The New EurOtop Neural Network Tool for an Improved Prediction of Wave Overtopping

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Abstract
The goal of this work is to present the Artificial Neural Network (ANN) tool released with the second edition of the wave overtopping manual, EurOtop, 2016. The ANN predicts the main parameters representative of the wave-structure interaction processes, i.e. the mean wave overtopping discharge q, the wave transmission and the wave reflection coefficients K_t and K_r. Such tool provides an improved prediction of q with respect to existing and available similar tools, and includes a correction factor accounting for scale effects in case of rubble mound structures with small overtopping rates. The accuracy of the ANN predictions is characterized by values of the coefficient of determination R^2 that are greater than 0.90 for all the outputs. A website and a Graphical User Interface have been developed to make the ANN tool a user-friendly, fast and reliable design instrument available to the coastal engineering community.

Introduction
The use of the ANNs in the field of Coastal Engineering is nowadays consolidated, and several successful examples of ANNs applied to model the wave-structure interaction process are available. Among others, it is worthy to mention the CLASH ANN (Van Gent et al., 2007) for the estimation of q, the ANNs by Panizzo & Briganti, 2007 and Zanuttigh et al., 2013, for the prediction of K_t and K_r, respectively and the ANN tool recently developed by the authors for the simultaneous prediction of q, K_t and K_r (Formentin et al., 2017).

Despite the fact that these ANNs are generally characterized by a satisfactory degree of accuracy and by a wide range of applicability, their usage is still limited. One of the main obstacles to the wider usage of the ANNs is the need of a software environment to run the source files and the availability of such interface to the community. So far only the ANN developed by Deltares for wave overtopping in the framework of the CLASH project (https://www.deltares.nl/en/software/overtopping-neural-network/) has been released and widely used by the designers.

The ANNs provide unreliable or meaningless estimates when applied beyond the field of validity, which depends on the training database. However, especially in case of numerous degrees of freedom (i.e. ANNs characterized by numerous input parameters and hidden neurons), it is rather hard to define the field of validity of an ANN and therefore know whether a new test falls inside or close to the field. The use of the bootstrap resampling approach and the presentation of the results as statistical distribution instead of deterministic values provides the designer with information when the ANN is applied outside the range of applicability.

Another relevant issue is the representation of model and scale effects. Indeed, the designers need to estimate the structure performance at prototype scale, but most of the existing predicting methods available from the literature, including the ANNs, are calibrated or trained against more or less wide datasets of laboratory tests, both in wave flumes and tanks, performed at various scales. According to EurOtop (2007, 2016), for rubble-mound structures the model and scale effects result in lower values of q than in prototype, especially when $q<10^{-3}$ m^3/s/m. Therefore, the predicting models may provide the user with optimistic estimates of q.

In order to overcome part of these problems, the ANN tool by Formentin et al., 2017, has been upgraded and modified: i) achieving an improved prediction of q in case of low-overtopping (Zanuttigh et al., 2016); ; ii) providing an approximate estimate of the model effects (Zanuttigh et al., 2016); iii) introducing an innovative method to roughly assess the reliability of the predictions, besides the use of confidence bands. The final version of this tool has been adopted by the updated wave overtopping manual, EurOtop (2016), and is now available upon registration at the website: www.unibo.it/Overtopping-NeuralNetwork. The use of the tool is supported and simplified through a specifically developed Graphical User Interface (GUI) .

The aim of this contribution is to illustrate the main characteristics and novelties of the EurOtop ANN tool and to present its GUI for the first time. To this purpose, a brief summary of the features and the performance of the ANN tool are first provided. Then, the paper focuses on the description of the GUI layout and on the new methodology to estimate the performance of the predictions. Afterwards, the description of the model effects and the application of the correction factor to the ANN predictions of q are detailed and discussed. Some conclusions are finally drawn.

Features of the ANN tool

Three key elements characterize an ANN: i) the database used for the training, that defines the field of validity of the ANN itself; ii) the input parameters; iii) the set of learning algorithms and inherent methodologies that constitute the architecture of the ANN itself. This Section shows the elements adopted for the EurOtop ANN tool.

The training database

The database used to train the ANN tool consists at present of 13,511 tests on wave overtopping, 7,371 tests on wave reflection and 3,587 tests on wave transmission, for a total amount of 17,942 tests (Zanuttigh et al., 2016; Formentin et al., 2017). In most cases, the experimental data on q were derived through the weighting of the overtopping volumes, while the values of K_r and K_t were deduced from the analysis of the signal of wave gauges placed before (K_r) and behind (K_t) the structures. Commonly, in case of 2D-tests (i.e. tests carried out in channel), the measures of K_r were computed following the method of Mansard and Funke (1987), while in case of 3D-tests (carried out in basins), it was performed a wave directional analysis. More details about the experimental data can be found in Formentin et al. (2017).
The information contained in the original datasets has been re-ordered and re-organized in the new database to describe the tested wave conditions and the geometry of the structures by means of the same set of physical parameters. The database adopts the same schematization already proposed by the CLASH project (Van der Meer et al., 2009), but includes some new parameters (a.o., the size representative of the armour layer) and introduces a different definition of the average slopes of the structures in the run-up/down area including or excluding the presence of the berm (parameters $cot\alpha_{incl}$ and $cot\alpha_{excl}$, respectively). Each test in the database is described by the following parameters:

- the hydraulic conditions (11 hydraulic parameters);
- the geometry of the structure cross-section (23 structural parameters);
- the test name/label, the reliability and complexity factors, *RF* and *CF* (3 general parameters);
- the 3 output parameters, i.e. the average wave overtopping discharge (q, m^3/s per m), the bulk wave reflection and the bulk wave transmission coefficients (K_r and K_t).

The main hydraulic and structural parameters charactering the database are shown in the schematization of Figure 1. The full description of the parameters and the variety of the wave conditions and the structure cross-sections collected in the database are provided in EurOtop (2016), Zanuttigh et al. (2016), Formentin et al., 2017.

The Input Parameters

Based on the previous work, an optimal set of 15 input parameters was identified. The full list of the input parameters is given in Zanuttigh et al., 2016 and Formentin et al., 2017, where the CLASH symbols and terminology are adopted (and here referred in Fig. 1).

All the 15 input parameters are made dimensionless, to reproduce the relevance of specific key geometrically and physically based parameters. Parameters related to the wave conditions

($H_{m0,t}/L_{m-1,0,t}$, β and $h/L_{m-1,0,t}$) account for the wave breaking due to wave steepness and water depth, the shoaling and the effects induced by wave obliquity. The structure heights (of toe, berm, crest, i.e.: h_t, h_b, R_c, A_c) are all made dimensionless with the significant wave height ($H_{m0,t}$) to represent the effects induced by local breaking and by wave run-up. The structure widths (of toe, berm, crest, i.e.: B_t, B, G_c) are all made dimensionless with the wave length ($L_{m-1,0,t}$), to account for the induced local reflection that might be in phase or not with the wave reflection from other parts of the structure slope. The main slopes of the structures are included in the input set to represent the shoaling (that may occur along the foreshore m, if present, or along the down slope, $cot\alpha_d$) and/or the breaking (along the down slope $cot\alpha_d$). The average slope in the run-up/down area ($cot\alpha_{incl}$) account for the effects of a composite cross-sections with multiple slopes and/or berms. Finally, the effects of the energy dissipation induced by the structure roughness and the permeability are represented by the parameters γ_f and $D/H_{m0,t}$, respectively.

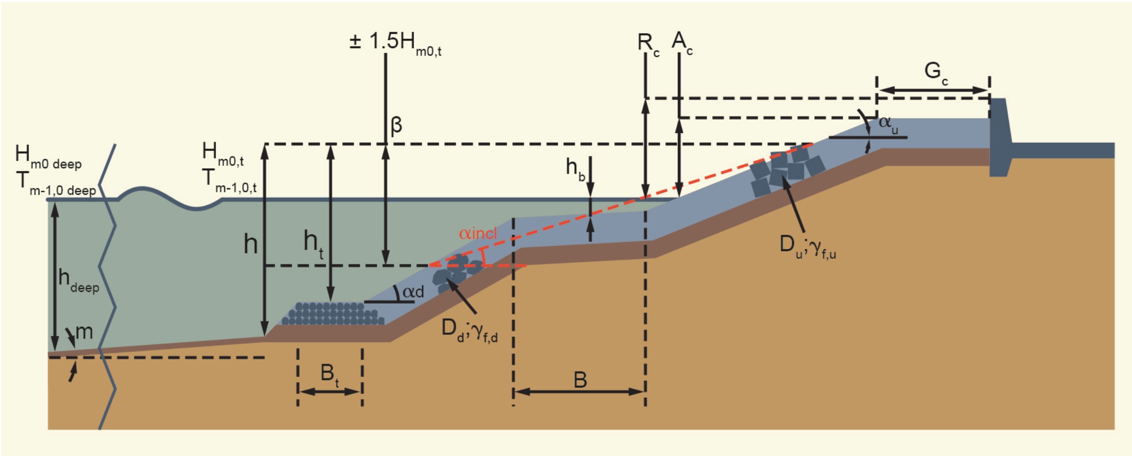

Figure 1. Schematization of the structure based on CLASH, including some of the most relevant geometrical and hydraulic parameters (from EurOtop, 2016).

The ANN architecture

The ANN tool, in its final version (Zanuttigh et al., 2016; EurOtop, 2016), consists of three similar but independent ANNs, one for each output parameter, i.e. K_r, K_t and q. The final and optimized architecture of these three ANNs is characterized by exactly the same features, the only difference being the training databases. Such features are resumed in the following:

- multilayer network, based on a “feed-forward back-propagation” learning algorithm;
- 15 dimensionless input parameters;
- one hidden layer only with 20 hidden neurons;
- one output neuron, that alternatively corresponds either to q, K_t and K_r;
- training algorithm: Levenberg – Marquardt (Marquardt, 1963; Hagan and Menhaj, 1994);
- hidden neurons transfer function: hyperbolic tangent sigmoid function;
- output neuron transfer function: linear transfer function;
- use of the “commitment” of networks and bootstrap resampling of the database for the improvement of the generalization capability, the statistical assessment of the performance and the computation of the statistical distribution of the output values;
- use of weight factors to drive the selection of the data for the training towards the “more reliable” tests.

For details and information about the working principle and the structures of an ANN, the concepts of “commitment of networks” and “generalization capability”, the description of the bootstrap technique and the weight factors, see Formentin et al. (2017).

Performance of the ANN tool

It is a common practice (Van Gent et al., 2007; Panizzo & Briganti, 2007; Zanuttigh et al., 2013) to assess the performance of an ANN by comparing the model predictions to the corresponding experimental data used already for the “training” process.

Three error indices have been used to characterize the performance of the ANN when applied to the prediction of the same data used for the training (for sake of brevity, the reader may refer to Formentin et al., 2017 for the definition of these indices): the root mean square error *(rmse)*, the Willmott Index *(WI)* and the coefficient R^2. The numerical values of these indices are reported in Tab. 1 in terms of average values of 500 bootstrapping resamples of the training database. The adoption of the bootstrap resampling technique in the training process (details in Formentin et al., 2017) allows to assess and contemporarily improve the ANN performance. Each bootstrapped database is used to re-train the ANN, and each differently trained ANN results in different predictions of the output parameters. The ensemble of the predicted outputs is a stochastic variable that can be used to derive average indices of performance and standard deviations and deliver the predicted values of the output in terms of percentiles.

Table 1: Synthesis of the performance of the ANN tool for the 3 output parameters. The values of the indices are averaged from 500 *bootstrap*s of the database.

Output	***Rmse***	***WI***	R^2
q	0.047 ± 0.002	0.977 ± 0.003	0.92 ± 0.01
K_r	0.035 ± 0.004	0.990 ± 0.003	0.96 ± 0.01
K_t	0.034 ± 0.008	0.995 ± 0.004	0.99 ± 0.02

The ANN provides a satisfactory representation of the training data, being R^2 and *WI* not lower than 0.92 and 0.977 respectively. The predictions of K_r and K_t are more accurate on an average (see R^2) with a more symmetric distribution of the error (see *WI*) than the predictions of q. K_t is characterized by the highest values of the standard deviations, revealing a larger dispersion of the error and a greater variability of the output values.

Figure 2 provides a qualitative analysis of the ANN performance by comparing the ANN predictions of the three outputs to the corresponding experimental values. In all the plots, the predictions are symmetrically distributed around the optimal condition (represented by the bisector line) and no evident bias characterizes the scatter. The 95% confidence bands are included in the diagrams to highlight the narrowness of the error distribution.

Previous work (Zanuttigh et al., 2016; Formentin et al., 2017) showed that the ANN accuracy is significantly greater than existing formulae from the literature, even when applied to the same datasets used to derive the formulae. Besides, the new ANN gives improved predictions with respect to existing ANNs specifically developed for the prediction of one single output (e.g., Van Gent et al., 2007 for q).

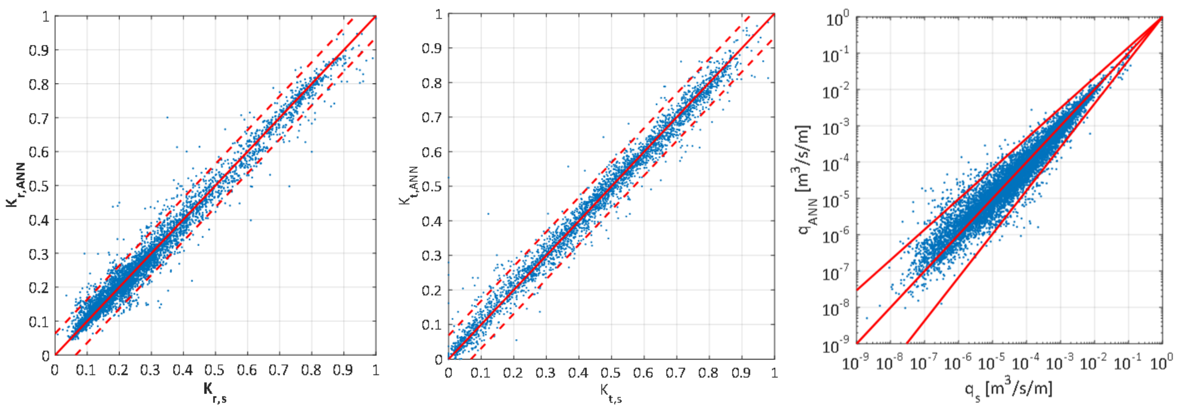

Figure 2: From left to right: performance for K_r, K_t and q. Comparison among predicted values (denoted by the 'ANN' subscript) and corresponding measurements ('s' subscript). The corresponding 95% confidence bands are shown. (From Formentin et al., 2016; Zanuttigh et al., 2017).

Scale and model effects

The training database of the ANN tool includes only data derived from laboratory tests, performed at different scales. A few (around 100) prototype data on wave overtopping (Yamamoto and Horikawa, 1992; Pullen et al., 2004; Briganti et al., 2005; De Rouck et al., 2005) are available but they have not been used to train the ANN to avoid inhomogeneous information (prototype and laboratory). According to De Rouck et al. (2005) and Franco et al. (2009), scale and model effects are inherent to the laboratory conditions and are mainly related to the structure properties (porosity, permeability, roughness) and to the hydraulic loads (wind, spray, currents). The predictions by ANNs and formulae are therefore affected by model and scale effects, which are significant for rubble mound structures in case of small overtopping (q<10^{-3} $m^3/s/m$). In case of impermeable structures, there are no significant model effects for dikes, while there might be effects due to wind in case of vertical structures.

Eurotop (2016) proposed a new approach to represent model and scale effects for rough permeable structures. This method consists of first up-scaling the model data to prototype and then of applying a correction factor f_q depending on the structure slope α_d and on the roughness γ_f. Such formulations for f_q (Eq.s 6.13, 6.14, 6.15 pf the EurOtop manual), that are automatically implemented in the tool, are reported in the following:

$$f_q=\min\left\{\begin{matrix}-\frac{\mathrm{Log}_{10}(q_{us}-2)^5}{14}+1\\ f_{q,max}\end{matrix}\right\}\text{, with}$$

$$f_{q,max}=\begin{cases}\min\{10\cdot\cot(\alpha_d)-9;\,31\}, & \text{for rubble mound slopes } (\gamma_f\le 0.7)\\ 5\cdot\gamma_f\cdot(1-f_{q,max})+4.5\cdot(f_{q,max}-1)+1, & \text{for "slopes with roughness" } (0.7<\gamma_f<0.9)\text{ ,}\\ 1, & \text{for smooth slopes } (\gamma_f\ge 0.9)\end{cases} \quad (1)$$

where q_{us} is the "up-scaled" value of the average predicted value of q at model scale.

The results of the application of such approach to the ANN have been checked by applying f_q to the small scale predictions of the ANN and by comparing these values to the corresponding prototype data. The application is limited to the only 3 datasets of tests available at both model and prototype scale: Zeebrugge (a rubble mound structure with Antifer cubes, De Rouck et al., 2005), Ostia (a rock permeable breakwater, Briganti et al., 2005) and Samphire Hoe (a smooth vertical wall with a rock berm).

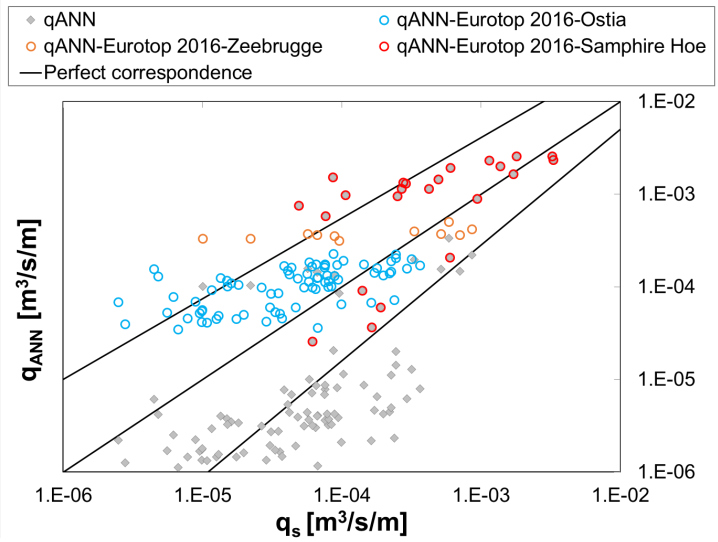

Figure 3: Outputs of the ANN (grey diamonds) and corrected outputs of the ANN including the EurOtop, 2016 corrections (void circles) versus the measured prototype values. The confidence 90% bands of the ANN are also shown.

Figure 3 shows the comparison among the ANN predictions, the ANN predictions corrected following Eurotop (2016) and the experimental values. No correction is applied to the case of Samphire Hoe. It can be observed that the corrected predictions are still cautious for small overtopping, which corresponds to q<1 l/s/m at prototype.

In order to adopt a cautious approach and avoid the risk of underestimation, in the last version of the ANN tool (Zanuttigh et al., 2017), the correction factor f_q proposed in EurOtop (2016) is applied to the predictions of q at model scale. Such correction is also implemented in the Graphical User Interface of the ANN tool. Further research finalized to the development of a modified and less cautious approach for the representation of the model effects is ongoing.

The Graphical User Interface of the ANN tool

The Graphical User Interface (GUI) has been conceived and built to share and promote the practical application of the EurOtop ANN tool. The use of the tool and the downloads free upon registration. The main features of the GUI are describedin this Section.

Overview

The main objective of the GUI was to make the use of the ANN tool as user-friendly as possible. For this purpose, the GUI is organized in sections, all accessible from the Home Page. A side bar is present in all the sections, to ease the exploration of the webpages.

There are three main sections: the Input, the Results, and the Downloads. In the Input section, it is possible to build the input scenario(s), either by uploading a file or by filling-in a dedicated web form. The Results section is in turn subdivided into three sub-sections, one for each output parameter (K_r, K_t or q). Once the user has built and uploaded the input scenario(s) and the tool has computed theresults, the predictions of the output parameter(s) are displayed in the corresponding sub-sections. A downloadable version of the ANN output is also available on the Downloads page. From the Downloads section the user can download the signed agreement form to obtain the Database by email. the User Guide containing the instructions for the use of the ANN tool and the Input file template. Further details about the Input and the Results pages are provided in the following.

The Inputs and the Outputs

The user is asked to provide the ANN with 22 dimensional Inputs describing the geometrical features of the structure(s) and the hydraulic boundary conditions. Since the ANN tool is scale-independent, it is up to the user to provide the Input in small scale units or prototype scale units. The list of these Inputs is reported here in Table 2.

Table 2: Inputs required for running of the ANN tool through the GUI.

#	Inputs	Unit	Definition of the parameter
1	Name	[-]	Label/ID of the scenario
2	m	[-]	Cotangent of the foreshore slope
3	h	[m]	Water depth at the structure toe
4	$H_{m0,t}$	[m]	Significant wave height at the structure toe
5	$T_{m-1,0,t}$	[s]	Spectral wave period at the structure toe
6	β	[°]	Wave obliquity
7	h_t	[m]	Toe submergence
8	B_t	[m]	Toe width
9	h_b	[m]	Berm submergence
10	B	[m]	Berm width
11	$\cot\alpha_d$	[-]	Cotangent of the angle that the structure part below the berm makes with a horizontal
12	$\cot\alpha_u$	[-]	Cotangent of the angle that the structure part above the berm makes with a horizontal
13	γ_{fd}	[-]	Roughness factor for $\cot\alpha_d$
14	γ_{fu}	[-]	Roughness factor for $\cot\alpha_u$
15	D_d	[m]	Size of the structure elements along $\cot\alpha_d$
16	D_u	[m]	Size of the structure elements along $\cot\alpha_u$
17	A_c	[m]	Crest height with respect to swl
18	R_c	[m]	Wall height with respect to swl
19	G_c	[m]	Crest width
20	Kr_Flag	-	Logical flag to get the prediction of Kr
21	Kt_Flag	-	Logical flag to get the prediction of Kt
22	q_Flag	-	Logical flag to get the prediction of q

The GUI includes two possibilities to provide the 22 Inputs: a) by directly filling-in the values in a formatted Table, available on the website; b) by uploading a properly formatted text file including all the Input. The first way (a) allows the user to run just one simulation at a time (i.e. to get the predictions of a single scenario), while the second way (b) allows to run multiple scenarios at the same time.

The 22 Inputs of Table 2 are not the input parameters of the ANN tool. The 15 input parameters (Formentin et al., 2017) are automatically computed by the ANN on the basis of the information contained in the 22 Inputs. Since the GUI includes the possibility to upload multiple scenarios (or tests) at once, the first Input i.e. the "Name" label, see Tab. 2) is used by the ANN to identify each "scenario" (or test) and organize the Output table accordingly. The last three Inputs (Kr_Flag, Kt_Flag, q_Flag) are logical flags necessary to indicate which output parameter(s) the ANN should compute. Through these flags, the user can choose to get the prediction of just one, or two, or all the three output parameters.

The numerical predictions are organized in tables, where the header row contains the labels of the percentiles and where the first column indicates the ID of the scenario (as defined by the user through the Input "Name", see Table 2). An extra column is present in case of *q* for the correction of the average value to the prototype conditions with respect to scale effects (small overtopping at rubble mound structures).

For all the output parameters and for each scenario, the Output Table provides also an indicator of the "reliability" of the prediction. Such indicator is the measure of the Euclidean distance (E) between the configuration of the scenario (defined by the values of its input parameters) and the NN domain of validity (defined by the values of the input parameters of the training data). The distance E is a positive quantity that is identically equal to zero for all the scenarios belonging to the NN domain of validity (i.e. the training tests). The greater the value of E, the lower the reliability on the NN predictions for the corresponding scenario, and the wider the confidence intervals associated to the predictions themselves. Roughly, it can be considered that the optimal values of E should be lower than 0.5, while the values of E close to (or higher than) 1 mean un-reliable predictions (i.e. very wide confidence intervals).

Table 3 presents an example of an Output Table for the prediction of q in case of seven scenarios (labelled progressively from G1 to G7) relative to the same structure. The structure is a rubble mound breakwater armoured with X-blocks with a wave wall, see Fig. 4. The tested scenarios are characterized by increasing values of the crest width (G_c), from 5 m (test G1) to 16 m (test G7).

Table 3: Example of an Output table for q delivered after the run of the ANN tool.

ID	q [m^3/s/m]	5.0%	95.0%	q [m^3/s/m] with scale corrections	E
G1	3.67E-02	1.72E-02	7.24E-02	3.66E-02	0.026
G2	2.55E-02	1.19E-02	5.13E-02	2.55E-02	0.026
G3	1.31E-02	5.28E-03	2.99E-02	1.31E-02	0.026
G4	7.18E-03	2.27E-03	1.96E-02	7.18E-03	0.026
G5	4.19E-03	1.14E-03	1.39E-02	4.19E-03	0.026
G6	2.56E-03	5.42E-04	1.06E-02	2.57E-03	0.026
G7	1.62E-03	2.73E-04	9.89E-03	1.65E-03	0.026

In the example of Tab. 3, G_c was increased a little in each consecutive calculation scenario. The average values of q () in Tab. 3 monotonically decrease with increasing G_c, revealing that the answer of the ANN tool for these scenarios is continuous and consistent with the physical process. In this case, the application of the EurOtop (2016) correction factor f_q to scale to prototype conditions is modest, because f_q is approximately 1 when the values of q at prototype scale are greater than 10^{-3} m^3/s/m (or 1 l/s/m).
As for the parameter E, the constant and very low value of 0.026 reported in Tab. 3 indicates that all the scenarios are equally close to the NN domain of validity. Overall, such values of E (and the limited width of the 90% confidence intervals (indicated by the percentiles 5% and 95%) suggest that these predictions are satisfactorily reliable.

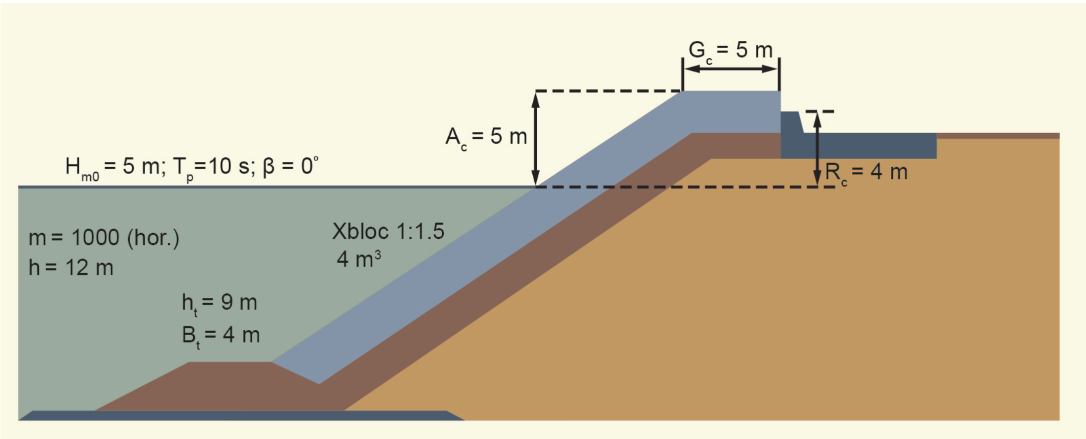

Figure 4: Cross-section of the example application of the ANN tool.
From EurOtop (2016).

The user gets also a graphical representation of the predicted output as function of the relative crest freeboard $R_c/H_{m0,t}$, which is considered one of the main representative and effective input parameters. Such plots can be considered as further qualitative indicators of the Output reliability, since the predictions are shown together with the distribution of selected datasets of the training ANN data. These data are automatically individuated by the tool on the basis of a criterion of “similarity” among the user scenario(s) and the tests available from the database.

An example of such Output Figures for K_r and K_t is reported in Figure 5. In this case, the tool has identified the user scenarios as a case of breakwaters with artificial armour units. For each Output, the ANN predictions (red stars) are compared to the corresponding experimental data (blue crosses). From these Figures the user is able to check whether the predictions fall within the available data and/or follow a similar trend of their distribution.

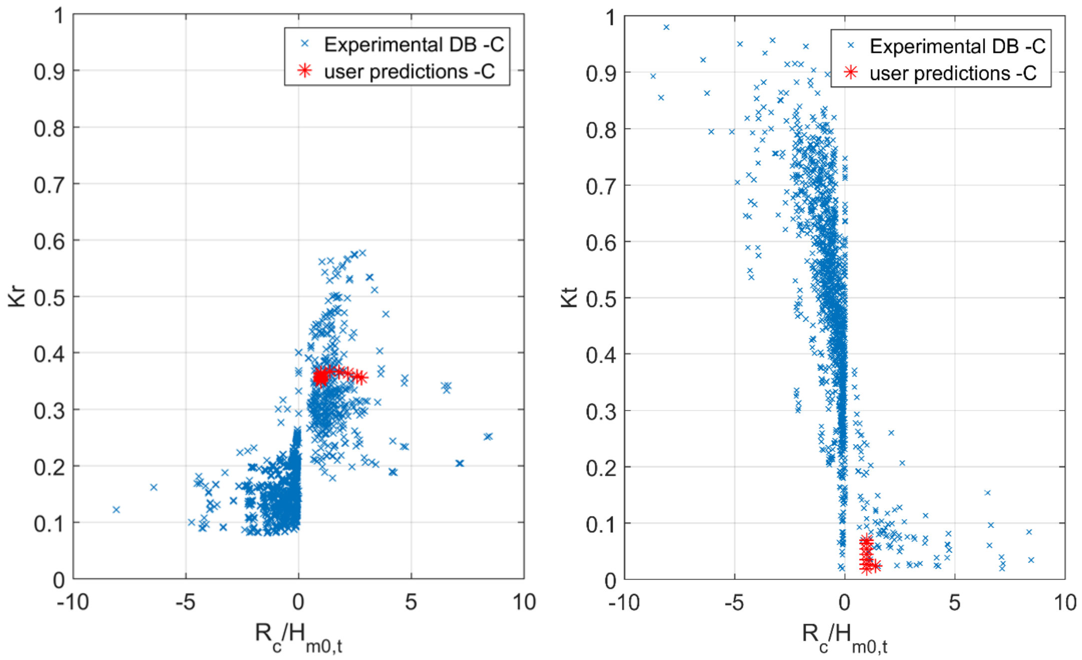

Figure 5: Example of two Output figures pritned after the run of the ANN tool. K_r (left) and K_t (right) values as functions of $R_c/H_{m0,t}$. The predictions of the user's scenarios (red stars) are compared to experimental tests (blue crosses) on similar structures.

Conclusions

This paper presents the main features of the new ANN tool recently developed by the authors for the prediction of q, a K_r and K_t (Zanuttigh et al., 2016; Formentin et al., 2017).

This ANN tool, has been adopted by the updated EurOtop (2016) manual, is characterized by an optimized performance with respect to other existing ANNs and traditional methods (Formentin et al., 2017) and has achieved an improved prediction of the low values of q (Zanuttigh et al., 2016). On average, the accuracy of the ANN is characterized by values of the coefficient of determination R^2 ranging between 0.92 (in case of q) and 0.99 (in case of K_t).

One of the most important features characterizing the ANN tool is the use of dimensionless input parameters that produce scale-independent predictions. This means that the ANN can deal with input scenarios at both model and prototype scale. If the input scenarios are supplied at a prototype scale, the predicted values of q do not require any up-scaling, which actually is similar to the use of dimensionless formulae.

As the ANN tool is trained on lab tests only, its predictions are affected by model effects in case of rubble mound structures and small overtopping discharges (mainly smaller than 1 l/s per m). A correction factor (f_q) is needed for the ANN predictions as well as application of formulae, to re-scale the values of q at prototype conditions. So far, the EurOtop (2016) correction is applied, leading to cautious estimates of q at prototype. Further research is ongoing and is focused on the development of a less cautious approach.

To share and promote the practical use of the ANN tool, a GUI has been created and uploaded on a dedicated website. Through the GUI, the tool is freely accessible to any potential user, as no knowledge or familiarity with the neural networks is required. The GUI allows to get nearly instantaneous predictions of the desired results for one or multiple scenarios. The output consists of tables and figures. The tables collect the predicted average values and the 90% confidence band for each input scenario, while the figures display the distribution of the average predictions as functions of the relative crest-freeboard.

Particular attention is paid to the assessment of the reliability of the predictions. A prediction can be considered reliable if the 90%-confidence bandis “narrow enough” and if the input scenario is “similar enough” to the data used for the ANN training, that define the ANN field of validity. In addition, the output tables include a measure of the Euclidean distance among the user scenarios and the ANN field of validity (the lower the distance, the more reliable the predictions). Finally, the “similarity” of the user scenarios with the ANN field of validity can be qualitatively assessed by comparing the distribution of the predictions with the distribution of similar experimental data.

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