Hierarchical Approaches to Train Recurrent Neural Networks for Wave-Body Interaction Problems

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ABSTRACT

We present a hybrid linear potential flow - machine learning (LPF-ML) model for simulating weakly nonlinear wave-body interaction problems. In this paper we focus on using hierarchical modelling for generating training data to be used with recurrent neural networks (RNNs) in order to derive nonlinear correction forces. Three different approaches are investigated: (i) a baseline method where data from a Reynolds averaged Navier Stokes (RANS) model is directly linked to data from a LPF model to generate nonlinear corrections; (ii) an approach in which we start from high-fidelity RANS simulations and build the nonlinear corrections by stepping down in the fidelity hierarchy; and (iii) a method starting from low-fidelity, successively moving up the fidelity staircase. The three approaches are evaluated for the simple test case of a heaving sphere. The results show that the baseline model performs best, as expected for this simple test case. Stepping up in the fidelity hierarchy very easily introduces errors that propagate through the hierarchical modelling via the correction forces. The baseline method was found to accurately predict the motion of the heaving sphere. The hierarchical approaches struggled with the task, with the approach that steps down in fidelity performing somewhat better of the two.

KEY WORDS: Wave-body interaction; hierarchical modelling; linear potential flow; hybrid modeling; machine learning; recurrent neural network.

INTRODUCTION

Linear hydrodynamic models remain the tools-of-the trade in marine and ocean engineering despite their well-known assumptions of small amplitude waves and motions. As of now, fully nonlinear simulation tools simply cannot be exclusively used in the design loop due to the computational speed required to evaluate numerous irregular sea states. In order to extend the capabilities of the linear tools, nonlinearities are often included as approximated corrections. The two main corrections are standard Morison type drag (quadratic in relative velocity) and nonlinear Froude-Krylov forces (varying with instantaneous body position in the undisturbed wave). In this paper we exchange these classical approximations with estimates based on machine learning (ML) algorithms.

Machine learning is getting established in the ocean engineering sector. Lift and drag coefficients for vortex-induced vibrations have been treated in Raissi et al. (2019) using physics informed neural networks (PINNs). A recent study (Mishra et al. 2023) used a nonlinear autoregressive with exogenous input (NARX) model to accurately predict heave plate dynamics, and there are examples of turbulence modelling using ML approaches (Duraisamy et al. 2019, Wu et al. 2018). Mooring tension has been treated in a fair number of studies using artificial neural networks (ANNs). For example, Qiao et al. (2021) used Long short-term memory (LSTM) network to predict mooring tensions in real-time using vessel motion as input. Zhao et al. (2021) also showed that ANN-based models were able to predict static and dynamic mooring tensions based on vessel motion input.

The present work is, however, more related to previous work on system identification for floating body problems and forecasting of body position or wave excitation forces within control of wave energy converters (WECs). Giorgi et al. (2016) used time-series from numerical wave-body models to establish wave-elevation-to-body-position, \( \eta \rightarrow z \), and force-to-body-position, \( f \rightarrow z \), functions by NARX and ANN models. It was shown that while the ANN model always showed the best performance during the training phase, it performed worse than NARX during the validation phase. Looking to forecast the wave excitation force \( f_c \), to control a gyroscopic WEC, Bonfanti et al. (2020) developed an ANN model for motion in 3 degrees of freedom \( z \rightarrow f_c \). It was shown that the model performed well with a goodness of fit always larger than 92% for the tested 12 sea states. Also focusing on forecasting wave excitation forces Mahmoodi et al. (2022) developed \( \eta \rightarrow f \) functions using NAR, group method of data handling (GMDH), and LSTM networks for a heaving WEC. They concluded that while NAR gave the best agreement to target data, the difference was minor and all three models gave satisfactory results.

In contrast to the studies mentioned above we do not seek find \( f \rightarrow z \) or \( \eta \rightarrow z \) functions to be used in control, but rather to establish an