Neural network-based motion prediction of semi-submersible floating platform for offshore wind

H H Mian haris.hameed.mian@nmbu.no

M S Siddiqui muhammad.salman.siqqiqui@nmbu.no

A Keprate arvind.keprate@oslomet.no

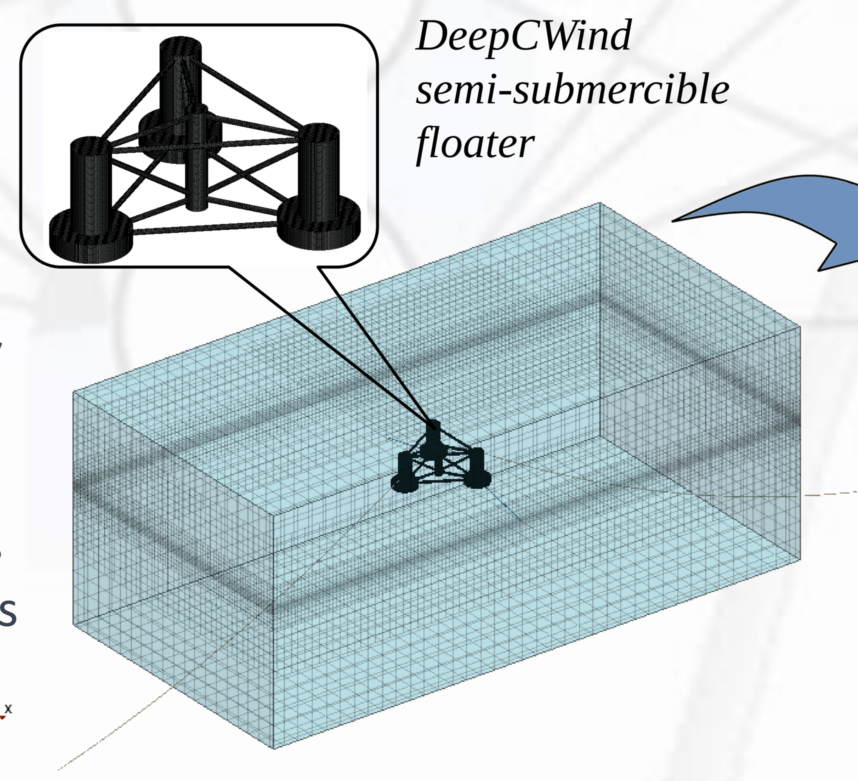
S Mathew sathyajith.mathew@uia.no

Research Objectives

- Develop LSTM neural network model to improve the accuracy of predicting hydrodynamic responses of semi-submersible floating platform.
- Explore the feasibility of using LSTM neural networks as a computationally efficient alternative to traditional computational fluid dynamics (CFD) simulations.
- Investigate the temporal dependencies within hydrodynamic responses of floater by analyzing how LSTM networks capture relationships between time series data.

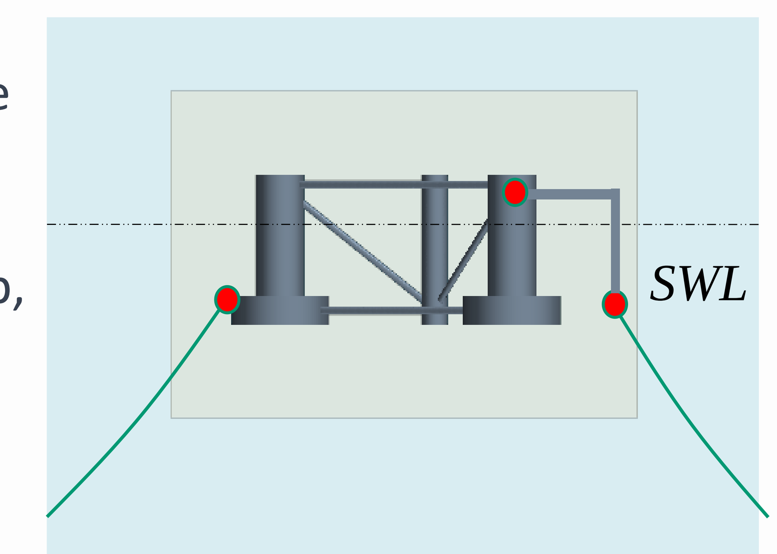
1. Background

- Understanding the dynamic behavior of floating offshore wind turbines (FOWT) is important. Accurate predictions of motion parameters is crucial for structural integrity and power generation efficiency. This study explores an alternative using Long Short-Term Memory (LSTM) neural networks, specifically tailored for handling time series data, to capture the temporal dependencies in FOWT floater hydrodynamic responses.



2. Test case

- A 1:50 Froude scaled OC5 semi-submersible floater model tested in the concept basin at the MAritime Research Institute Netherlands (MARIN was simulated. A numerical wave tank model was developed to validate this test setup, and the results were compared with the available experimental data. The floater was equipped with two catenary mooring lines (in the front and back) and two linear springs (on the right and left sides of the floater) to control its motion response.

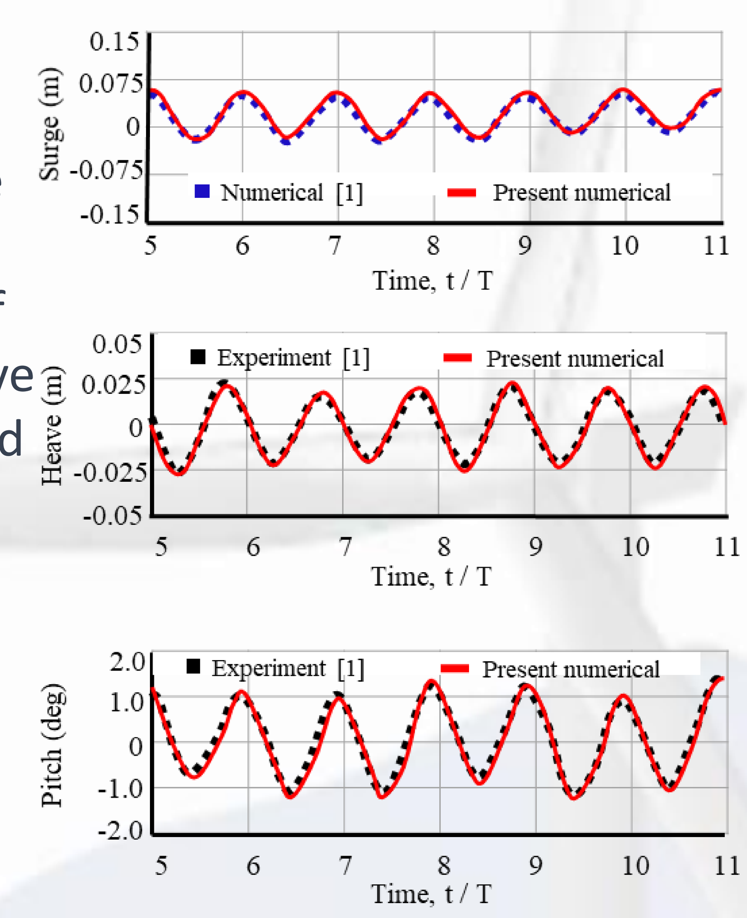


3. Database generation

- A total of 64 CFD simulations (using Star CCM+ solver) have been performed by varying the wave amplitude, wave period, and wave direction. These parameters are varied across different levels to study their influence on the FOWT floater's motion response. Wave amplitude is explored at four levels (0.07, 0.09, 0.13, and 0.17 m), capturing a range of sea states from mild to severe. Similarly, the wave period is examined at four levels (1.71, 2.0, 2.3, and 2.6 s), representing varying wave frequencies. Wave direction is investigated at four angles (0°, 15°, 25°, and 45°), encompassing different incident wave directions that the floater may encounter.

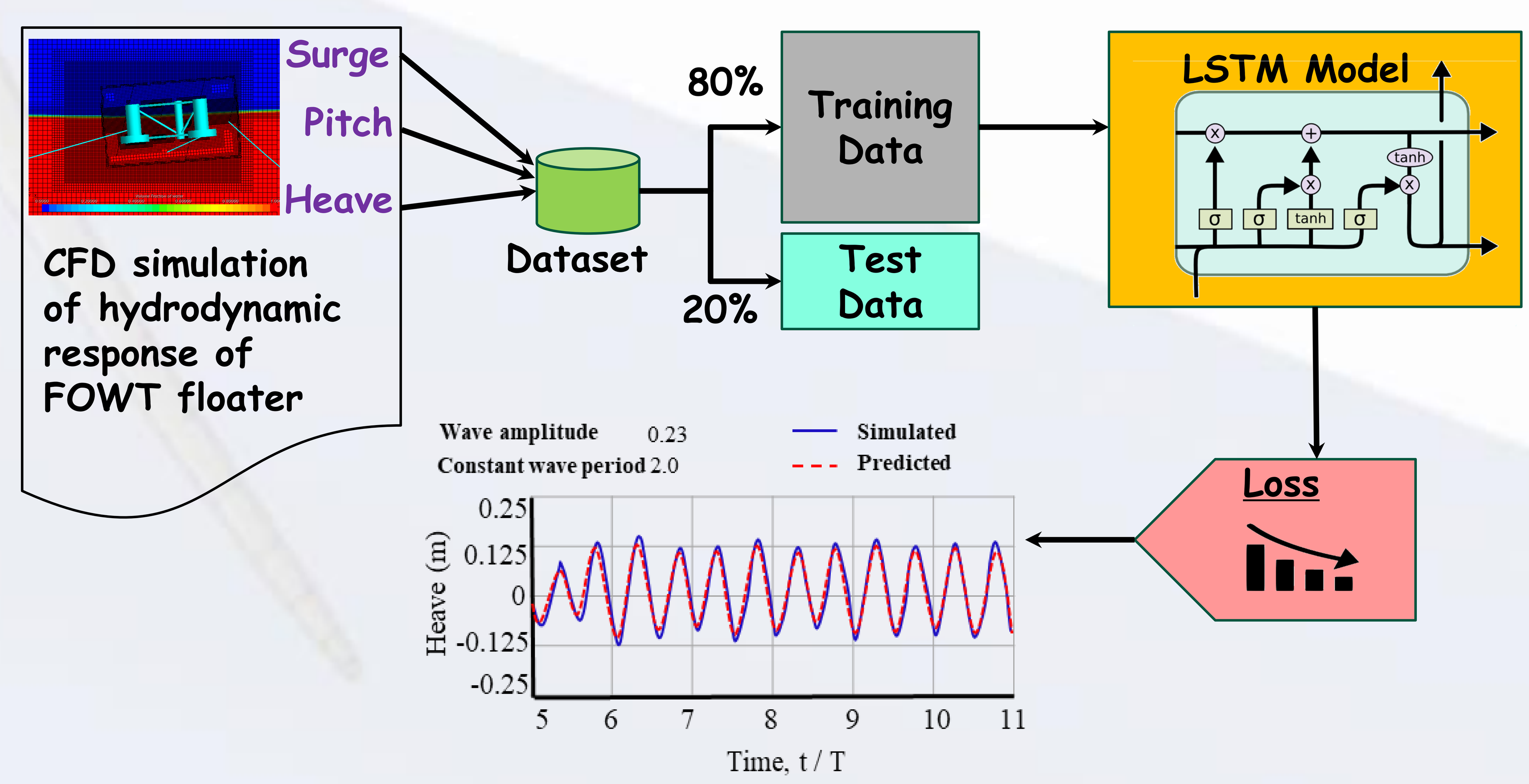
4. Model validation

- Comparison of the numerical estimation with the actual measured data for the heave and pitch response of the FOWT floater under the action of regular waves (wave amplitude of 0.07m and wave period of 1.71 s). The surge motion was compared with the numerical simulation of the dynamic mesh solver in OpenFOAM using a quasi-static mooring system. The numerical results are satisfactory when compared with the previously available data.



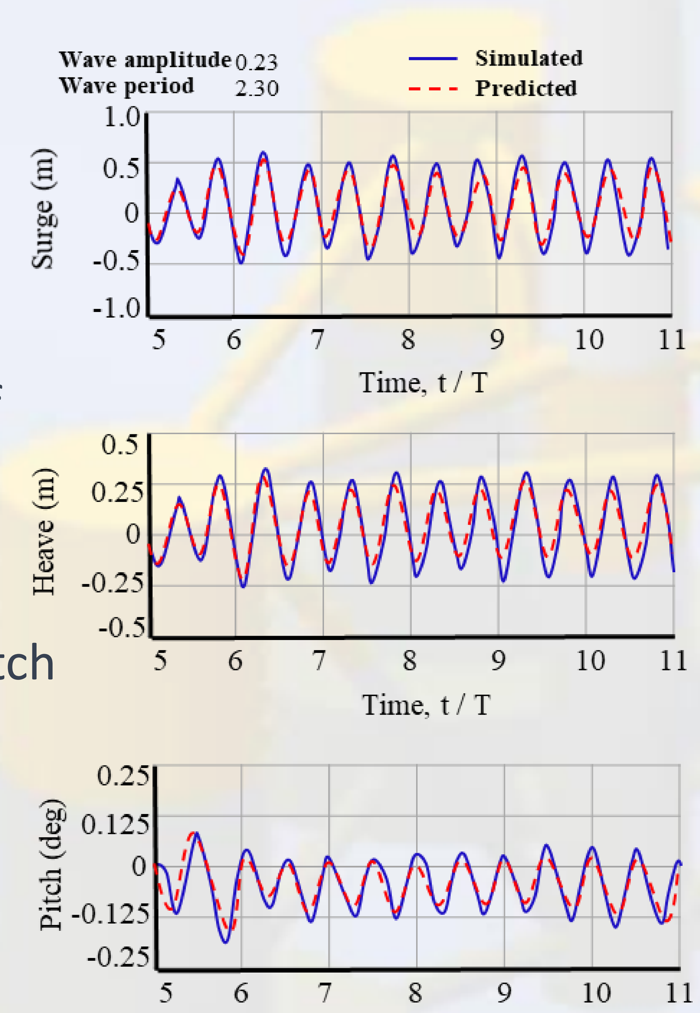
5. Long-short term memory (LSTM) neural network

- LSTM, a variant of RNN, use gated structures and sigmoid activation functions to effectively address the challenges of gradient vanishing and explosion.
- In the **input layer**, a time series of 200 data points, representing the motion response, is utilized. The multi-input model incorporates 3 dimensions.
- For the **hidden layer**, 200 nodes are employed. The output layer is dense with a linear activation function, yielding the motion response at the target time.
- The LSTM network is optimized using the Adam algorithm, which combines the adaptive learning method with the Momentum method.
- To mitigate overfitting, a Dropout layer is strategically placed after both the input layer and the hidden layer. The chosen loss function is the Mean Squared Error (MSE).
- The output layer is dense, the activation function is linear, and the output result is the motion response



6. Results

- The simulated and predicted motions (surge, heave, and pitch) are presented here.
- Overall, the LSTM predicted results for a single wave with an amplitude of 0.23 and a period of 2.3 align well with the simulated data.
- While the surge motion is accurately predicted throughout the entire time period, some discrepancies are observed in the heave and pitch plots. These discrepancies could potentially be improved through hyperparameter tuning.
- It is observed that increasing the number of Epochs, Loss (MSE) decreases rapidly in the beginning and then finally becomes stable.



7. Conclusion and Future work

- The results demonstrate the LSTMs ability to predict FOWT floater motion under diverse conditions accurately.
- The LSTM model was tested on a platform affected by second-order hydrodynamics, revealing improved predictive accuracy for the response of the semi-submersible platform. Additionally, the multi-input model demonstrated good performance in cases where nonlinearity was more prominent.
- This is an ongoing work, and to further enhance the robustness of the model, additional input parameters are continually being incorporated, expanding the dataset and refining the LSTM's capacity to discern and predict FOWT floater motion responses under a wider range of conditions.

8. Reference

- Bruinsma N, Paulsen BT, Jacobsen NG. Validation and application of a fully nonlinear numerical wave tank for simulating floating offshore wind turbines. Ocean Engineering. 2018 Jan 1;147:647-58.

Norwegian University of Life Sciences

OSLOMET

UiA University of Agder