A Method for Operational Guidance in Bimodal Seas

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ABSTRACT
Shipboard operational guidance for improved seakeeping is typically performed by looking up data in pre-computed response tables based on the expected or forecasted sea conditions. However, this may not be possible for situations in which the expected sea state is not in these response tables, especially when considering bimodal seas. In this paper, operational seakeeping guidance based on the volume-based SimpleCode, enhanced by Long Short-Term Memory (LSTM) neural networks, is described and compared with higher fidelity models with a particular focus on bimodal seas. The LSTM neural network correction provided improved results as compared with SimpleCode without incurring the computational expense of the higher fidelity model.

Keywords: *Operational Guidance, Neural Networks, Bimodal Seas, Seakeeping*

1. INTRODUCTION

The safety of a ship and its crew in rough weather demands proper operational guidance. Operational guidance is provided in the form of selection of speeds and headings, and is generally based on a look-up in a database for the given conditions. However, the ocean environment is random and complex, and the environmental conditions in the database likely do not describe accurately the forecasted multi-directional, sea state. Accordingly, efforts must be made to estimate quickly ship responses in these multi-directional conditions without being data-exhaustive.

Operational guidance is an important consideration in the survival of a ship and has been the focus of many International Maritime Organization (IMO) publications (IMO 1995, IMO 2007, IMO 2020). Recommendations for ship-specific operational guidance has been developed and discussed in the interim guidelines of the second generation intact stability by IMO (IMO 2020). While these guidelines are certainly useful in design and at sea, they are not comprehensive. Further work and study can be done on more complicated sea states, particularly multi-directional waves or simply including the swell component as well as the wind-generated waves.

Multi-directional considerations were made in Yano et al. (2019), where wave radar data generate a multi-directional wave spectrum in simulations for a Ropax ship. By Grim's effective wave and a reduced-order roll equation, the maximum roll angle was estimated for various ship headings in the provided directional wave spectrum for multiple metacentric height scenarios. While the maximum roll angle is very useful, access to additional seakeeping data is necessary for investigation into other extreme motions and loads.

In this paper, a method to provide guidance in a bimodal wave spectrum environment is demonstrated. The method applies two seakeeping codes of lower and higher fidelity, which are SimpleCode (Weems and Wundrow 2013) and the Large Amplitude Motion Program, or LAMP (Shin et al. 2003), respectively. By running the lower fidelity code (SimpleCode) under the same conditions of the higher fidelity code (LAMP), the motions predicted by SimpleCode can be improved to approximate those from LAMP by a Long Short-Term Memory (LSTM) neural network. After training a number of these LSTM networks, many LAMP-quality runs can be generated with LSTM-corrected SimpleCode results in a much more computationally efficient manner.

In the following sections, the network architecture for training an LSTM network included SimpleCode roll and pitch as input and LAMP produced roll and pitch as a target. Then, an application with the flared variant of the Office of Naval Research Flared hull, or ONRFL (Bishop et al. 2005,) over various headings in a bimodal wave environment is described. Also, different training methods for the neural networks are developed and explained.

2. METHODOLOGY

SimpleCode and LAMP

SimpleCode is a reduced order seakeeping code that can quickly produce acceptable results (Smith et al. 2019). One of the key simplifications is in the local variation of wave pressure, where the hydrostatic and Froude-Krylov equations can instead use volume integrals rather than integrating over the surface of the ship (Weems and Wundrow 2013). With pre-computed Bonjean curves, the instantaneous submerged volume and geometric center; therefore, sectional hydrostatic and Froude-Krylov forces can be calculated quickly.

LAMP is a higher fidelity code that considers all forces and moments acting on the ship in the time-domain in a 6-DOF, 4th order Runge-Kutta solver (Shin et al. 2003). Central to the code is the solution to the 3-D wave-body interaction problem. Within LAMP, the complexity of this solution can be altered. LAMP-2 is used, where the pertubation velocity potential is solved over the mean wetted hull surface and the hydrostatic and Froude-Krylov forces are solved over the instantaneous wetted hull surface. LAMP has effectively estimated motions comparable to model tests (Lin et al. 2007) but is, of course, much more computationally expensive than a code like SimpleCode. Though some parameters e.g., number of wave frequency components, free surface panel definition, hull offsets, can be altered, LAMP-2 runs in nearly real time i.e., 30 minutes are required to generate 30 minutes of data. In the same 30 minutes and the same number of frequency components, SimpleCode can produce upwards of 5,000 independent realizations.

SimpleCode has produced an approximation to LAMP, especially with tuned radiation and diffraction forces included (Weems and Belenky 2018, Pipiras 2022). However, a fidelity gap exists, especially when considering a bimodal wave spectrum.

Long Short-Term Memory

One of the major drivers of the presented method is the Long Short-Term Memory (LSTM) neural network (Hochreiter and Schmidhuber 1997). A LSTM neural network is a recurrent neural network that incorporates both long- and short-term effects that are learned and developed during the training process. These memory effects are stored in weight matrices where they, along with other operations, transform input matrices to the target output matrices. The following set of equations describe the operations that occur in a LSTM layer.

$$f_1 = \sigma\left(W_{f_1} x^{[t]} + U_{f_1} h^{[t-1]} + b_{f_1}\right) \tag{1}$$

$$f_2 = \sigma\left(W_{f_2} x^{[t]} + U_{f_2} h^{[t-1]} + b_{f_2}\right) \tag{2}$$

$$f_3 = tanh\left(W_{f_3} x^{[t]} + U_{f_3} h^{[t-1]} + b_{f_3}\right) \tag{3}$$

$$f_4 = \sigma\left(W_{f_4} x^{[t]} + U_{f_4} h^{[t-1]} + b_{f_4}\right) \tag{4}$$

$$c^{[t]} = f_1 \odot c^{[t-1]} + f_2 \odot f_3 \tag{5}$$

$$h^{[t]} = f_4 \odot \tanh\left(c^{[t]}\right) \tag{6}$$

where W and U are weight matrixes, b are the bias vectors, $x^{[t]}$ is the input vector, standardized by the respective standard deviations and means for each input channel, by the respective at time t, $h^{[t]}$ is the hidden state vector at time t, $c^{[t]}$ is the cell state vector at time t, σ is the sigmoid function, *tanh()* is the hyperbolic tangent function, and $\odot$ represents the Hadamard product. The output or target at time t is equal to the hidden state vector at time t, $h^{[t]}$. The weight matrices and bias vectors are progressively learned during the training process to minimize the specified loss between the training data and the test data. The present work uses the mean-squared error to quantify the error between the training and test sets. Equation (7) is the formula for the mean-squared error.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_T(t_i) - y_L(t_i)\right)^2 \qquad (7)$$

where N is the number of points in the time series, y is the response matrix which contains the time series of heave, roll, and pitch, subscript T is the target time series, subscript L is the LSTM produced time series, and t_i is the *i-th* time instant in the time series.

The input time series are the heave, roll, and pitch quantities provided from 3-DOF SimpleCode as well as the input wave elevation at the ship's center of gravity. The target time series are the heave, roll, and pitch quantities from 3-DOF LAMP. The LSTM architectures were two layers of 30 cells each.

To train the LSTM networks, two fundamental approaches were taken. In the first approach, multliple LSTM networks were trained with unimodal data and tested in a bimodal configuration. Throughout this work, this approach is referred to as the unimodal approach. In the second approach, a single LSTM network was trained with bimodal data and tested on different bimodal systems. This approach is referred to as the bimodal approach. The unimodal and bimodal approaches are separately compared with SimpleCode as a baseline, and in the case of the unimodal, also compared with different training data selection methods.

Experimental Set-up

For the presented method in practice, the ONRFL hull was employed. The following figure is a rendering of the ONRFL and Table 1 provides the particulars for the vessel.

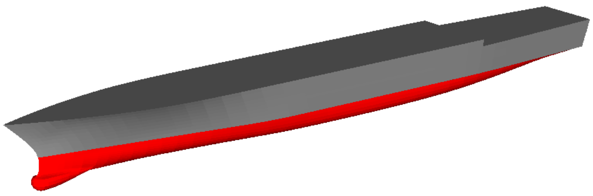

Figure 1: 3-dimensional rendering of the ONRFL.

Table 1: Particulars for the ONRFL.

Particular	Symbol	Value
Length between perpendiculars	L_{PP}	154.0 m
Beam	B	22.0 m
Draft	T	5.5 m
Radius of gyration about X-axis	k_{xx}	8.8 m
Radius of gyration about Y-axis	k_{yy}	37.2 m
Vertical center of gravity (w.r.t baseline)	KG	7.5 m
Longitudinal center of gravity (w.r.t midships)	L_{cg}	-2.5 m
Displacement mass	Δ_m	8730.0 t

For this experiment, a primary International Towing Tank (ITTC) spectrum (ITTC 2002) characterizing wind-generated waves was applied with $H_s = 7.5$ m and $T_p = 15.0$ s (NATO 1983 standard sea state 7 and most probable modal period,) and the relative wave heading set to bow-quartering seas (135°). The secondary ITTC spectrum, characterizing the swell component, was added with $H_s = 3.0$ m and $T_p = 20.0$ s with a relative wave heading that varied from $0 - 360°$. Additionally, the primary ship speed was set to 8.0 knots.

In the unimodal approach, three training data grouping schemes were formed. In the three schemes, the fundamental characteristics of the simulations included in the training set were altered. Essentially, each training data simulation was exposed to different environmental conditions centered on the primary ITTC spectrum. For all of the schemes, 81 training simulations of were performed. Each simulation contained 18,000 samples with a time step of 0.1 seconds. In the "narrow" scheme, only the primary parameters were used i.e., 81 simulations with $H_s = 7.5$ m, $T_p = 15.0$ s, a heading of 135°, and a speed of 8.0 knots. In the "medium" scheme, H_s varied from 7.0-8.0 m, T_p varied from 14.0-16.0 s, the heading varied from $125 - 145°$, and the speed ranged from 6.0-10.0 knots. Lastly, in the "wide" scheme, H_s varied from 6.5-8.5 m, T_p varied from 13.0-17.0 seconds, the heading varied from $115 - 155°$, and the speed ranged from 4.0-12.0 knots. In both the "medium" and "wide" schemes, three values were selected from each parameter range, and one simulation was used for training from each of the 81 permutations. The idea behind these training schemes was to train the neural network to understand how the ship responded to different spectra and to adapt to a bimodal spectrum. The scheme parameter ranges are summarized in Table 2.

Table 2: Summary of the unimodal LSTM approach training data schemes.

	Narrow	Medium	Wide
Significant Wave Height [m]	7.5	[7.0,7.5,8.0]	[6.5,7.5,8.5]
Modal Period [s]	15.0	[14.0,15.0,16.0]	[13.0,15.0,17.0]
Sea Heading Angle [deg]	135	[125,135,145]	[115,135,155]
Ship Speed [kts]	8.0	[6.0,8.0,10.0]	[4.0,8.0,12.0]

In the bimodal approach, a singular neural network was trained on 81 simulations with primary spectrum characteristics drawn from the "wide" unimodal training set. Of these 81 simulations, 72 were randomly selected to be trained by the secondary spectrum with evenly spaced headings between $0-360°$ in $15°$ increments. The remaining 9 simulations were generated without including the secondary spectrum to introduce more variety and flexibility to the network.

In both approaches, the absolute error between the single significant amplitude (*SSA*) of the LSTM provided output and the *SSA* of LAMP provided output for roll and pitch was compared to the absolute error between the SimpleCode *SSA* and LAMP SSA for roll and pitch. The SSA is a measure of the average of the one-third largest peaks of the response and can be estimated for Gaussian processes by the following equation.

$$SSA = 2.0\sqrt{\hat{V}_x} \tag{8}$$

where $\hat{V}_x$ is the estimated variance of the process, x. The absolute error between the *SSA* values produced from LSTM data and LAMP was compared to the absolute error between the SimpleCode *SSA* and LAMP. The equation for the absolute error ϵ is as follows.

$$\epsilon = |\hat{X}_L - \hat{X}_E| \tag{9}$$

where $\hat{X}_L$ represents the *SSA* of LAMP data and $\hat{X}_E$ represents the *SSA* of the LSTM estimate or SimpleCode.

To test the networks, 36 SimpleCode and LAMP test simulations, unseen by the networks during the training phase, were produced using the combination of the primary spectrum and the secondary spectrum. While the primary spectrum was held constant for the test simulations, the secondary spectrum was varied in heading between $0-360°$ in $10°$ increments.

The next section compares the roll and pitch results of the unimodal and bimodal LSTM approaches to LAMP and SimpleCode.

3. RESULTS

Unimodal Approach

In the unimodal approach, a primary wind-sea state that was characterized by an ITTC spectrum with a significant wave height of 7.5 m, a modal period of 15.0 seconds, and a direction of $135°$ was combined with a secondary swell wave spectrum that was characterized by a significant wave height of 3.0 m, a modal period of 20.0 seconds, and a variable direction. However, the LSTM neural networks from the three presented schemes were only trained by unimodal spectra with ranges varying from "narrow" to "wide". These networks were applied to SimpleCode output under the given bimodal spectrum with the wave elevation for a range of secondary headings and the *SSA* values were recorded.

The absolute error is indicated in Figure 2 between the *SSA* values produced from the unimodal LSTM schemes and LAMP as well as the absolute error between the *SSA* values produced from SimpleCode and LAMP in roll and pitch for secondary sea headings ranging from $0° - 360°$.

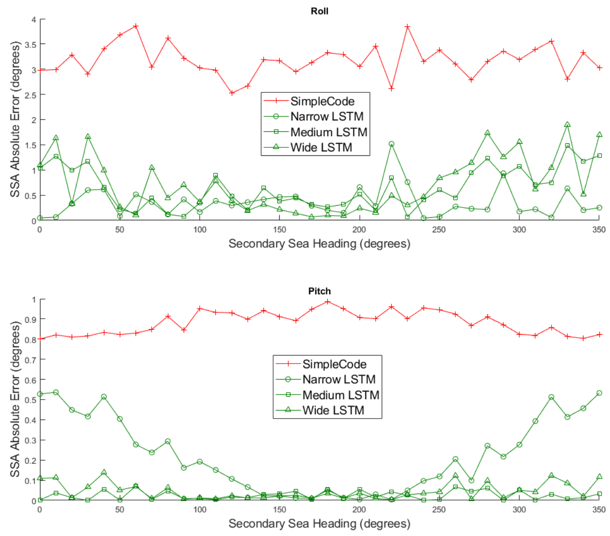

Figure 2: Absolute *SSA* error between unimodal LSTM and LAMP as well as SimpleCode and LAMP in roll and pitch for various secondary sea headings.

The initial insight gathered from the above plots is that any LSTM method was an improvement over SimpleCode. The LSTM schemes started with the SimpleCode results as a baseline and, therefore, were expected to make at least some improvement. The performance of the LSTM schemes also generally seemed to be the best when the secondary sea heading was near the primary sea heading of 135°. Again, the training for each of the schemes was centered on the heading of 135°. That said, the Medium LSTM and Wide LSTM were more robust than the Narrow LSTM in pitch. In roll, however, the performance of the schemes was more scattered over the various secondary headings, but overall the narrow LSTM seemed to perform the best, especially at non-roll impacting secondary wave headings. Since the primary heading was at 135°, the roll was driven by the considerable primary significant wave height and effective modal period. The increased focus during training at the primary direction, wave height, and wave period improved performance, except at secondary wave headings that influence roll and that approach the ship from the opposite side. These cases are most evident at a secondary wave heading of 220° and 290°.

The actual roll time series produced by the narrow LSTM at these non-roll impacting headings differed considerably from the LAMP roll time series. The locally averaged absolute difference between the narrow LSTM roll and the LAMP roll time series at a secondary heading of 0° is in Figure 3.

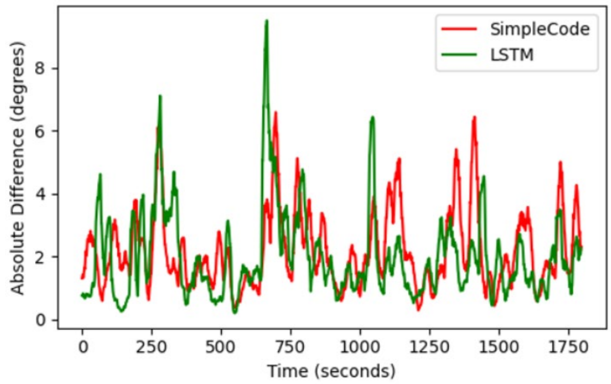

Figure 3: The locally averaged absolute difference between the narrow LSTM and LAMP roll time series at a secondary heading of 0°.

While the narrow LSTM was able to capture the *SSA* at the secondary heading of 0°, the time series generated by the LSTM was fundamentally different and had little to no improvement compared to SimpleCode. While the magnitude of the response was captured, the change in the wave elevation time series at the center of gravity due to the secondary system was enough to affect the phasal relationship.

Bimodal Approach

In the bimodal approach, a single neural network was trained with simulations generated from the "wide" unimodal primary spectra and wave directions as well as the secondary spectrum with headings ranging from $0 - 360°$ in 5° increments. These simulations accounted for 72 of the 81 simulations in the training process. The remaining 9 simulations were obtained from solely the primary wave spectra and directions as input.

Figure 4 shows the absolute error between the bimodal LSTM *SSA* and the LAMP *SSA* as well as the absolute error between the SimpleCode *SSA* and the LAMP *SSA* for roll and pitch.

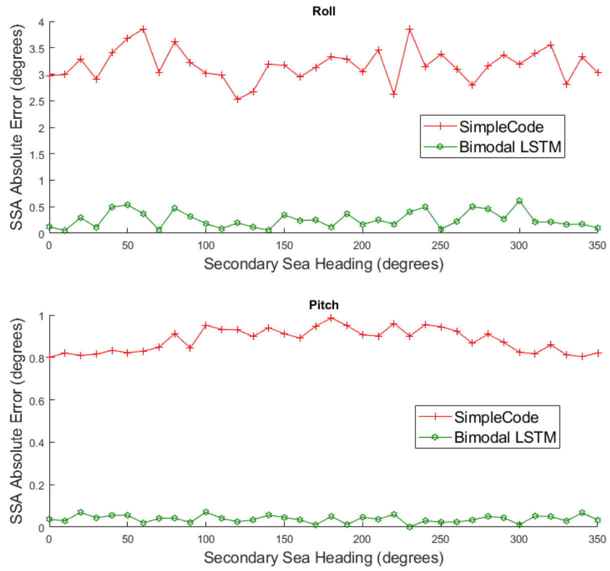

Figure 4: Absolute *SSA* error between bimodal LSTM and LAMP as well as SimpleCode and LAMP in roll and pitch for various secondary sea headings.

The improvement of the LSTM over SimpleCode was much more stark and consistent in the bimodal approach than in the unimodal approach. The errors were somewhat sporadic and are reflective of the random pairings between the "wide" unimodal dataset permutations, the 72 secondary system headings, and 9 simulations with solely a primary spectrum.

Furthermore, the bimodal approach resulted in reduced time series errors between LSTM-generated roll and LAMP roll. Figure 5 indicates the absolute error between the bimodal LSTM roll time series and the LAMP roll time series at a secondary heading of 0°.

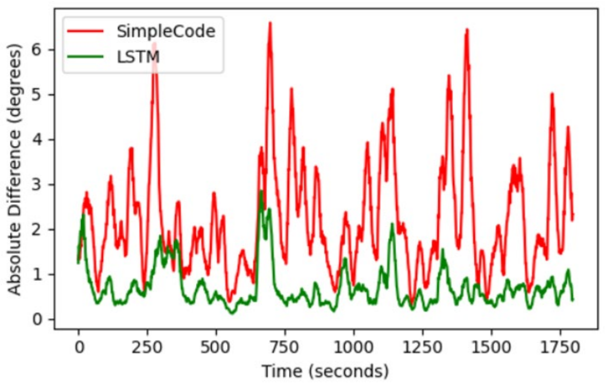

Figure 5: The absolute error between the bimodal LSTM and LAMP roll time series.

The differences in the bimodal LSTM network and LAMP time series were more muted than in the unimodal LSTM approach and considerably less than the SimpleCode errors. The relationships within the weight matrices were more likely flexible to a noisier wave elevation signal and therefore had less impact on the roll time series generated by the LSTM network.

4. CONCLUSION

In this paper, a method to improve prediction of ship seakeeping statistics in rough, bimodal seas was introduced. Using a LSTM network, corrections were applied to the roll and pitch time series produced by SimpleCode to achieve results in line with LAMP. Two different approaches to training the LSTM network were discussed: the unimodal approach and the bimodal approach.

In the unimodal approach, a LSTM network was trained with input from a primary spectrum and was applied to the SimpleCode time series that were influenced by a primary and secondary spectrum. Three different schemes were formulated to investigate the effect on performance: the narrow, medium, and wide schemes (Table 2). In the narrow scheme, a number of simulations were drawn from a single spectrum. In the medium and wide schemes, single simulations were drawn from permutations of multiple spectra generated from ranges of significant wave height, modal period, ship speed, and primary wave heading. In roll, the three schemes performed closely in secondary headings within about ±50° of the primary heading of 135° but the narrow scheme generally performed the best outside of that 50° range. However, the time series errors in roll were significant. In pitch, the medium and wide schemes performed better than the narrow scheme. Overall, all of the schemes significantly out-performed SimpleCode.

In the bimodal approach, an error reduction and consistency were improved as compared with the unimodal approach. Furthermore, the time series errors were much reduced as well.

These networks are not storage intensive, and many of these networks could be trained and applied quickly and effectively aboard a ship. Furthermore, additional studies can be done to investigate the flexibility of the bimodal system on other primary and secondary spectra parameters. Some combination of the unimodal and bimodal approaches reduce the error with respect to LAMP while also reducing the amount of time spent on training these networks.

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