Efficient wave condition predictions for coastal structures based on machine learning and phase-resolving numerical simulations

Widar Weizhi Wang, Norwegian University of Science and Technology, widar.w.wang@ntnu.no
Konstantinos Christakos, Norwegian Meteorological Institute, konstantinosc@met.no
Hans Bihs, Norwegian University of Science and Technology, hans.bihs@ntnu.no

INTRODUCTION

Coastal wave conditions are complex and inhomogeneous due to the irregular bathymetry and coastline and the associated wave transformations. This makes the site assessment, monitoring and design for coastal structures challenging, as the offshore wave conditions based on hindcast data or global forecasting model do not represent the local reality, including wave height, period, principal directions and energy distributions. The prediction of coastal near-site wave conditions requires phase-resolved numerical modelling to represent all relevant wave transformations. However, such simulations over a large coastal area show a high demand for computational resources and time. A more efficient and near-instant wave condition prediction method is thus desired for future-proof design and operational forecasting and maintenance. With the rapid development of data-driven approach, machine learning (ML) based methods have proven to be an attractive alternative to meet such a demand. Makarynskyy et al. (2005) attempted to predict the significant wave height at the west coast of Portugal using an artificial neural network (ANN). Mooneyham et al. (2020) developed a spectral, residual deep-learning model for improving short-term wave forecasts based on buoy observations. Minuzzi and Farina (2022) introduced a deep-learning approach to predict significant wave height based on seven wave buoy data sets. Though some procedures using machine learning methods based on measurement data have been developed, the prediction of future scenarios requires a wider range of input data, including extreme wave conditions and potential sea level changes. This data set can be obtained from numerical simulations. This work proposes to use validated numerical models to produce the wave data with a large matrix of scenarios. The open-source hydrodynamic model REEF3D::FNPF (Wang et al. 2022) has a proven record of flexible and efficient modelling of large-scale wave propagations and transformations in challenging coastal conditions. The open-source model is used together with the open-access hindcast dataset NORA3 (Haakenstad et al., 2021) to create wave data that can be used for training and validating an artificial neural network for future wave predictions. This procedure is demonstrated using a case study in southern Norway for navigational signal towers and a small boat harbour.

METHODOLOGY

The proposed approach utilises the fully nonlinear potential flow model REEF3D::FNPF with a flexible coastline algorithm and breaking wave algorithms to simulate a matrix of offshore waves propagating towards the coastal area. The coastal waves obtained from the numerical simulations are used as training data for a supervised artificial neural network based on the Sikit-learn Python package to identify the coastal waves using the offshore wave inputs. An additional set of simulations is used to validate the machine learning algorithm. An iterative process is applied to improve the accuracy and to avoid overfitting. The procedure achieves a direct prediction of coastal significant wave height, peak period, wave spectrum, principal direction, as well as wave force estimation on structures from the ML algorithm without further need for simulations. The training data also considers potential sea level changes for future scenarios. The procedure is summarised in Figure 1.

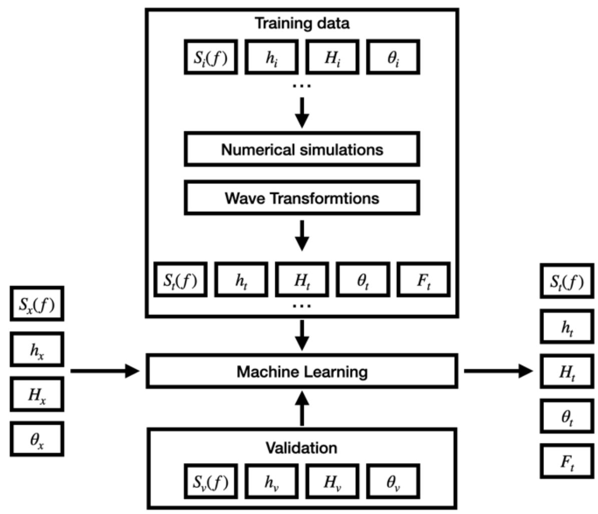

Figure 1 - Flow chart of the wave condition prediction procedure based on machine learning and phase-resolving numerical simulations.

NUMERICAL MODEL

The efficient and flexible open-source phase-resolving wave model REEF3D::FNPF solves the Laplace equation for the velocity potential ϕ and free surface elevation η together with the fully nonlinear kinematic and dynamic free surface boundary conditions and kinematic seabed boundary condition.

$$\frac{\partial^2\phi}{\partial x^2}+\frac{\partial^2\phi}{\partial y^2}+\frac{\partial^2\phi}{\partial z^2}=0.$$

High-order spatial discretisation and temporal advance schemes such as the 5th-order WENO algorithm and 3rd-order Runge-Kutta schemes are used to ensure the accuracy of the free surface. A bottom and free surface-following sigma grid is used in the vertical direction with a grid clustering towards the free surface. The sigma grid includes the bathymetry variations intrinsically, ensures the accurate positions to apply the free surface boundary conditions, and ensures sufficient resolution near the free surface while maintaining a low cell count, usually 10 cells in the vertical water column. Both depth-induced and steepness-induced breaking wave criteria are included, and an artificial viscosity-based wave energy dissipation algorithm is deployed to represent the correct wave-breaking process. A level-set method is used to represent the complex coastline geometry in the entire domain at one step (Wang et al., 2022).

RESULTS AND DISCUSSION

The area of interest for the study case in southern Norway is shown in Figure 2. Lyngholmsboen and Hanegalsboen are the two navigational signal towers planned on two shoals and are exposed to the ocean swells. The bathymetry-related wave transformations and wave forces will be predicted from the supervised neural network. The Alviga small boat harbour is located in a relatively sheltered coastal area, where wave diffraction is predominant.

Figure 2 – Map of the study case, Lyngholmsboen and Hanegalsboen are the two navigational signal towers; Alsviga is a small boat harbour.

The free surface elevation in the adjacent area around the signal towers from the numerical simulation with a south-eastern wave input is shown in Figure 3 as part of the large set of numerical simulations with various offshore wave inputs and sea levels.

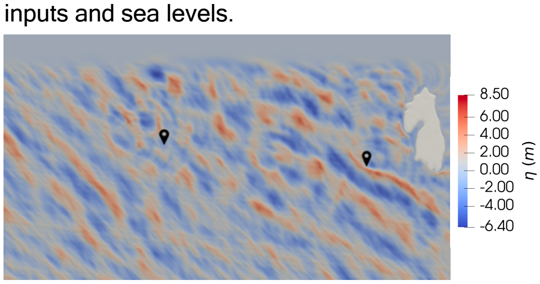

Figure 3 – Wave free surface elevation from the phase-resolved numerical simulations around the area of the navigational towers with south-eastern offshore waves

The significant wave heights are calculated in the entire domain from the numerical simulation as well. The wave forces at the two signal towers marked as black markers are also obtained from the simulations directly. The automatic offshore-nearshore wave correlation will then be established from the supervised ANN for any future scenarios. Figure 4 shows the new significant wave height distribution in the same area with a different offshore wave direction that can be directly predicted by the ML algorithm.

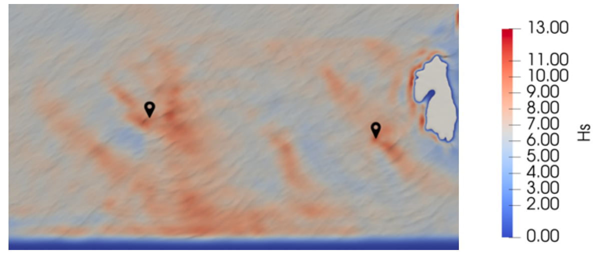

Figure 4 – Significant wave height from a different offshore wave condition that can be predicted by the supervised ANN ML algorithm based on the training data from the phase-resolved numerical simulations

CONCLUSIONS

A machine learning-based near-instant coastal wave condition prediction procedure is introduced for coastal structure designs, operations and maintenance. The numerical wave simulations are used to provide the training and validation data. The resulting supervised artificial neural network is a powerful and future-proven tool to predict coastal wave conditions at an entire coastal region using offshore wave inputs without further need for simulations or measurements. This approach is also compatible with digital-twin models and real-time monitoring.

ACKNOWLEDGEMENTS

This study is funded by the European Union (ERC, PARTRES, 101045646). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

REFERENCES

Haakenstad, H., Breivik, Ø., Furevik, B., Reistad, M., Bohlinger, P., & Aarnes, O. J. (2021). NORA3: A nonhydrostatic high-resolution hindcast of the North Sea, the Norwegian Sea, and the Barents Sea. Journal of Applied Meteorology and Climatology. pp. 1443-1464.

Makarynskyy, O., Pires-Silva, A., Makarynska, D. and Ventura-Soares, C. (2005). Artificial neural networks in wave predictions at the west coast of Portugal. Computers Geosciences, vol. 31(4), pp. 415–424.

Minuzzi, F.C. and Farina, L. (2022). A deep learning approach to predict significant wave height using long short-term memory, Ocean Modelling, vol. 181, pp. 102151.

Mooneyham, J., Crosby, S.C., Kumar, N. and Hutchinson, B. (2020). Swrl net: A spec- tral, residual deep learning model for improving short-term wave forecasts. Weather and Forecasting, vol. 35(6), pp. 2445 – 2460.

Wang, W., Pákozdi, C., Kamath, A., Fouques, S. and Bihs, H. (2022). A flexible fully nonlinear potential flow model for wave propagation over the complex topography of the Norwegian coast. Applied Ocean Research, vol. 122, pp. 103103.