A Deep Learning Model for Short-term Prediction of Irregular Long-crested Waves Using Probabilistic Strategies

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ABSTRACT

Wave prediction is of vital importance in offshore engineering. A phase-resolved wave prediction model based on recurrent neural networks is developed in this paper. Considering the fat-tailed distribution of the experimental waves, we introduce the Student’s t-distribution to recognize uncertainty in the future, improving the accuracy. The comparable performance indicates that the Student’s t-distribution is appropriate for wave prediction.

KEY WORDS: Phase-resolved wave prediction; Recurrent neural networks; Fat-tailed distribution; Student's t-distribution.

INTRODUCTION

Numerical wave models (NWMs) are classified into phase-averaged and phase-resolved models, both of which are based on governing equations to accomplish the objective of wave prediction. The phase-averaged models can only predict the wave's statistical characteristics (e.g., significant wave height ($H_s$), peak spectral wave period ($T_p$), wave direction, etc.) and cannot provide deterministic information over time. This limits their applicability to more complicated offshore operations, such as helicopter/rocket take-off/landing, the control of offshore energy structures and platforms, etc. The phase-resolved models have filled this gap. The results of a phase-resolved model are deterministic wave time series, which is beneficial for offshore workers in ensuring the stability of structures. Although NWMs have achieved development, they require a high level of technical expertise to attain the desired prediction accuracy. Therefore, developing a framework for real-time wave prediction that combines simplicity and generalizability is of great practical importance.

To improve the performance of NWMs, numerical simulations or wave tank experiments are utilized to get a better understanding of wave physics and embed them into NWMs. Naaijen and Huijsmans (2008) and Blondel-Couprie et al. (2013) experimentally validated that linear wave models may predict weakly non-linear wave fields. To accommodate waves with stronger nonlinearities, more sophisticated weakly nonlinear wave models such as enhanced second-order and cubic Nonlinear Schrodinger models were suggested (Blondel et al., 2010; Perignon, 2011). Klein et al. (2019) solved the governing equations with the High-Order Spectral method (Donnemuth and Yue, 1987). This method allows the order of the equation to be modified based on the strength of the nonlinearity, making it appropriate not just for weakly nonlinear but even for considerable steepness. Though the existing NWMs are adequate for most sea states, the tedious equation-solving procedure is an inevitable pain point. And the computing cost increases substantially as the model's complexity increases, rendering real-time predictions impractical (Desmars et al., 2020).

Artificial intelligence (AI) techniques have been popularly applied to time-series prediction issues (Sprangers et al., 2022), and several researchers have adopted AI to predict waves. Mandal and Prabaharan (2006) and Salcedo-Sanz et al. (2015) successfully predicted $H_s$ using recurrent neural networks (RNNs) and support vector regression, respectively, proving that AI may predict wave statistical properties at large scales. With the high-speed development of AI and high-performance computing technologies, researchers have shifted their attention in recent years to applying AI to predict deterministic wave information timestep-by-timestep into the future. Duan et al. (2020) achieved deterministic predictions for experimental waves by a multilayer perceptron named ANN-WP. They found that the ANN-WP's accuracy is nearly independent of wave steepness variation, whereas the linear wave model is not. Considering the strong randomness of waves, Liu et al. (2022) assumed that the wave surface elevation satisfied the Gaussian distribution and trained a model using a 'probabilistic' strategy. The model's robustness is enhanced by its ability to sense uncertainty. The probability density under ideal conditions has a thin-tailed distribution; however, it is fat-tailed in reality, i.e., there are more data in the tail of the probability distribution. Even though the data in the tail region have a low likelihood of occurrence, this does not mean they are impossible. Suppose these ‘special’ samples are ignored from the model's construction, the model's overall performance will not vary dramatically, but it may be biased in predicting extreme wave surface elevations. Therefore, an accurate prediction of this portion is key to determining whether the model can be improved by one level. The Student's t-distribution resembles the Gaussian, just with fatter tails. This