

NEURAL NETWORK CALIBRATION METHOD FOR VARANS MODELS TO ANALYSE WAVE-POROUS STRUCTURES INTERACTION

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ABSTRACT

This study develops a calibration method for the porous media to properly model the interaction between waves and coastal structures using VARANS models. The proposed method estimates the porosity, n_p , and the optimum values of the Forchheimer coefficients, α and β . Physical tests were conducted in a 2D wave flume for a homogeneous mound breakwater. Numerical tests were carried out using the IH-2VOF model to simulate the corresponding physical tests and incident wave conditions (H_i , T). The numerical tests covered a wide range of Forchheimer coefficients found in the literature, α and β , and the porosity, n_p , with a total of 555 numerical tests. The results of 375 numerical tests using IH-2VOF were used to train a Neural Network (NN) model with five input variables (H_i , T , n_p , α and β) and one output variable (K_R^2). The NN model explained more than 90% ($R^2 > 0.90$) of the variance of the squared coefficient of reflection, K_R^2 . This NN model was used to estimate the K_R^2 in a wide range of n_p , α and β , and the error (ε_a) between the physical measurements and the NN estimations of K_R^2 was calculated. The results of ε_a as function of n_p , α and β showed that for a given porosity, n_p , it was difficult to obtain a pair of α and β values that gave a common low error if few physical tests are used for calibration. The minimum root-mean-square error of K_R^2 (ε_{rms}) was calculated to find the optimum values of porosity and Forchheimer coefficients: $n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$ for the tested structure. Blind tests were conducted with the remaining 180 numerical tests using IH-2VOF to validate the proposed method for VARANS models.

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1 INTRODUCTION

Breakwaters, low-crested structures and other porous structures are commonly used to protect harbors, beaches and other highly valuable natural areas and artificial infrastructures. These coastal structures must be designed to provide safety and service during a given lifetime, and they must be designed considering the expected extreme wave conditions during lifetime. Numerical modelling arises as a useful tool, with relatively low cost and time consuming, to analyze the hydraulic performance of coastal structures. Numerous studies use numerical models to analyze different types of coastal structures and the processes involved in the wave-structure interaction; thus Croquer et al. (2023) analyzed wave loads, Lara et al. (2011) studied the wave-breaking on the structure, and Mata and Van Gent (2023) analyzed overtopping discharges and hydraulic stability. The correct numerical modelling of the flow through the porous media is fundamental to characterize the relevant physical processes involved in the wave-structure interaction. The wave-porous media interaction is mainly modeled with mathematical formulations based on solving two coupled models: (1) the flow outside the porous media, acting on the structure, by the Reynolds Averaged Navier-Stokes (RANS) equations, and (2) the averaged flow through the porous media, by the Volume-Averaged Reynolds-Averaged Navier-Stokes (VARANS) equations. The representation of the flow within the porous media, characterized by a nominal diameter, D_{n50} , and a porosity, n_p , is generally based on the extended Darcy-Forchheimer equation (Eq. 1), which relies on some coefficients calibrated with physical tests.

$$I = \left(\alpha \frac{(1-n_p)^3}{n_p^2} \frac{\mu}{D_{n50}^2} \right) \bar{\mathbf{u}} + \left(\beta \left(1 + \frac{7.5}{KC} \right) \frac{1-n_p}{n_p^2} \frac{\rho}{D_{n50}^2} \right) \bar{\mathbf{u}}|\bar{\mathbf{u}}| + (\gamma_p(1-n_p)) \frac{\partial(\rho\bar{\mathbf{u}})}{\partial t} \quad (1)$$

where $\bar{\mathbf{u}}$ is the velocity vector, KC is the Keulegan-Carpenter number, and α , β and γ_p are three empirical coefficients. The coefficient γ_p yields good results with a constant value of $\gamma_p = 0.34$ (Losada et al., 2008). Although different authors have proposed Forchheimer coefficients, α and β , in a wide range of values for the same wave conditions and structure typologies, there is a large uncertainty in selecting the adequate values for α and β to correctly model the flow through the porous media. The physical measurement of the porosity, n_p , is not reliable as it may slightly change during the laboratory tests, and “in situ” measurement is almost impossible.

Consequently, the main objective of this study is to develop a method to estimate the most appropriate Forchheimer coefficients, α and β , and porosity, n_p , to correctly model the interaction between waves and coastal structures using VARANS numerical models. The calibration method provides the optimum values of the Forchheimer coefficients and the porosity from the error prediction of a Neural Network (NN) model developed using physical and numerical tests. Physical tests were conducted at the University of Granada for a homogeneous mound breakwater under non-overtopping and non-breaking conditions. Numerical tests were conducted to reproduce the physical tests using the IH-2VOF model (Lara et al., 2008), with different combinations of porosity and Forchheimer coefficients. A total of 555 numerical tests using IH-2VOF were calculated, and 375 of them were used to develop the NN model. To calibrate the porous media, the proportion of the reflected wave energy, K_R^2 , was compared between the physical and numerical tests estimated with the NN model. Results corresponding to the remaining 180 numerical tests of IH-2VOF were used for blind testing to validate the method.

2 METHODOLOGY

2.1 Physical and numerical tests

2D physical tests were conducted in the wave flume of the University of Granada. The physical model was a homogeneous mound breakwater with a crown width $B_b = 0.24$ m, a height $F_{MT} = 0.55$ m, and seaward and landward slope $V/H = 1/2$ and $2/3$, respectively. The porous media was a homogeneous rock material with a nominal diameter $D_{n50} = 30$ mm, density $\rho_s = 2.64$ g/cm³, and a porosity measured, $n_p = 0.46$. Fig. 1 shows a scheme of the wave flume and the resistance wave gauges (G) to measure the wave free surface. The proportion of the reflected wave energy, K_{RLAB}^2 , was measured and considered as the main variable of this study. A total of 37 physical tests of regular waves characterized by H_I and T were tested.

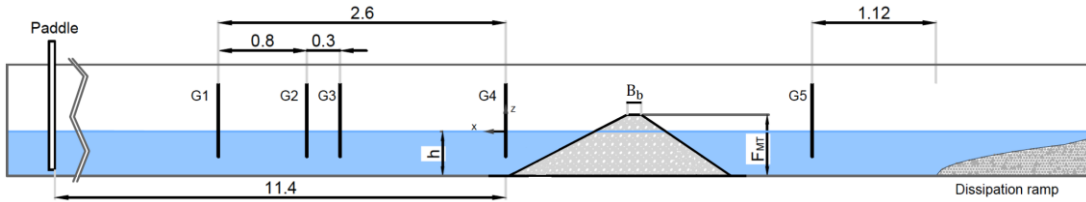


Figure. 1. Longitudinal cross section of the wave flume and location of wave gauges (dimensions in meter).

2.2 Numerical experiments

2.2.1 Model description

The IH-2VOF numerical model (Lara et al., 2008) was used in this study to model the interaction between waves and the porous breakwater tested at laboratory, since it is able to simultaneously solve the flow both inside and outside the porous media. IH-2VOF solves the two-dimensional Reynolds Averaged Navier-Stokes (RANS) equations outside the porous media using the $k - \epsilon$ turbulent model to calculate the kinetic energy (k) and the turbulent dissipation rate (ϵ). The free-surface is tracked by the Volume of Fluid (VOF) method (Hirt and Nichols, 1981). The flow through the porous media is solved by the Volume-Averaged Reynolds Averaged Navier-Stokes (VARANS) equations (see Eqs. 1).

2.2.2 Numerical set-up

A 2D domain of the wave flume described in Fig. 1 was reproduced in the IH-2VOF model. The numerical domain was slightly shorter in the x -direction (15.6 m long) than the wave flume as the dissipation ramp was substituted by an active absorption condition to reduce the number of cells. A mesh sensitivity analysis was performed to assess the computational cost and the accuracy of the results. A uniform mesh on the y -direction was used with a grid cell size of 0.5 cm. The x -direction was divided in 2 subzones as defined in Fig. 2a: (1) the 10.4 m-long outer region corresponding to the wave generation zone with a cell size of 2 cm, (2) the region corresponding to the breakwater (wave-structure interaction), where higher accuracy is needed, with a cell size of 1 cm. The total number of cells in the numerical domain was 1017 (x -direction)

x 201 (y-direction). The active wave absorption condition was considered at the generation boundary and at the end of the domain to reproduce the same conditions as in the laboratory experiments (see Fig. 2b). Numerical wave gauges G01 to G05 correspond to the physical wave gauges G1 to G5.

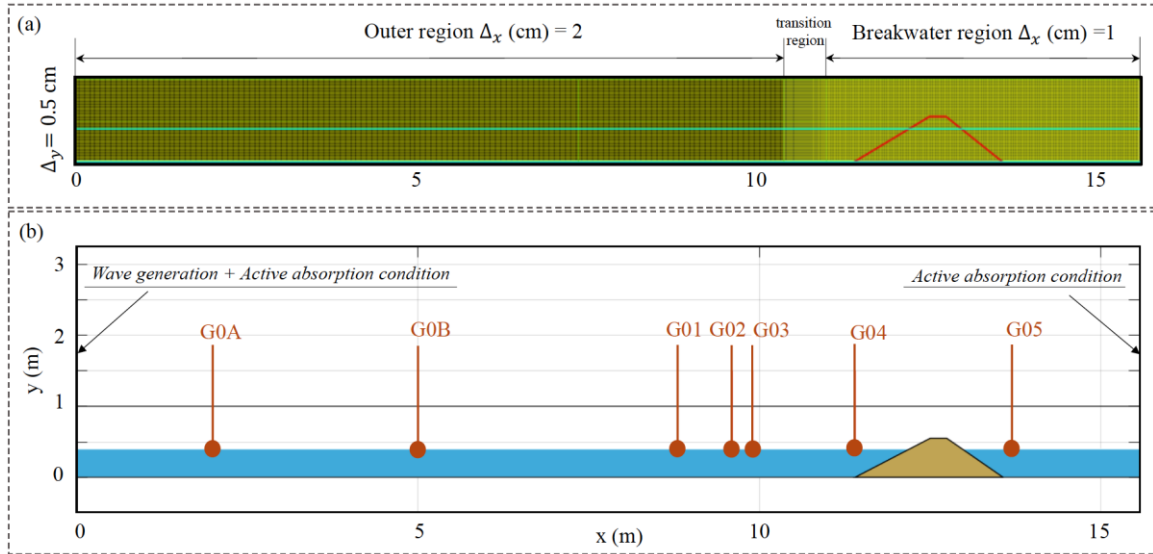


Fig. 2. Numerical domain in IH-2VOF model: (a) mesh grid, (b) wave gauges position.

The porous structure was modelled in the IH-2VOF model using the physical characteristics, D_{n50} and n_p , and the Forchheimer coefficients: α , β and γ_p . The physical homogeneous breakwater model with D_{n50} (m) = 0.03 was reproduced in the numerical model considering different combinations of n_p , α and β . The value of $\gamma_p = 0.34$ (Van Gent, 1995) was assumed to be invariable because the results are practically insensitive to its variation (Losada et al., 2008; Higuera et al., 2014). To cover the full range of α and β values used in the literature (Table 1), this study considered the following range parameters given in the literature: $200 \leq \alpha \leq 20,000$ and $0.4 \leq \beta \leq 4.0$. As discussed in Introduction, the porosity measurement at laboratory is not reliable; thus, the porosity (n_p) was considered in this study as an additional parameter to be calibrated. The porosity values were chosen in the range $0.37 \leq n_p \leq 0.46$, which corresponds to the possible porosities for homogeneous stones of size D_{n50} (m) = 0.03 following the recommendations of CIRIA-CUR (2007). A total of 555 numerical cases were simulated in IH-2VOF model with 555 results of the squared coefficient of reflection, K_{RVOF}^2 .

3 NEURAL NETWORK MODEL

A Neural Network (NN) model was developed from the results of the 375 numerical tests using IH-2VOF. The NN model was structured with five input variables ($N_I = 5$), 20 hidden neurons ($N_H = 20$) and one output variable ($N_O = 1$). For the same material of the porous media characterized by a D_{n50} , the selected input variables were: H_t , T , n_p , α and β . The output variable was the squared coefficient of reflection, K_{RNN}^2 .

The number of parameters of this NN model was $P = N_O + N_H(N_I + N_O + 1) = 1 + 20(5 + 1 + 1) = 141$. Although a total of $N_T \times N_R = 37 \times 15 = 555$ numerical tests using IH-2VOF were available, only 25 physical tests (randomly selected from the total 37 tests) with their corresponding combination of $\{n_p, \alpha, \beta\}$, that is $25 \times 15 = 375$ numerical tests were considered to build up the NN model. The results from the remaining $12 \times 15 = 180$ numerical tests were used only for a final blind test.

The NN model was trained and tested using the NN toolbox (Beale et al., 2019) in the MATLAB® environment (MATLAB®, 2022) with the following characteristics:

- (1) Early stopping criterion to prevent overlearning,
- (2) Randomly selection of data using 263 cases (70%) for training, 56 cases (15%) for validation and 56 cases (15%) for testing,
- (3) Levenberg-Marquardt training algorithm, and
- (4) hyperbolic tangent sigmoid transfer function for hidden neurons.

Fig. 3 shows that the NN model predicted very well the numerical results of IH-2VOF model, with a coefficient of determination $R^2 = 0.99$ for training data (70%) and $R^2 = 0.92$ for testing data (15%). This NN model is computationally much faster than IH-2VOF model and can be used as an auxiliary tool to find the best combination of $\{n_p, \alpha, \beta\}$.

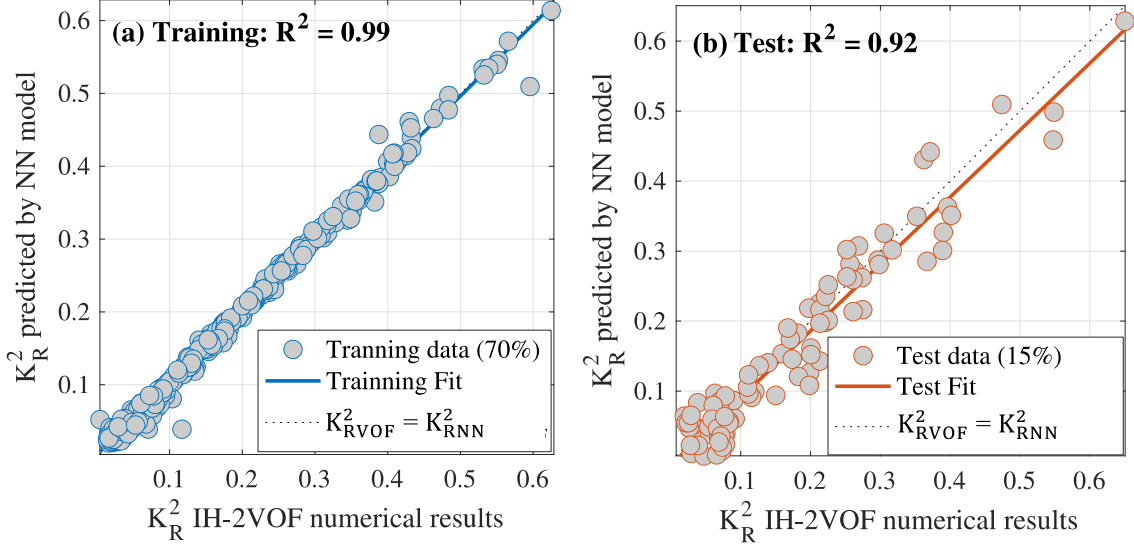


Figure 3. K_R^2 predicted by the NN model against K_R^2 calculated with IH-2VOF: (a) training (b) test.

4 NEURAL NETWORK RESULTS

The NN model developed is computationally much faster than IH-2VOF model and was used as an auxiliary tool to find the best combination of $\{n_p, \alpha, \beta\}$. A huge number of combinations of $\{n_p, \alpha$ and $\beta\}$ for each pair tested H_l and T were considered to obtain many numerical estimations of K_R^2 using the NN model. The estimation of K_{RNN}^2 , was compared with the results of physical tests, K_{RLAB}^2 .

4.1 Estimations of porosity and Forchheimer coefficients for each test

Fig. 4 represents the results of the absolute errors, $\varepsilon_a = |K_{RLAB}^2 - K_{RNN}^2|$, expressed as a percentage, for each pair of α (x-axis) and β (y-axis) according to the NN estimations for two porosities ($n_p = 0.38$ and 0.45) and two physical tests: (1) $H_{l1} = 0.03$ m, $T_1 = 1.12$ s (Figs. 4a, 4b), and (2) $H_{l2} = 0.10$ m, $T_2 = 2.46$ s (Figs. 4c, 4d). The minimum value of ε_a for each case is marked with a red circle. Assuming a constant porosity for the numerical model, the optimum values $\{\alpha, \beta\}$ with minimum value of ε_a are different for each test $\{H_l, T_i\}$. For example, if $n_p = 0.38$ (Figs. 4a, 4c), the minimum errors were given by $\alpha = 4,341$ and 802 , and $\beta = 3.745$ and 2.695 for $\{H_{l1}, T_1\}$ and $\{H_{l2}, T_2\}$, respectively. For the same test $\{H_{li}, T_i\}$, the minimum error corresponds to optimum values of $\{\alpha, \beta\}$ which are different depending on the porosity. For example, for $\{H_{l2}, T_2\}$ (Figs. 4b, 4d), the minimum was obtained with $\alpha = 802$ and $1,761$, and $\beta = 2.695$ and 3.925 for $n_p = 0.38$ and $n_p = 0.45$, respectively.

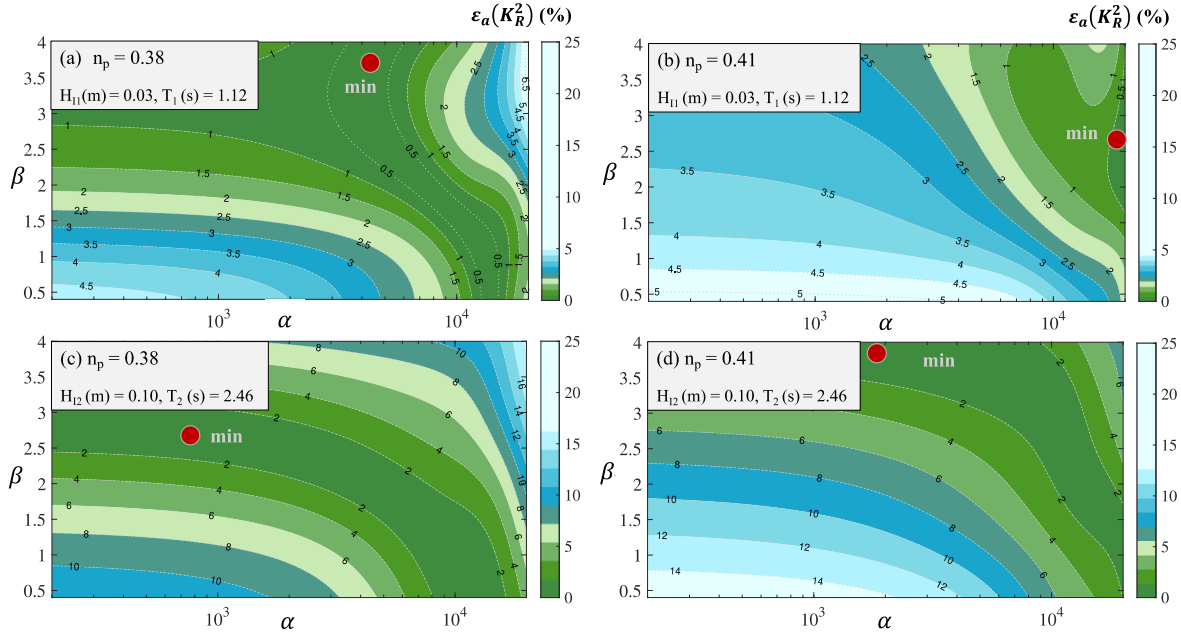


Fig. 4. Results of the absolute error, $\varepsilon_a(K_R^2)$ %, calculated with Eq. 9, for each pair of α (x-axis) and β (y-axis) according to the NN estimations for two porosities, $n_p = 0.38$ and 0.45 , and two tests: (a, b) H_{I1} (m) = 0.03, T_1 (s) = 1.12; (c, d) H_{I2} (m) = 0.10, T_2 (s) = 2.46. The minimum error is marked with a red circle.

The results obtained in Fig. 4 are pointing out that selecting one or a few physical tests $\{H_I, T\}$ to calibrate the values of n_p , α and β (as reported in the literature) is not sufficient to obtain the best representation of the hydraulic performance of wave-porous structure interaction.

4.2 Optimum values for porosity and Forchheimer coefficients (n_p , α , β)

The previous section calculates values of n_p , α and β which gave a minimum error between the K_R^2 estimated by NN and the measured in laboratory for each physical test $\{H_I, T\}_i$ ($i = 1, \dots, 25$). However, as observed in previous studies found in the literature and for greater computational efficiency, an optimum combination of n_p , α and β for all physical tests related to the best performance of wave-porous structure interaction should be calculated. For that, the NN estimations for each combination of $\{n_p, \alpha, \beta\}$ common to all 25 physical tests were compared with the measured result of the physical test as follow: for each porosity, “ k ” ($k = 1, \dots, 19$), and for each pair “ j ” of $\{\alpha, \beta\}$ ($j = 1, \dots, 200 \times 721$), the root-mean-square error (ε_{rmskj}) between the NN estimations and measurements of K_R^2 from the 25 physical tests ($i = 1, \dots, 25$) were calculated as,

$$\varepsilon_{rmskj}(K_R^2) = \sqrt{\frac{\sum_{i=1}^{25} (K_{RLABi}^2 - K_{RNNkij}^2)^2}{25}} \quad (2)$$

A total of $19 \times 200 \times 721 = 2,739,800$ root-mean-square errors, ε_{rmskj} , were calculated. Each value of ε_{rmskj} is characteristic of a $\{n_p, \alpha, \beta\}$ combination for all 25 physical tests. The minimum root-mean-square error between K_{RNN}^2 and K_{RLAB}^2 equal to $\varepsilon_{rms} = 2.28$ % gave an optimum combination of $n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$, which calibrates the porous media in the IH-2VOF model. Because of the NN model emulates the numerical IH-2VOF model, the calibrated porosity and Forchheimer coefficients ($n_p = 0.44$, $\alpha = 200$, $\beta = 2.825$) obtained in this study are adequate to characterize the interaction between the waves and the porous media of the tested homogeneous mound breakwater.

5 VARANS AND NN MODEL VALIDATION

The remaining $37 - N_T = 12$ available physical tests, corresponded to $12 \times 15 = 180$ numerical cases from the IH-2VOF model, were used in this study for a blind test of the proposed calibration method for VARANS models in two ways:

(1) Validation of the NN model: new estimations of K_{RNN}^2 were obtained with the NN model for the wave input parameters $\{H_I, T\}$ corresponding to the 12 physical tests not used for calibration; the calibrated parameters ($n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$) were fixed. The comparison between the measured, K_{RLAB}^2 , in the 12 physical tests used for validation and the new NN estimations K_{RNN}^2 , lead to a root-mean-square error $\varepsilon_{rms} = 2.56\%$, slightly higher than $\varepsilon_{rms} = 2.28\%$ obtained during the calibration process ($N_T = 25$ tests).

(2) Validation of the IH-2VOF model: numerical results using IH-2VOF, K_{RVOF}^2 , were obtained for the 12 additional physical tests taken for validation; the calibrated parameters ($n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$) were fixed. The comparison between the measured, K_{RLAB}^2 , in the 12 physical tests used for validation and the new IH-2VOF numerical simulations, K_{RVOF}^2 , lead to a root-mean-square error $\varepsilon_{rms} = 1.90\%$, slightly lower than $\varepsilon_{rms} = 2.28\%$ which were obtained during the calibration process ($N_T = 25$ tests).

The combination of $n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$, which was the result of the calibration method, was validated with new physical tests and performed well in both IH-2VOF and NN model. Numerical IH-2VOF estimations of K_R^2 were better than NN estimations ($\varepsilon_{rms} = 1.90\% < 2.28\%$), but NN estimations require a much lower computational effort, which is adequate to calibrate the parameters of the porous media $\{n_p, \alpha, \beta\}$.

6 CONCLUSIONS

The main results of this study are published in Díaz-Carrasco et al. (2024). Here, we summarized the main conclusions:

1. The NN model developed with the input variables $\{H_I, T, n_p, \alpha, \beta\}$, generate estimations K_{RNN}^2 which explained more than the 90% ($R^2 > 0.90$) of the variance of the numerical K_{RVOF}^2 results obtained using IH-2VOF model. The NN model correctly emulated the IH-2VOF model and was a computationally efficient tool to predict numerical VARANS results.
2. The selection of one or a few physical tests $\{H_I, T\}$ to calibrate the values of n_p , α and β , as reported in the literature, is usually not sufficient to obtain an adequate representation of the wave-porous structure interaction.
3. The blind test conducted in this study resulted in a root-mean-square error $\varepsilon_{rms} = 2.56\%$, slightly higher than $\varepsilon_{rms} = 2.28\%$ obtained during calibration. NN estimations, K_{RNN}^2 , were in agreement with the numerical IH-2VOF calculations, K_{RVOF}^2 , and the physical measurements, K_{RLAB}^2 , when using the calibrated parameters: $n_p = 0.44$, $\alpha = 200$ and $\beta = 2.825$. The selection of a porosity, $n_p = 0.44$, and Forchheimer coefficients, $\alpha = 200$ and $\beta = 2.825$, was the optimum combination of $\{n_p, \alpha, \beta\}$ for the porous media of a homogeneous mound breakwater with D_{n50} (m) = 0.03.

The proposed method based on a NN model is a robust, accurate and computational efficient tool to calibrate the porous media of a coastal structure under wave attack using VARANS models. This method not only obtains the optimum combination of Forchheimer coefficients $\{\alpha, \beta\}$, but also estimates the actual porosity of the physical model, characterized by a nominal diameter D_{n50} .

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REFERENCES

- Beale, M.H., Hagan, M.T., Demuth, H.B., 2019. Deep Learning Toolbox -User’s Guide. Matlab R2019a, Mathworks.
- CIRIA/CUR/CETMEF, 2007. The Rock Manual. The Use of Rock in Hydraulic Engineering (2nd edition). C683, CIRIA, London (UK).
- Croquer S., Díaz-Carrasco P., Tamimi V., Poncet S., Lacey J., Nistor I., 2023. Modelling wave–structure interactions including air compressibility: A case study of breaking wave impacts on a vertical wall along the Saint-Lawrence Bay. *Ocean Eng.*, 273, 113971.
- Díaz-Carrasco P., Molines J., Gómez-Martín M.E., Medina J.R., 2024 Neural Network calibration method for VARANS models to simulate wave-coastal structures interaction. *Coastal Engineering*, 188, art. no. 104443
- Higuera, P., Lara, J.L., Losada, I.J., 2014. Three-dimensional interaction of waves and porous coastal structures using OpenFOAM. Part II: Applications. *Coastal Engineering*, 83, 259-279.
- Hirt, C.W., Nichols, B., 1981. Volume of fluid (VOF) method for dynamics of free boundaries. *Journal of Computational Physics*. 39, 201–225.
- Lara, J.L., Ruju, A., Losada, I.J., 2011. Reynolds averaged Navier–Stokes modelling of long waves induced by a transient wave group on a beach. *Proc. R. Soc. A* 467, 1215–1242.
- Lara, J.L., Losada, I.J., Guanche, R., 2008. Wave interaction with low-mound breakwaters using a RANS model. *Ocean Engineering* 35, 1388-1400.
- Losada, I.J., Lara, J.L., Guanche, R., González-Ondina, J.M., 2008. Numerical analysis of wave overtopping of rubble mound breakwaters. *Coast. Eng.*, 55 (1), 47–62.
- Mata, M.I., Van Gent, M.R., 2023. Numerical modelling of wave overtopping discharges at rubble mound breakwaters using OpenFOAM®. *Coast. Eng.*, 181, 104274.
- Van Gent, M.R., 1995. Wave Interaction with Permeable Coastal Structures. Ph.D. thesis. Delft University.