

### 3DWaveBI: Wave Operator Network (WaveONet)

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The increasing impact of global warming has led to a growing frequency of extreme oceanic events such as typhoons, as well as greater severity of catastrophic hazards including tsunamis. At the same time, the global transition toward renewable energy has accelerated the development of marine energy technologies, including offshore wind turbines and tidal power systems. These challenges highlight the importance of accurately modeling ocean wave dynamics for both ocean hazard mitigation and sustainable energy exploitation.

Constructing reliable and efficient physical models capable of predicting the spatio-temporal evolution of surface waves remains a central objective in ocean hydrodynamics. Such models aim to infer wave evolution from limited information, including boundary conditions, bathymetry, and initial wave fields.

Conventional approaches for wave modeling include computational fluid dynamics (CFD) models that solve the Navier–Stokes equations, as well as reduced-order formulations such as the Shallow Water Equations, Boussinesq-type models, and Fully Nonlinear Potential Flow (FNPF) models. Although these approaches have achieved significant success, they are often limited by high computational cost, numerical stability constraints, grid dependency, and restrictions associated with particular wave regimes or water depths.

Recent advances in machine learning, particularly neural networks, have opened new possibilities for surrogate modeling of complex physical systems. However, maintaining physical consistency and interpretability in neural network models remains a major challenge for scientific applications. Physics-Informed Neural Networks (PINNs), introduced by Raissi et al. (2019), incorporate governing equations as soft constraints in the training process through additional loss terms. Among recent developments in operator learning, the Deep Operator Network (DeepONet) has attracted particular attention because of its ability to learn nonlinear mappings between function spaces.

In previous work, we developed a physics-informed operator-learning framework based on DeepONet and demonstrated the reconstruction of regular wave fields, including solitary and periodic waves propagating over a bathymetry with a trapezoidal bar. In this framework, the Laplace equation, together with the nonlinear kinematic and dynamic

free surface boundary conditions and the impermeable bottom condition, are incorporated into the loss function. Using time-series measurements of wave elevation from a single gauge location, the complete flow field can be reconstructed within flexible spatio-temporal coordinates.

The next challenge is to extend this framework to irregular wave conditions. Compared with regular waves, irregular waves exhibit more complex characteristics and stronger stochasticity, which places higher demands on the generalization capability of the neural network. Preliminary investigations have therefore been conducted on several aspects of the network design, including the orthogonality of learned basis functions, the width of the output layer, and strategies for selecting training waves. These studies provide useful insights for improving the robustness and predictive capability of the operator learning framework.

Another limitation of the current model is that the network is trained for a fixed bathymetry. The proposed research will extend the framework to account for varying bathymetirs by enriching the training dataset and enhancing the encoding capability of the input branch. This extension will allow the model to learn wave transformations under different bathymetric conditions and significantly improve the flexibility of the surrogate model.

The objective of this project is therefore to develop a physics-informed operator learning framework capable of reconstructing complex ocean wave fields, including irregular waves and varying bathymetric conditions, from limited observational data. By combining operator learning with physical constraints, the proposed approach aims to provide an efficient and generalizable surrogate model for wave dynamics. Such developments could significantly accelerate wave simulations and contribute to improved prediction and analysis of coastal and offshore processes.