

# Neural network modelling of wave overtopping at coastal structures

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## Abstract

A method has been developed to estimate wave overtopping discharges for a wide range of coastal structures. The prediction method is based on Neural Network modelling. For this purpose use is made of a data set obtained from a large number of physical model tests (collected within the framework of the European project CLASH, see e.g. [Steendam, G.J., Van der Meer, J.W., Verhaeghe, H., Besley, P., Franco, L. and Van Gent, M.R.A. (2004). The international database on wave overtopping. World Scientific, Proc. 29th ICCE, vol. 4, pp. 4301–4313, Lisbon, Portugal.]). Moreover, a method was developed to obtain confidence intervals for the overtopping predictions of the neural network.

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## 1. Introduction

For the design, safety assessment and rehabilitation of coastal structures reliable predictions of wave overtopping are required. Several design formulae exist for simplified types of dikes, rubble-mound breakwaters and vertical breakwaters. Nevertheless, often no suitable prediction methods are available for structures with non-standard shapes.

This paper describes a method that leads to a conceptual-design tool to estimate wave overtopping discharges for a wide range of coastal structures. Only one schematisation is used for all types of coastal structures, where not only dikes, rubble-mound breakwaters or vertical breakwaters are defined, but also other non-standard structures are included. Additionally, not only is the effect of the most common parameters (i.e. wave height, wave period and crest freeboard) analysed herein, but also the effects of many other wave and structural characteristics are considered. The prediction method described is based on Neural Network modelling. Neural network modelling is discussed in Section 3 of this paper. For the preparation of the

neural network a data set is used that was obtained from about 10,000 physical model tests. The present investigation focuses on the development of a neural network for estimating mean overtopping discharges. Moreover, a method is developed to obtain confidence intervals for the overtopping predictions of the neural network. The latter is an essential extension since the neural network model results in a tool that acts for users as a kind of black box. Therefore, it is important that predictions are extended with information regarding their reliability or uncertainty.

## 2. Description of database and parameters involved

### 2.1. Description of the database

The data set used for the set up of the present neural network (hereafter: NN), is the database created within the framework of the European project CLASH. This database includes tests collected from several laboratories. This database is described in detail in Verhaeghe et al. (2003) and Steendam et al. (2004).

Results from about 10,000 overtopping tests are included in the database. Each of these tests is described by a number of parameters that represent hydraulic information (i.e. incident wave characteristics and measured overtopping discharges) as well as structural information (i.e. parameters characterising the

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test sections). Moreover, the database includes some general information regarding the reliability of the test and the complexity of the structure. The reliability of each test was estimated and defined in terms of a *Reliability Factor* (RF). In the present database the values of the RF ranged from RF=1 for a ‘very reliable’ test to RF=4 for a ‘non-reliable’ test. RF=1 was given to tests for which all required information was available in the corresponding reports and no variable estimation was needed, while RF=4 was given to tests for which the estimation of some parameters was not acceptable and for which the measurements included many uncertainties. In a similar way, the complexity of each test was estimated and defined in terms of a *Complexity Factor* (CF). CF=1 was given to tests with a ‘very simple’ structure in which the parameters describe the cross-section exactly, while CF=4 was given to tests with a ‘very complex’ structure in which the cross-section cannot accurately be described by the chosen parameters.

These *Reliability* and *Complexity Factors* played an important role in the configuration and construction of the NN. With the purpose of giving more weight to tests with high reliability in the NN configuration, the RF and the CF were combined into a *Weight Factor*. This *Weight Factor* was defined for each of the tests and was taken into account in the *training (calibration)* of the NN model (see Section 3.3).

## 2.2. Reduction of the database

Since erroneous data can severely degrade the performance of the NN models, the initial database of more than 10,000 tests was reduced by removing the data that was qualified as ‘non-reliable’ tests (RF=4) or the data for which the cross-section was considered as ‘very complex’ (CF=4). All remaining tests related to measured overtopping events were considered (i.e. all tests with  $q \neq 0$  m<sup>3</sup>/s/m where  $q$  is the mean overtopping discharge). Some data corresponding to overtopping events with  $q > 10^{-6}$  m<sup>3</sup>/s/m were rather randomly checked, some inconsistencies within the database were detected, and clear inconsistencies within the database were eliminated. The resulting reduced database consisted of 8372 tests.

## 2.3. Weight factors

As mentioned in Section 2.1, a *Weight Factor* (hereafter: WF) was defined for each of the tests in the above-mentioned database. The purpose of this WF was to assign more importance to tests with higher reliability and simplicity. This WF was defined as a combination of the RF and CF according to  $WF = (4 - RF) \cdot (4 - CF)$ .

The values of this WF ranged from WF=9, for a ‘very reliable’ test with a ‘very simple’ structure (RF=CF=1), to WF=1 for a ‘low-reliable’ test with a ‘quite complex’ structure (RF=CF=3). These weights were included in the NN’s *calibration* process. A test with a weight factor WF=9 has 9 times more influence on the final estimates of the calibration coefficients of the NN than a test with WF=1. See also Table 1.

Since most of the tests in the database originate from small-scale tests, very low overtopping discharges are likely to be less

Table 1

Values of the Weight Factor for different combinations of RF and CF in the database

RF/CF	1	2	3
1	9	6	3
2	6	4	2
3	3	2	1

accurate due to measurement errors in these small-scale tests. Relatedly, it should be noted that for the NN configuration, all the tests with observed overtopping discharges  $q < 10^{-6}$  m<sup>3</sup>/s/m were considered as less accurate than larger overtopping discharges, and were given a weight factor WF=1, corresponding to RF=CF=3.

## 2.4. Parameters involved

Due to the large number of parameters involved in wave overtopping processes, it is difficult to describe the influence of all of them. The technique of NN-modelling is suitable to analyse the influence of a large number of parameters on wave overtopping.

For the description of the wave field, the effects of 3 parameters were considered here: the spectral significant wave height at the toe of the structure ( $H_{m0}$ ), the mean spectral wave period at the toe of the structure ( $T_{m-1,0}$ ), and the direction of wave attack ( $\beta$ ). For the description of the geometrical shape of the structure, the effects of 12 parameters were considered: the water depth in front of the structure ( $h$ ), the water depth at the toe of the structure ( $h_t$ ), the width of the toe berm ( $B_t$ ), the roughness/permeability of the armour layer ( $\gamma_f$ ), the slope of the structure downward of the berm ( $\cot \alpha_d$ ), the slope of the structure upward of the berm ( $\cot \alpha_u$ ), the width of the berm ( $B$ ), the water depth on the berm ( $h_b$ ), the slope of the berm ( $\tan \alpha_b$ ), the crest freeboard of the structure ( $R_c$ ), the armour crest freeboard of the structure ( $A_c$ ) and the crest width of the structure ( $G_c$ ). Fig. 1 illustrates the physical meaning of the 15 parameters used as input to the NN model.

## 2.5. Froude's similarity law

Since it was the aim of the NN to be applicable both for small-scale and prototype conditions, all the input and output parameters in the database were scaled to  $H_{m0,toe}=1$  m using Froude’s similarity law. Taking into account that the database was mainly based on small-scale tests, Froude’s similarity law provides the best generalisation for large-scale applications. This approach required somehow a less complex configuration of the NN, since the number of input-patterns used reduced by one parameter because all input-patterns were scaled to  $H_{m0,toe}=1$  m.

For user applications, when a prediction of the wave overtopping discharge is required for a certain input-pattern [ $H_{m0}$ ,  $T_{m-1,0}$ ,  $\beta$ ,  $h$ ,  $h_t$ ,  $B_t$ ,  $\gamma_f$ ,  $\cot \alpha_d$ ,  $\cot \alpha_u$ ,  $B$ ,  $h_b$ ,  $\tan \alpha_b$ ,  $R_c$ ,  $A_c$ ,  $G_c$ ] this input-pattern is scaled according to Froude’s similarity law to an input-pattern with a wave height on which the NN was trained ( $H_{m0}=1$  m). The NN prediction of the

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