$cot\alpha$	[-]	structural	4401	0	7	2.358368	1.201393	2.393872	2.3228641
γ_f	[-]	structural	4401	0.38	1	0.7116471	0.2764768	0.7198177	0.7034766
D	[m]	structural	4401	0	0.1	0.025248	0.0263332	0.0260262	0.0244698
R_c	[m]	structural	4401	0	2.5	0.1689386	0.1565094	0.1735638	0.1643134
A_c	[m]	structural	4401	−0.03	2.5	0.1620663	0.1578372	0.1667308	0.1574019
G_c	[m]	structural	4401	0	0.94	0.1187116	0.1490705	0.123117	0.1143062
q	[m^3/s per m]	output	4401	0.000001	0.0256	0.0008461	0.0022807	0.0009135	0.007787

For this study, which focused on estimating wave overtopping discharge in coastal structures with straight slopes, only data from structures with straight slopes were used, representing 24.53% of the EurOtop database. The data employed were specifically designated for training machine learning models. Given the wide range of dimensional parameters in the database, 12 fundamental parameters affecting coastal structures with straight slopes were selected. Figure 2 shows the schematization of these coastal structures. To summarize the dataset's characteristics, statistical measures such as means, standard deviations, ranges, and 95% confidence intervals were calculated. Table 1 and Figure 2 present the statistics of the key parameters.

III. RESULTS AND DISCUTION

Selecting the right input and output variables is crucial in developing machine learning models. In this study, 12 of the 31 parameters from the database were chosen for overtopping prediction, providing a streamlined overview of the overtopping discharge test. Prior to inputting training patterns into the network, a specific amount of data processing is necessary. Since some data come from small-scale models and others from full-scale prototypes, the new CLASH database recommends avoiding basic parameters as model inputs. Therefore, the basic data should be dimensionless to prevent large variations in raw values. Dimensionless parameters improve the accuracy and reliability of MPNN and GRNN models. To represent local breaking and wave run-up effects, parameters describing structural heights were made dimensionless with respect to significant wave height. Similarly, parameters for structure widths were dimensionless with the wavelength to account for local reflection, which may vary in phase with the wave reflection from other parts of the structure slope[16]. Since the wave overtopping rate is measured in m^3/s, a scaling factor, the product of the length and velocity scaling factors, is required. As a result, the non-dimensional wave overtopping rate is expressed as $Sq = \frac{q}{\sqrt{gHm0\ toe^3}}$.

A crucial step in the creation of any ML technique is the choice of input and output variables; *m*, *β*, *h*/*Lm*1,0*t*, *Hm*0 toe/*Lm*1,0*t*, ht/Lm1,0t, *Bt*/Lm1,0t, Cotα, γf, D/Hm0 toe, *Rc*/*Hm0toe*, Ac/Hm0 toe, and *Gc/Lm1,0t* are the input variables for the ML models, and the desired result is the *q*. The statistical features listed in Table 2 were used to evaluate the ML models in this study.

Both the training and validation subsets are derived from the training data. After training, the models were tested to assess their ability to generalize to previously unseen cases. Approximately 70% of the dataset was randomly selected for training, while the remaining 30% was used for testing. Each model was implemented using its own MATLAB code.

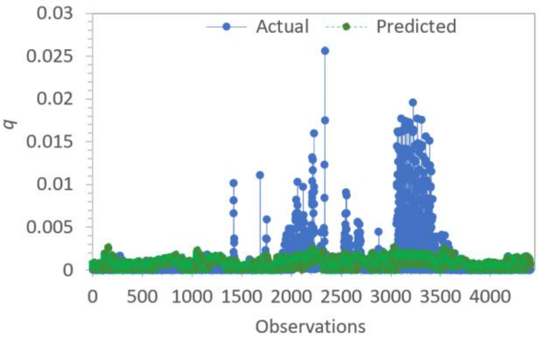
Table 2. Description of Statistical Features.

Features	Description
MSE	$MSE = \frac{1}{N}\sum_{i=1}^{N}(Qp_i - Qo_i)^2$
MAE	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert Qp_i - Qo_i\rvert$
RMSE	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Qp_i - Qo_i)^2}$
SI	$SI = \frac{RMSE}{\overline{Qo}}$
R	$R = \frac{\sum_{i=1}^{N}\left(Qp_i - \overline{Qp}\right)\left(Qo_i - \overline{Qo}\right)}{\sqrt{\sum_{i=1}^{N}\left(Qp_i - \overline{Qp}\right)^2 \sum_{i=1}^{N}\left(Qo_i - \overline{Qo}\right)^2}}$
E_F	$E_f = \left[\sum_{i=1}^{n}(Qo_i - \overline{Qo})^2 - \sum_{i=1}^{n}(Qp_i - Qo_i)^2\right] / \left[\sum_{i=1}^{n}(Qo_i - \overline{Qo})^2\right]$

Qo_i : the observed value; Qp_i : the predicted value; *N*: the number of observations; $\overline{Qo}$: the mean value of the observations; and $\overline{Qp}$: the mean value of the predictions.

Table 3. Model parameters of the MPNN and GRNN models.

Model	Parameters
MPNN	- Training method: conjugate gradient algorithm. - Transfer function: sigmoid for the hidden layer and linear for the output layer. - Architecture of MPNN: 12, 20, and 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



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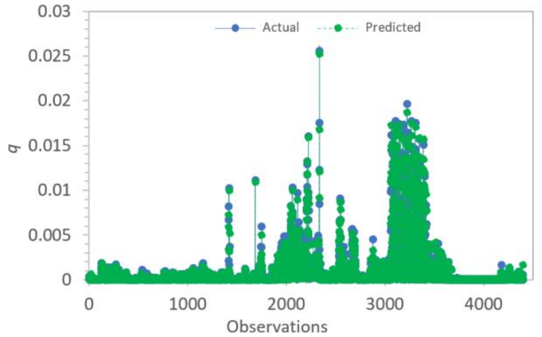

b.

Fig. 3. Plot of the measured and predicted values of wave-overtopping, a. MPNN, and b. GRNN.

Both the training and validation subsets are derived from the training data. After training, the models were tested to assess their ability to generalize to previously unseen cases. Approximately 70% of the dataset was randomly selected for training, while the remaining 30% was used for testing. Each model was implemented using its own MATLAB code.

The MPNN model was evaluated using 10-fold cross-validation, with results averaged over each fold. The GRNN, on the other hand, used a leave-one-out validation method. Selecting the optimal number of hidden neurons in a hidden layer is more challenging than determining the number of layers. Too many hidden neurons can lead to overfitting, where the model captures noise rather than patterns, while too few neurons prevent the network from approximating the desired outcome. To determine the optimal network size, a genetic algorithm (GA) was used for the MPNN. The analysis revealed that a hidden layer network with 20 neurons produced the best and most stable results in this study. The training parameters for the MPNN model are summarized in Table 3.

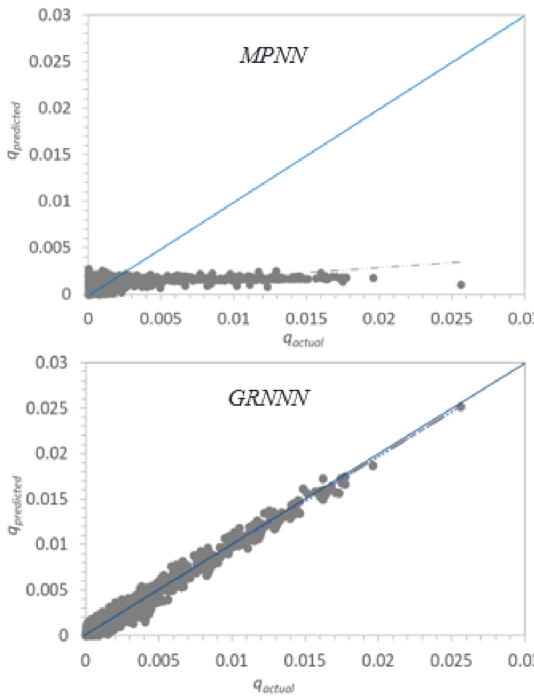

Fig. 4. Scatter Plot of the measured and predicted wave-overtopping values for MPNN and GRNN models.

For the MPNN model's predicted wave overtopping, the results were as follows: MSE = 0.000004, *MAE* = 0.00103, *RMSE* = 0.00209, *SI* = 2.475, E_f = 0.157, R = 0.414, with a maximum error of 0.02457. Figures 3 and 4 show the relationship between actual and predicted wave-overtopping values based on the ML models.

The GRNN model's results were *MSE* = 0.0000001, *MAE* = 0.00014, *RMSE* = 0.0003, *SI* =

0.353, E_f = 0.983, R = 0.991, and a maximum error of 0.00255. The predicted values closely match the actual measurements, indicating high accuracy in the GRNN model's predictions.

Comparison between MPNN and GRNN models

The GRNN model outperformed the MPNN model in predicting wave overtopping discharge, as evidenced by better *MSE*, *MAE*, *RMSE*, *SI*, E_f, and *R* values. The GRNN model significantly reduced overall error and accurately predicted the wave overtopping discharge, whereas the MPNN model showed the worst predictive performance, failing to represent the discharge accurately.

Compared to the MPNN, the GRNN produced SI values that were 600.11% lower and RMSE values that were 620.69% lower. Additionally, the GRNN outperformed the MPNN by 82.6% in terms of E_f. Overall, the GRNN model provided more accurate predictions and demonstrated superior predictive accuracy, speed, convenience, and interpretability, making it the most reliable model for estimating wave overtopping discharge

IV. CONCLUSION

In this study, MPNN and GRNN were used to predict wave overtopping discharge. The EurOtop database (4401 data points) was utilized to train and validate the MPNN and GRNN models for coastal structures with straight slopes. Twelve non-dimensional parameters were selected as input vector elements: *m*, *β*, *h*/*Lm*1,0*t*, *Hm*0 toe/*Lm*1,0*t*, *ht*/Lm1,0t, *Bt/Lm1,0t*, *Cotα*, *γf*, *D/Hm0 toe*, *Rc*/*Hm0 toe*, *Ac/Hm0 toe*, and *Gc/Lm1,0t*.

The conjugate gradient algorithm was used to train and adjust the weights of the MPNN and GRNN models. MPNN model was trained and tested using cross-validation, while the GRNN model was trained and tested with a leave-one-out validation method. This approach ensured that all dataset instances were used in both training and testing stages. The predictive performance of each model was evaluated using statistical features (*MSE, MAE, RMSE, SI*,E_f,and*R*).

The GRNN model demonstrated superior accuracy in predicting wave overtopping discharge. Its SI was 600.11% and 124.08% lower than that of the MPNN, and its *RMSE* was 620.69% lower. The GRNN also outperformed the MPNN in efficiency, with an E_f value 82.6% higher. These results highlight the GRNN model’s ability to significantly reduce error and accurately estimate wave overtopping discharge, offering superior precision compared to the MPNN model.

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