WIND EFFECTS ON RUNUP AND BREAKWATER CREST DESIGN

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Abstract

Estimation of the run-up and overtopping rates corresponding to breakwaters is a critical aspect for designing. Although it is widely assumed that onshore winds significantly increase runup and overtopping, very few design rules and experimental data have been published to estimate the effects of wind on runup and overtopping. A conventional and several *cuenco amortiguador* breakwater cross sections were tested at the UPV wind and wave test facility using wind velocities up to 10 m/s. A neural network modeling using simulated annealing was developed to analyze the experimental results. A preliminary analysis of the results found that wave overtopping was sensitive to wind speed (U>0), while runup seems sensitive only to high wind speed (U> 8 m/s). The runup measurements using capacitance wave gauges placed along the slope are dependent on the distance from the theoretical profile; therefore, a pair of wave gauges placed at $D_{n50}/3$ and 2 $D_{n50}/3$ were used to calculate the measured runup on the conventional breakwater. A significant discrepancy was found between the visual observations of runup on the conventional breakwater and the measured runup using the capacitance wave gauges; it seems that capacitance wave gauges underestimate the runup because of the alteration of the capacity of the water due to air intrusion during the breaking process.

Introduction

Runup and overtopping are two very important issues in planning and designing mound breakwaters. Both the overestimation and the underestimation of runup and overtopping rates of sloping structures during a lifetime have a major impact on the long-term economic efficiency, they unnecessarily increase construction costs or damage to ships, equipment and property protected by the structure. Runup

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and overtopping depend on a variety of structural and environmental variables; armor roughness, structural shape, water depth, bottom slope and core permeability must be taken into consideration for an adequate estimation of the runup during its lifetime. Furthermore, wind waves (heights, periods and directions), long waves (tides, storm surges, shelf waves, seiches, etc.), and onshore winds must be properly characterized in order to define the environmental conditions at the construction site.

Although it is widely assumed that onshore winds significantly increase runup and overtopping, very few design rules and experimental data have been published to estimate the effects of wind on runup and overtopping. SPM(1984) provided the following empirical correction factor for overtopping rates to take into account the winds

$$k = 1.0 + W_f \left(\frac{h - d_s}{R} + 0.1 \right) \sin \alpha \tag{1}$$

in which α is the structure slope, h is the height of the structure crest from the bottom, d_s is the depth at the structure toe, R is the runup on the structure that would occur if the structure were high enough to prevent overtopping corrected for scale effects, and W_f is an empirical coefficient depending on wind speed (W_f = 0.0, 0.5 and 2.0 for wind speed = 0, 30 and 60 miles per hour). However, the wind correction factor given by Eq. 1 can only be used as a general guide with little reliability because no reference to experimental observations is given by SPM(1984).

Ward et al.(1994 and 1996) used the wind and wave test facility at Texas A&M University (32.0 m-long, 0.6 m-wide and 0.9 m-deep). The effects of strong onshore winds on runup and overtopping of both smooth and rough coastal revetments were studied. Wind speeds of 6.5 m/s (50% of blower capacity) showed little effect on runup and overtopping, but wind speeds of 12 m/s (75% of blower capacity) or higher greatly increased both runup and overtopping. The maximum wind speed used in the experiments by Ward et al.(1994 and 1996) was 16 m/s. One of the most relevant final comments of Ward et al.(1994) was that scaling relationships need to be explored to allow runup and overtopping to be considered and applied to prototype coastal structures.

Troch et al.(1996) compared runup and rundown measurements obtained from the prototype monitoring system of the Zeebrugge breakwater, using vertically placed step gauges, with measurements on scaled models from a number of laboratories. Compared to the laboratory runup measurements, it appears that runup on prototype is about 50% higher than runup estimated in laboratories. On the contrary, wave rundown on the prototype was in accordance with laboratory data. An obvious difference between the prototype and laboratory experiments compared by Troch et al.(1996) is the onshore wind, which is present in the prototype but not in the laboratories; therefore, there is a point to support the idea that onshore wind may be the main factor used to explain the difference in dimensionless runup obtained in the prototype and laboratories.

The spray of salt-water particles transported by strong winds over breaking waves, usually related to high runup and overtopping events, may also cause significant losses in coastal areas (see Matsunaga et al., 1994); experiments in wind tunnels seem to be of critical importance to provide adequate design guidelines to face these phenomena. Matsunaga et al.(1994) and Hashida et al.(1996) used a wind and wave test facility of 32.0 m-long, 0.6 m-wide and 1.30 m-deep. The wind speeds used ranged from 9 m/s to 19 m/s.

Because of the importance of accurate estimates of runup and overtopping rates for adequate breakwater crest designing, within the project OPTICREST (see Rouck et al., 1998) prototype measurements of runup, overtopping and spray will be taken at Zeebrugge (Belgium) and laboratory tests will be conducted in the wind and wave facility at the *Universidad Politécnica de Valencia* (UPV). This paper shows some preliminary results from tests on deep water models of breakwaters: (1) *cuenco amortiguador* type and (2) Zeebrugge type. The dimensions of the UPV wind and wave facility are 30.0 m-long, 1.2 m-wide and 1.2 m-deep, and the maximum wind speed used in the experiments was 10 m/s.

Wave and Wind Tunnel Testing

Most of the work published on wind tunneling is refers to experimental information useful for solving aerodynamic problems for the aeronautical industry. Compared to supersonic and hypersonic wind tunnels, low-speed wind tunnels are facilities using $U<150$ m/s; however, our problem belongs to a very special case of the relatively small nonaeronautical group classified as boundary-layer wind tunnels (BLWT) which typically use air at atmospheric pressure and operating speeds in the range of 10 m/s to 50 m/s (see WTMBS, 1987). Aeroelastic simulations in BLWT for buildings and structures and experiments in meteorological and environmental wind tunnels are under relatively similar constrains to those necessary for modeling waves, run-up, overtopping and spray; however, maritime applications have additional problems like the variations of MWL induced by wind and the resonant infragravity waves in wave flumes and basins. As a first approximation, Froude and Reynolds numbers appear to be more important than Cauchy, Rossby and Mach numbers for modeling run-up and overtopping.

Fig. 1 shows a longitudinal cross section of the UPV wind and wave test facility (dimensions in cm). The wavemaker is a piston type hydraulic controlled able to generate regular and irregular waves without active absorption. The power of the blower is controlled manually to fix a specific wind speed for each test; the wind speed is measured between the air intake and the model. Only regular waves were used in the experiments described in this paper; the maximum wind speed was 10 m/s and the number of waves was selected to prevent multirreflected waves from attacking the model. The time series for controlling the wavemaker movement were calculated using the classical frequency domain transfer function for piston movement (see Goda, 1985) with an additional linear transition function in the time domain to prevent unrealistic accelerations of the wave paddle at the beginning and the end of each test. The maximum estimated incident wave heights attacking the model was compared to the maximum measured and visual runup.

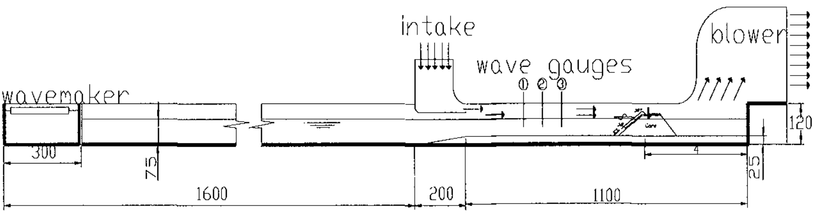

Figure 1. Longitudinal Cross Section of the UPV Wind and Wave Test Facility

The appropriate scaling relationships between wind speed, wave celerity and wave group velocity are not known for a proper modelization of the runup and overtopping phenomena (see Ward et al., 1994). Therefore, Froude similarity was chosen and a variety of wind speeds in the range of 0 to 10 m/s were used to study runup in the UPV wave and wind test facility. A neural network modeling was used to analyze the results given the lack of knowledge about the proper dimensionless variables to be considered and the number of significant structural variables to be taken into account.

Neural Network Modeling Using Simulated Annealing

The Neural Network (NN) systems belong to a group of relatively new optimization techniques commonly used in artificial intelligence (see Ansari and Hou, 1997). Neural networks (NN), simulated annealing (SA), genetic algorithms (GA) and fuzzy systems (FS) are some of the new optimization techniques which have proven to be very effective in solving difficult optimization problems. In particular, the NN are a computing device inspired by the function of the neurological system of the brain; they are composed of many parallel and interconnected computing units named artificial neurons. There are a variety of NN models which may be classified (see Kosko, 1992) depending on whether they learn with supervision and whether they contain feedbacks. On the one hand, the human brain belongs to the group of highly complex unsupervised NN with feedbacks; on the other hand, the relatively simple supervised feedforward NN is the most common structure used for NN modeling.

Usually, a supervised feedforward multilayer NN with only one hidden layer and a backpropagation learning algorithm is used for NN modeling of laboratory experiments. Mase et al.(1995) used a NN model with backpropagation to re-analyze laboratory measurements first examined by Van der Meer(1988) in assessing the stability of rubble-mound breakwaters. Van Gent and Van den Boogaard(1998) used a NN model with backpropagation to analyze horizontal forces on vertical breakwaters measured by a group of laboratories. The number of artificial neurons in the first layer is fitted to the number of input variables (structural and environmental variables), the number of neurons in the third layer is fitted to the number of output variables (structural response variables), and the number of neurons in the hidden layer has to be subjectively chosen to avoid both over-simplicity and overlearning. If the number of neurons in the hidden layer is too small, the NN may be too simple to properly describe the relationship between input and output variables. If the number of neurons in the hidden layer is too large, the NN model fits the data used for learning but it does not fit the test data which are not used in the learning process. Therefore, the NN has not captured the characteristics of the underlying process and it is said that the NN has overlearned. The overlearning problem in this kind of NN modeling is related to the ratio between number of parameters in the NN model and the number of data sets used in the learning process; if this ratio is higher than 10%, the overlearning problem is likely to occur. Because the number of NN parameters roughly grows linearly with the product of the number of neurons in the input layer by the number of neurons in the hidden layer, the complexity of the model is greatly limited by the amount of data available. Furthermore, because the backpropagation algorithm used in the NN teaching is a gradient descent method, the model may probably find a local optimum NN instead a global optimum NN.

In order to reduce the shortcomings in the use of the gradient descent backpropagation algorithm, a simulated annealing (SA) algorithm has been implemented to define the appropriate NN for modeling the results of the runup experiments described in this paper. The SA is a common tool in artificial intelligence (see Ansari and Hou, 1997); SA simulates the process in which liquids crystalize: at high temperatures the energetic particles are free to rearrange, while at low temperatures the particles lose mobility, finally reaching a state of equilibrium, having minimum energy. The entropy of a substance decreases monotonically during annealing, leading the substance to an ordered crystalline structure if the temperature is slowly lowered to relax to thermal equilibrium at each temperature. Alternative implementations of the SA concept are described by Laarhoven and Aarts(1992) who also provide a review of SA methods and their applications. In the tests presented in this paper, incident and reflected waves were separated using the new LASA method (see Medina, 1998) which is a time-domain method able to deal with nonstationary and nonlinear wave trains using local approximations and simulated annealing.

In this paper, a NN structure similar to that used by Mase et al.(1995) was considered, but instead of using a backpropagation algorithm, a SA algorithm was used in the NN learning process. Two-parameter artificial neurons similar to those used by Mase et al.(1995) were considered; the sigmoidal curve was defined by one threshold parameter and one amplification parameter for the logistic function. Each connection between neurons of consecutive layers has its corresponding weighting parameter. In addition to the common multilayer feedforward NN structure (named principal NN), a parallel structure of boolean parameters was considered to either activate or disactivate the parameters of the NN (named activation structure). Each parameter of the principal NN has its corresponding boolean activation parameter in the activation structure. If a boolean parameter is set to "1" the corresponding parameter in the principal NN works normally; on the contrary, if a boolean parameter is set to "0" the corresponding parameter in the principal NN works with the corresponding defect value. The defect values are zero for the weighting parameters in connections among neurons, zero for threshold parameters in neurons, and one for amplification parameters of the logistic function in neurons. The use of a feedforward NN associated with a parallel activation boolean structure allows for an optimization of the NN topology. The SA algorithm will not only optimize the parameters of the NN, but also the topology, disconnecting parameters, neurons, and inputs if they are not relevant to improve the NN model. Fig. 2 shows a typical NN model using SA for optimization; in addition to the disconnected input and hidden neurons, some of the remaining active neurons have one or no active parameters.

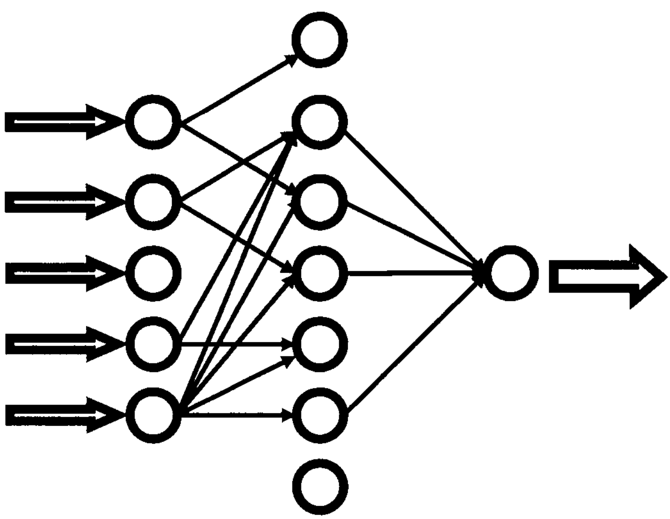

Figure 2. Typical NN Model Using Simulated Annealing

The NN model after the SA optimization is a parsimonious NN. The ratio between the number of NN active parameters and the number of data sets used for the learning process ranged from 3% to 5%; therefore, it is easy to understand why no overlearning problem was detected in any of the applications made in this paper. The use of a SA algorithm to optimize the NN model provided more than just good models to relate input variables (H, Ir, ...) with output variables (runup); it gave a clear indication of what input variables were irrelevant for modeling the process under study. This characteristic is quite convenient when NN modeling is used to analyze phenomena and processes which are little known, as is the case of the influence of wind on runup and overtopping considered in this paper.

In order to obtain the parsimonious NN mentioned above, certain details of the most critical aspects of the SA algorithm used in this paper must be described. Medina(1998) defines a SA algorithm in seven steps: (1)cost function, (2)generation mechanism, (3)initial solution, (4)initial control parameter, (5)reduction of control parameter, (6)length of Markov chains, and (7)stop criterion. In this paper, the most critical points are the cost function and the generation mechanism; the initial solution was a principal NN of parameters with random values in a given interval and the activation structure with all activation parameters set to "1". Steps 4 to 7 may be critical given time constrains, but in this case a reasonably good NN model can be obtained in a few minutes with a personal computer.

The cost function used in this paper for the SA algorithm has two components: the relative mean squared error and the ratio between the number of active parameters and the number of data sets used for the NN learning process. If only the relative mean squared error is used as a cost function, the resulting NN model using SA would be a least squares model similar to that obtained with the backpropagation algorithm. It may pose as an additional advantage for the SA algorithm because it prevents becoming trapped in a local minimum. However, the main advantage of the SA algorithm is obtained when a factor measuring parsimony is added to the cost function; in this case, the SA not only find good estimates of the NN parameters, but SA also eliminates those which are not significant to explain the relationship between input and output variables. The relative weight between the two factors in the cost function is decided by the operator; in this paper, the weight of relative mean squares error factor was three times the weight of the parsimony factor. Indeed, although the relative weight of the parsimony factor was very low, the impact on the NN topology is significant.

The generation mechanism defines the new NN in the neighborhood of the old NN. In this paper, a random change of parameters and magnitude of parameters, as well as a random change of the boolean parameters in the activation structure is made to create the new NN in the neighborhood of the old NN. However, the probability of changes in the activation structure must be controlled for an adequate exploration of the search space. During the first Markov chains, when the temperature is high and the NN parameters are far from the optimum, the activation structure must be set to "1" to prevent its anticipated convergence to a sub-optimal solution. Once the SA has found a reasonably good NN model, a solution similar to what would be obtained using a backpropagation algorithm, then a small probability of change from "1" to "0" and from "0" to "1" is fixed for the parameters in the activation structure. With this small probability of activation and disactivation of parameters and connections between neurons, the SA also explores alternative NN topologies by pruning the useless NN connections.

Experiments with *Cuenco Amortiguador* Breakwater Models

Fig. 3 shows the two *cuenco amortiguador* type breakwater cross sections tested in the UPV wave and wind tunnel shown in Fig. 1. The *cuenco amortiguador* concept is a special breakwater crest design introduced two decades ago in Spain by Aguado-Gallego and Sánchez-Naverac(1978). The idea was to reduce the breakwater crest elevation in cases where the aesthetic conditions were very restrictive, as is the case in many touristic areas. During the last two decades, several *cuenco amortiguador* type of breakwaters have been built in Spain (Fuengirola, Marbella, Torre del Mar, Denia, etc.). The design rules currently used in Spain for this type of breakwaters are based on a series of scale model tests provided by Aguado-Gallego and Sánchez-Naverac(1978) with regular waves without wind. These authors identified twelve structural and environmental variables, not the wind, but the experiments only covered a limited number of cases. The main conclusion was that breakwater crest elevation could be reduced by about 30% with respect to the currently used Iribarren rule: *crest elevation is approximately equal to 1.5 the design wave height.* However, it is obvious that the crest width and cap elevation depends critically on runup and overtopping which are related to onshore winds. Therefore, a series of experiments were conducted to check the influence of onshore winds on the runup as measured on the crown wall of the *cuenco amortiguador* breakwater cross section shown in Fig. 3, which is related to the overtopping rate of the conventional armor.

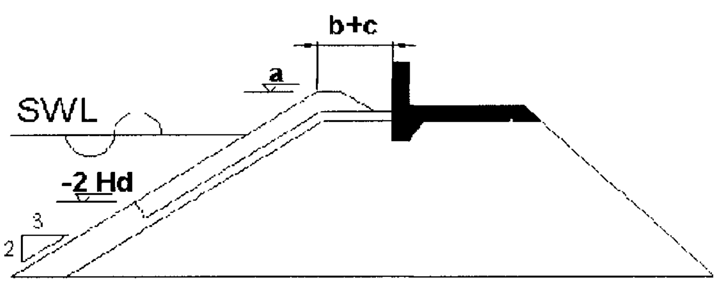

Figure 3. *Cuenco Amortiguador* Breakwater Cross Section.

The armor was built of angular quarrystones for deep water conditions; the median weight was W_{50}= 130g, the slope was 3/2 and the armor, filter and core stones were the same as those used in the tests described by Medina(1992). In the experiments described in this paper, a conventional and a D-armor cross section were also tested but no significant difference in runup was observed; therefore, in this paper the test results refer only to the conventional armor section shown in Fig. 3. Based on the preliminary results found by Aguado-Gallego and Sánchez-Naverac(1978), the structural variables selected to be analyzed in this paper were the armor crest elevation and the total width of the *cuenco.* The higher the armor crest elevation on the SWL (a) and the wider the *cuenco amortiguador* (b+c), the lower the runup measured on the crown wall. The selected environmental variables were: wave height, Iribarren's number and wind speed. The armor crest elevation refers to the SWL and was fixed to {a}= 4.0 D_{n50} for the first series of experiments; however, the tests were repeated increasing and decreasing the water level by 1.35 D_{n50} in order to analyze the influence of a change in the armor crest elevation. Three *cuenco amortiguador* widths were considered in the experiment: {b+c}= 5.0 D_{n50}, 6.5 D_{n50} and 10.0 D_{n50}.

Because of the special profile of the *cuenco amortiguador* breakwater, the runup measured on the crown wall is directly related to the overtopping rate on the crest of the armor layer. Therefore, the effects of onshore wind on runup measured on the crown wall of the *cuenco amortiguador* breakwaters may be considered similar to the effects of wind on the overtopping of conventional breakwaters. If the volume of water overtopping the armor layer is small, the overtopped water is drained through the *cuenco amortiguador* without reaching the crown wall and the measured runup is null. On the contrary, if the overtopped volume is large, the runup on the crown wall increases with increasing overtopping rates. The runup was visually measured on a scale fixed on the crown wall and was defined as the distance between the maximum water elevation on the crown wall and the SWL; if the water did not reach the crown wall, the runup was considered zero.

375 tests with regular waves were completed using wind speeds between 3 and 10 m/s; in addition, 875 tests were completed without wind. In only 25% of the tests the observed overtopping rate was large enough to reach the crown wall; in the other 75% of the tests, the measurement of runup was Ru=0. NN modeling is usually appropriate to analyze multivariable nonlinear relationships between input and output variables when there is a large amount of data and the knowledge about the underlying process is low (see Kosko, 1992). However, a first direct application of the NN methodology using SA described above gave only a poor result with a correlation coefficient lower than 60% between measured Ru and estimated Ru. The main reason for this poor result was attributed to the extremely high nonlinear relationship between the measured Ru (the output variable) and the structural and environmental variables (input variables), with 75% null Ru in the data.

The analysis of the poor results obtained with the first direct application of the NN methodology shown above led to a second NN modeling considering a chain of two different NN for two different purposes. The first NN were used as classifiers of data in two groups: input associated with Ru=0 and input associated with Ru>0. The second NN were used to estimate the Ru when the first NN identified conditions for reaching the crown wall (Ru>0). This NN modeling using a chain of two different neural networks gave satisfactory results with a correlation coefficient between measured Ru and estimated Ru higher than 90%. About 80% of the data were randomly chosen for the NN learning process while the rest of the data was used for testing the NN model. The ratio between the number of parameters in the NN using SA ranged from 3% to 5% and no overlearning problem was detected. Fig. 4 compares the observed Ru on the crown wall and the estimated Ru using the described NN modeling.

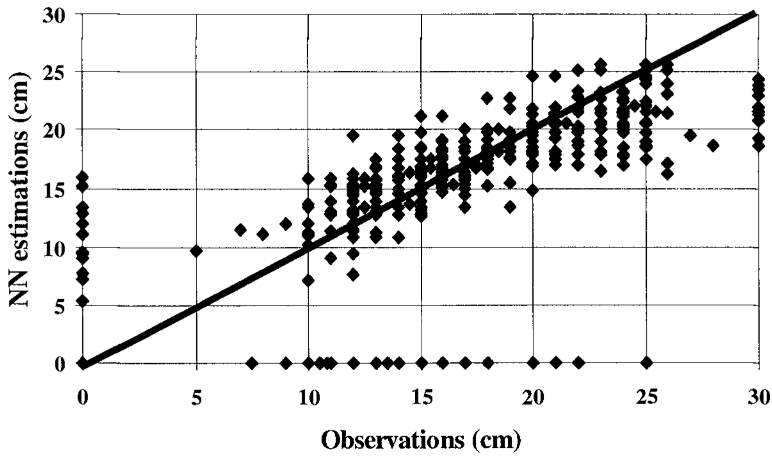

Figure 4. Measured vs Estimated Ru of the *Cuenco Amortiguador*

Five input variables were used in both NN: wave height (H), Iribarren's number (Ir), wind speed (U), crest elevation (a) and *cuenco amortiguador* width (b+c). It is interesting to point out that the SA process eliminated only the input wind speed (U) from the NN used as classifier; this fact suggests that the wind speed is not relevant for predicting if the water will reach the crown wall or not. However, the wind speeds were not eliminated from the NN which predicted the Ru once the conditions were classified as Ru>0 by the first NN. This asymmetric behavior suggests that onshore wind has an irrelevant effect on runup of conventional breakwaters but a significant effect on large overtopping discharges of conventional breakwaters.

Experiments with the Zeebrugge Type Breakwater Model

Troch et al.(1996) described the prototype monitoring system of the Zeebrugge breakwater, equipped with high precision vertical step resistance wave gauges to measure runup and rundown. Fig. 5 shows the deep water Zeebrugge type breakwater cross section tested in the UPV wind and wave facility (dimensions in cm); the armor layer was made of regular cubes instead of the antifer cubes placed in the Zeebrugge breakwater. The nominal diameters of the armor layer, secondary layer and core were D_{n50}=6.00 cm, 1.71 cm, and 1.26 cm respectively. The runup was measured visually placing cubes with different colors at different levels, using two capacitance wave gauges placed along the slope at distances of 2 cm and 4 cm from the theoretical profile, and using two wave gauges placed vertically through the armor layer. The maximum elevation of water on the armor was directly measured by the two inclined wave gauges and by visual observation; the vertical wave gauges provided additional measurements at fixed points, but this additional information is not analyzed in this paper.

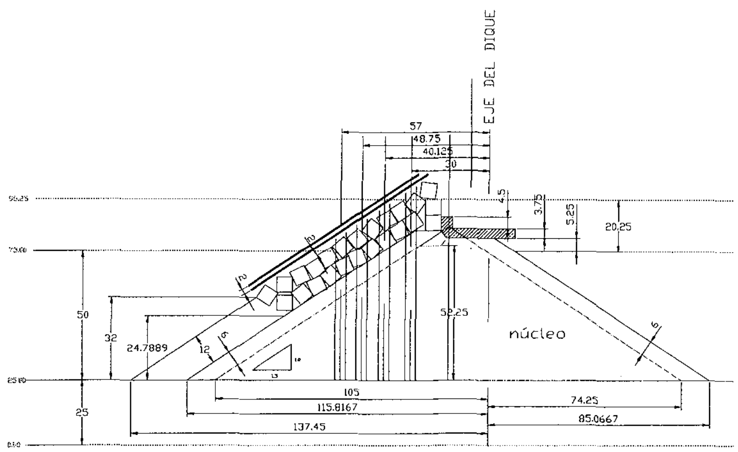

Figure 5. Cross Section of Deep Water Zeebrugge Type Breakwater Model

A series of tests with regular waves, changing wave height (H), Iribarren's number (Ir), and wind speed were carried out in the UPV wind and wave facility. 385 data sets relating the input conditions (H, Ir and U) and the output (Ru) were used to apply the NN methodology using SA described above. However, before starting the NN modeling of runup corresponding to this conventional breakwater, it was first necessary to clarify what should be considered the runup of a wave breaking on a sloping structure. Visual observation of runup may be biased in comparison to measurements of runup taken with wave gauges. On one hand, the human eye is subjective in estimating the maximum elevation of the water level on the slope. On the other hand, it is impossible to place the wave gauge exactly in the external profile of the armor where the runup should be measured, and wave gauges are not calibrated to take into consideration the air intrusion generated during the breaking process.

The Ru measured by the two inclined wave gauges were highly correlated but biased; usually, the runup measured by the wave gauge nearest to the theoretical profile were higher. Therefore, a linear estimation of the runup on the theoretical profile was calculated from the runup measurements taken by the two wave gauges parallel to the slope at distances 1/3 D_{n50} and 2/3 D_{n50} respectively. Fig. 6 compares this linearly estimated runup versus visual observations of runup and measured runup by the wave gauge closest to the theoretical profile (sensor 4). Because measured runup decreases depending on the distance of the inclined wave gauge from the theoretical profile, and it is impossible to place the wave gauge exactly in the theoretical profile, the two wave gauges linearly estimated runup were considered in Fig. 7 as the actual measured runup of the sloping structure. Fig. 6 clearly shows a significant bias between measured and visual observations of runup on a conventional sloping structure. In this case, the wave gauges measured the capacity of the instrument in the water and were unable to take into consideration the air intrusion always present during the breaking process. Therefore, runup measured on a prototype scale should be expected to be higher than runup measured in the laboratory with wave gauges, although the measured runup in the laboratory was corrected to take into consideration the distance of the wave gauge from the theoretical profile. Additionally, a precise description of the experimental setup and the variables is necessary to compare results from different laboratories.

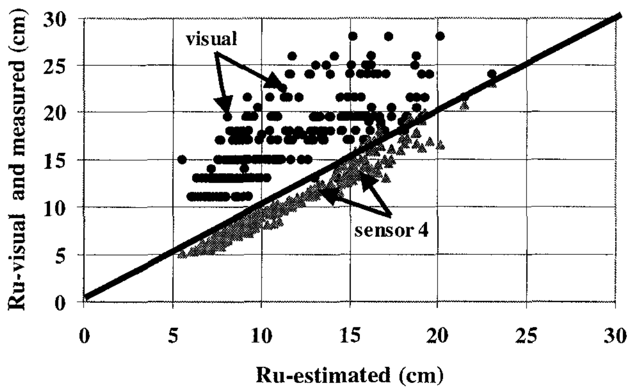

Figure 6. Comparison of Visually Observed vs Measured Runup

The visually observed runup was significantly higher than the linearly calculated runup based on the measurements taken by the two wave gauges placed parallel to the slope, but the dispersions of the visual observations shown in Fig. 6 were also much higher. The NN modeling methodology described previously was applied to the input-output data sets using the linearly calculated runup as the output Ru on the sloping structure. Wind speed was not eliminated as a significant input variable by the SA process, but the NN produced Ru very sensitive only to inputs H and Ir. According to the result of the NN modeling, Ru was insensitive to low wind speed and increased slightly only to high wind speed (U>8m/s).

Fig. 7 compares the output of the NN model and the runup measured using the two wave gauges parallel to the slope; the overlearning problem was not detected, the correlation coefficient was higher than 90% and the ratio number of parameters to number of data sets was lower than 5%.

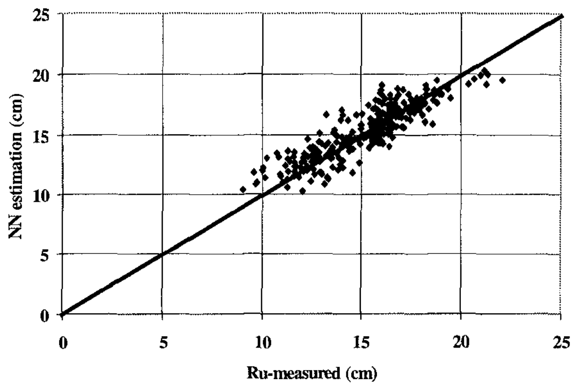

Figure 7. Neural Network Estimation of Ru

Conclusions

Deep water model tests on breakwaters models of the *cuenco amortiguador* type and a Zeebrugge type were conducted in the UPV wind and wave facility using regular waves and windspeeds up to 10 m/s. The parsimonious neural network models obtained by simulated annealing were found to be very effective in modeling both the runup and the overtopping of conventional breakwaters. The preliminary results from the tests described in this paper are qualitatively in agreement with those obtained by Ward et al.(1996) referring to runup, in the sense that runup is affected only by high onshore wind speeds (U> 8 m/s). Contrary to the results obtained by Ward et al.(1996), a significant influence of onshore winds on overtopping was also found for low wind speeds. The NN modeling using SA not only provided adequate models but also guided the research indicating the most significant variables to be considered in describing the processes under study. Therefore, the NN methodology presented in this paper may be useful not only to analyze runup and overtopping, but also to analyze other little known phenomena.

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