Generative AI for Extreme Ship Motions

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1 INTRODUCTION

The design of ocean-going ships requires the identification of the largest motions and loads that the vessel will experience during its operational lifetime. These critical events may include the largest midship bending moment, the most severe green-water on deck occurrence, and loads during propeller emergence. These processes are inherently nonlinear and necessitate the use of time-domain simulation tools for accurate assessment. However, nonlinear simulations are computationally expensive, and since the limiting design events are rare occurrences, traditional Monte Carlo simulation approaches become impractical due to the prohibitive number of realizations required to capture the extreme events with statistical confidence.

Despite decades of research into extreme event prediction methodologies, failures at sea continue to occur, underscoring the need for improved design tools. New Wave Theory[1] can predict the most likely large wave in a seaway, yet it is insensitive to the system dynamics and does not account for the vessel's response characteristics. The First-Order Reliability Method (FORM)[2] can generate a wave condition that leads to the most likely failure event, but it relies on linearization of the limit state function and may struggle with highly nonlinear systems or multiple failure modes. The Critical Wave Group method[3] can assess the probability of threshold exceedance, although it depends on a simplified description of the wave group that may not capture the full complexity of realistic sea states.

Generative AI is rapidly transforming multiple sectors of society, particularly with the emergence of large language models. The random ocean surface can be conceptualized as a high-dimensional space of interacting waves with varying amplitudes, frequencies, and directions. Recent work has constructed a language model of ocean and ship dynamics, called GenWave, enabling users to investigate design events through a novel AI-driven framework[4]. In this abstract, GenWave is extended to study green-water on deck of a naval vessel. The primary contribution of this abstract is the integration of a Higher-Order Spectral (HOS) method for ocean wave simulation to provide more accurate forcing for the ship dynamics model, thereby improving the physical fidelity of extreme event predictions.

2 METHODS

The GenWave method consists of three interrelated components: ocean wave generation, ship dynamics simulation, and iterative learning of phase distributions. The ocean surface is described using either a linear Longuet-Higgins Fourier series or the Higher-Order Spectral

(HOS) method[5]. In both approaches, each wave component is assigned a random phase, with HOS using these phases as initial conditions for nonlinear wave evolution. Ship motions are determined using a dynamics model forced by wave excitation. This work employs a Cummins equation model for computational efficiency, though GenWave's wave fields are compatible with high-fidelity CFD for detailed analyses. Fast evaluation methods like the Cummins equation are critical during training, as thousands of wave fields must be evaluated.

GenWave's core innovation is learning the phase distributions that produce increasing dynamical responses. The method begins by sampling uniformly distributed random phases to generate wave realizations and corresponding ship responses. These are sorted by the response metric of interest (e.g., roll angle, deck submergence), and the top quantile is selected. A probabilistic model is then trained on these extreme-response phase distributions. GenWave's architecture mirrors large language models: where LLMs use syllables as tokens from a word dictionary, GenWave uses wave phases as tokens from a dictionary of discrete angles in the range of 2π. The trained model generates additional wave fields, and the process of sorting, selecting, and retraining iterates progressively toward rarer, more extreme events.

Ocean Wave Generation The linear wave model is the Fourier sum

$$\eta(x,t) = \sum_{i=1}^{N} a_i \cos(\omega_i t + k_i x + \phi_i), \tag{1}$$

where the amplitudes a_i are determined from the energy spectrum, the frequencies and wave numbers satisfy the dispersion relation, and the wave phase angle ϕ_i is a random variable. In large events wave nonlinearity can play a role, and in this work the GenWave method is used with nonlinear waves determined from the Higher-Order Spectral (HOS) method of [5]. The HOS simulations are computed to order $M = 3$, use $N = 128$ wave components, and start with an initial random phase vector ϕ_i.

Ship Dynamics Simulation The first step for the dynamics simulation is to determine the frequency-domain added mass, damping, and excitation with the frequency-domain code called HOBEM[6, 7]. Then the ship motion is determined with the Cummins equation is solved for the heave and pitch

$$\sum_{j=3,5} \left[\left(M_{ij} + A_{ij}(\infty)\right) \ddot{\eta}_j(t) + \int_0^t K_{ij}(t-\tau)\dot{\eta}_j(\tau)d\tau + C_{ij}\eta_j(t) \right] = F_i^{ex}(t) \tag{2}$$

$$\hat{x}_i(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} X_i(\omega_e)e^{j\omega_e t}d\omega_e, \quad F_i^{ex}(t) = \int_{-\infty}^{\infty} \hat{x}_i(\tau)\eta(t-\tau)d\tau, \tag{3}$$

$$K_{ij}(t) = \frac{2}{\pi}\int_0^{\infty} B_{ij}(\omega)\cos(\omega t)d\omega. \tag{4}$$

Finally the relative motion at the bow $\eta_{r,\text{bow}}(t)$, is calculated as

$$\eta_{r,\text{bow}}(t) = \eta_3(t) - x_{\text{bow}}\eta_5(t) - \eta_{\text{bow}}(t) + z_{\text{bow}}, \tag{5}$$

where $\eta_{\text{bow}}(t)$ is the wave elevation at the bow from either the linear wave or HOS, and $(x_{\text{bow}}, z_{\text{bow}})$ is the location of the forward-most point of the foredeck in the body coordinate system.

GenWave GenWave is a method for creating ocean environments that lead to interesting marine dynamical events [4]. The method samples distributions for wave phases, propagates the waves either linearly or nonlinearly, and evaluates the dynamical process of interest. This sequence is repeated to collect statistics of the response, allowing the distribution of wave phases for the top quantile to be approximated. At the innermost level of the method is a neural network that takes a sequence of phases as input and produces the distribution of the next phase in the sequence. The method is summarized in the schematic shown in Figure 1. In iteration 0, a Monte Carlo simulation is performed in which 128 phase angles are selected from a uniform distribution. Eqn. 1 or the HOS is used to feed the Cummins equation for 10,000 different wave fields, and the top $1/q$ wave fields are selected to train the neural network ($q = 4$). The trained network can then be sampled to generate new wave fields in place of the uniform distribution, and the process is repeated until sufficiently extreme responses are found.

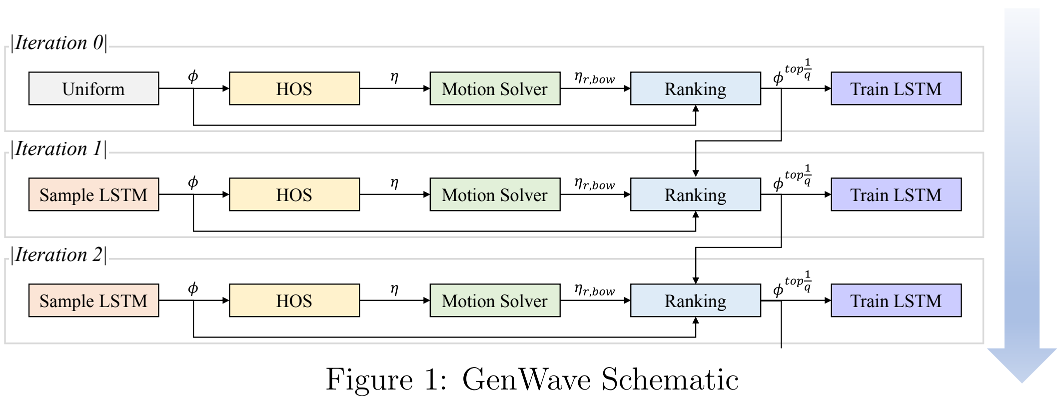

Figure 1: GenWave Schematic

3 RESULTS

The ONR tumblehome is studied for green-water-on-deck. The principal particulars are shown in Table 1. Additional information can be found at `www.w2025.nl`.

Parameter	Full Scale
Length of Waterline (L_{WL})	154.0 m
Beam (B_{WL})	18.8 m
Draft (T)	5.50 m
Displacement (Δ)	8790 t
Longitudinal centre of buoyancy aft of FP (L_{CB})	79.7 m
Wetted Surface (S_0)	3693.8 m^2
Pitch Gyradius (k_{yy})	38.65 m

Table 1: Ship Principal Particulars

The ship is moving in head seas at a speed of Froude number $F_n = 0.2$ ($U = 15.1$ kn). The irregular long-crested sea is from a JONSWAP spectrum with $N = 128$ equally-spaced components on the frequency axis range of $\omega \in [0.135, 1.530]$ (rad/s). The JONSWAP spectrum corresponds to sea-state 7, and is specified by $(H_s, T_p, \gamma) = (9.0\ \mathrm{m}, 12\ \mathrm{s}, 3.3)$.

Figure 2 presents 1,000-member ensembles of relative motion and wave elevation time histories, comparing nonlinear HOS results (left column) with linear wave predictions (right column). Each panel displays the ensemble mean alongside the single response corresponding to the minimum relative motion (deepest bow immersion). The most significant difference between the two approaches is evident in the bow submergence depth: the linear wave model predicts a more deeply submerged bow, with the dimensionless mean relative motion reaching $\eta_{r,\text{bow}} \approx -3$, whereas the HOS method yields a less extreme mean value of $\eta_{r,\text{bow}} \approx -2.23$. This discrepancy highlights the influence of nonlinear wave effects on the prediction of extreme relative motion events, with the linear model overestimating the severity of bow submergence compared to the more physically realistic HOS simulation.

Current work is focused on incuding nonlinearity in the motion solver with both CFD and potential-flow-based strategies.

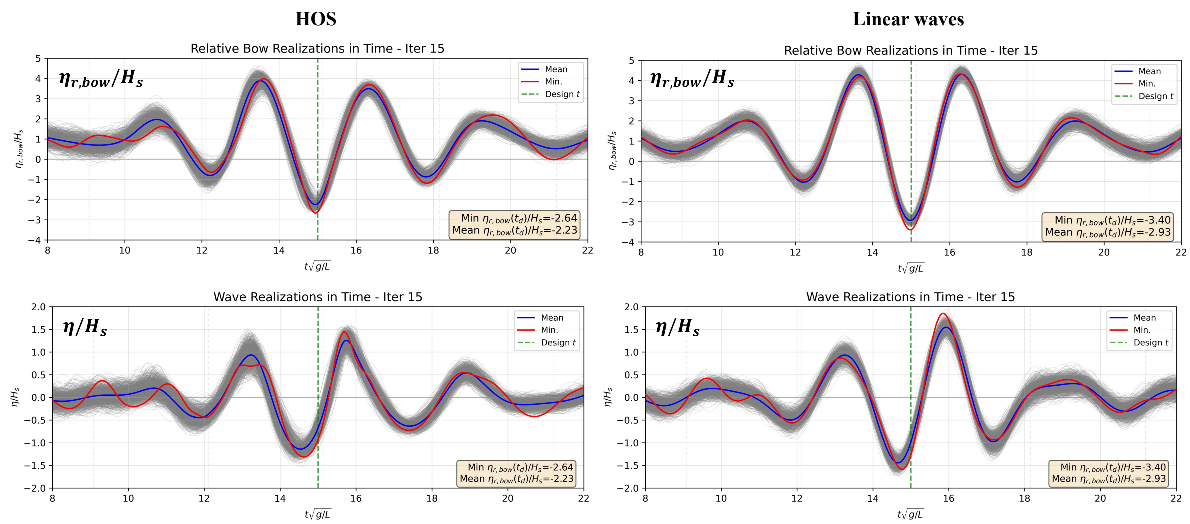

Figure 2: Comparison of relative motion and wave elevation for linear and HOS waves

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