Prediction of motion responses for a semi-submersible FOWT platform using a grey-box model integrated with a GRU-based deep learning approach

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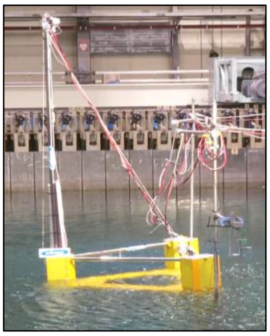
1. Introduction

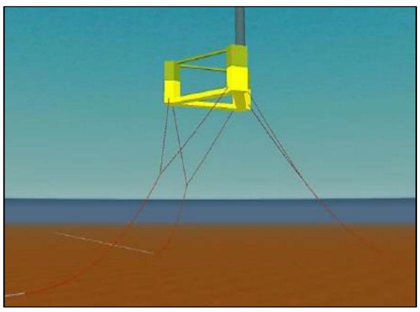
In recent times, there has been a growing global interest in floating offshore wind turbines(FOWTs), particularly in deep-sea environments. They are considered a rational and cost-effective solution compared to onshore wind turbines. However, FOWTs face several technical challenges, such as combined harsh environmental loads, a sustainable mooring system, and strong coupling effects between the turbine and platform. To overcome these technical issues and enable smart operation, high-fidelity simulation models for FOWTs are essentially required. In this study, a new grey-box model is introduced to enhance the accuracy of motion prediction for a semi-submersible FOWT platform. Basically, this study utilizes the aero-hydro-servo-elastic coupled dynamic simulation software OpenFAST, incorporating hydrodynamic coefficients from WADAM as a white-box model. Additionally, a grey-box model is constructed to enhance fidelity, utilizing the white-box model outcomes as inputs for a Gated Recurrent Unit (GRU)-based deep learning approach. The results are then directly compared with the experiment data.

2. Experiment and Numerical Method

2.1 Model Test

A series of model tests for a semi-submersible FOWT platform were conducted at the deep ocean engineering basin by KRISO. Fig. 1 displays the experimental model, mooring system, and the main dimensions of the platform in the prototype. The scale ratio was 1:42.25. The target platform features a forward-mounted turbine with 3 pontoons and incorporates triangular-shaped dampers between the pontoons. The wind turbine used was NREL 15MW reference wind turbine. It should be noted that, in the model test, the force-matching technique was used for the wind turbine, combined with direct numerical simulation. Regarding the mooring system, Yaw Control Catenary Mooring(YCCM) was considered.





Parameter	Value
In-place Draft (m)	16.75
Freeboard (m)	15.00
Column Height (m)	31.75
Pontoon Width (m)	9.00
Pontoon Height (m)	3.50
Pontoon Length (m)	60.00
Column Side Length (m)	9.25
Distance from Column Center to Hull Center (m)	42.57
Distance Column Center to Column Center (m)	73.73
Corner Plate Length (m)	15.00
Corner Plate Elevation from keel (m)	3.50

Figure 1 Experimental model(left), mooring system(center) and main dimensions(right)

2.2 White-Box Model

In this study, a white-box model refers to a numerical simulation model based on conventional physical modelling related to floating body dynamics, mooring dynamic, and wind turbine dynamics. As a white box model, OpenFAST was employed to predict the motion responses of the semi-submersible FOWT given wave time series and wind conditions. OpenFAST integrates aerodynamics, hydrodynamics, structural, control and electrical systems, enabling coupled nonlinear simulations in the time domain (Jonkman, 2003). Equation (1) shows Kane's method to solve the multi-body dynamics problem, and F_i encompasses all types of dynamic forces acting on offshore wind energy systems (Jonkman, 2003). In particular, the HydroDyn module in OpenFAST computes hydrodynamic loads using the hydrodynamic coefficients from potential flow analysis, as well as drag forces based on Morison's equation, as shown in Equation (2). In this study, the hydrodynamic coefficients such as added mass, damping, wave exciting forces, and wave drift forces are obtained from the WADAM results

$$F_i + F_i^* = 0 \; (i = 1,2, \dots, 22) \tag{1}$$

$$F_i^{Hydro} = F_i^{Waves} + F_i^{Viscous} + \rho g V_0 \delta_{i3} - C_{ij}^{Hydrostatic} q_j - \int_0^t K_{ij}(t-\tau)\dot{q}_j(\tau)d\tau \tag{2}$$

2.3 Grey-Box Model

The grey-box model combines elements of both white-box and black-box modeling. In this approach, the system is considered partially understood, incorporating known information while acknowledging unknown features treated as black-box components. This method relies on a dynamic model (white-box) rooted in real-world phenomena for high reliability. Additionally, it integrates black-box modeling to address limitations in the white-box model and enhance capabilities. In this study, motion responses and tension values from the white box model, along with incident wave elevation data, are utilized as inputs to the grey-box model. Regarding the black-box model, a Gated Recurrent Unit (GRU) was employed, which is a type of Recurrent Neural Network (RNN) in deep learning known for effectively capturing long-range dependencies in sequential data.

3. Results and Discussions

3.1 Prediction Results of White Box Model

To accurately predict the wave-frequency and low-frequency motions, appropriate white-box simulation models should be carefully selected. Regarding the potential-flow hydrodynamic forces for the semi-submersible platform, second-order slow-drift wave force modeling should be introduced for not only the surge (sway) mode but also pitch (roll) mode. Practically, Newman's approximation may be applied for low-frequency wave force modeling. In addition, drag and damping forces should be optimized to reflect equivalent viscous forces. Fig. 2 illustrates the influence of the Morison drag, the application of second-order mean drift wave forces, and the additional incorporation of the Newman's approximation on the pitch motion responses of a semi-submersible FOWT platform in the low-frequency range. When introducing the Newman's approximation along with the Morison drag, the results demonstrated a noticeable increase in the pitch motion energy in the low frequency range consistent with the experimental results.

To investigate the overall performance of the white-box model, the OpenFast simulation results are directly compared with the experimental motion responses. Fig. 3 shows the power density spectra (PSD) and time series of motion response under the survival irregular wave condition (Load Case 19 – Hs: 10.72m, Tp: 16.37s). This figure demonstrates good agreement between the experiment and the numerical simulation if the white-box simulation models are well-designed. However, locally in time series, some discrepancies due to over- and underpredictions can still be found between the experiment and simulation results, which are expected to be enhanced when using a grey-box model.

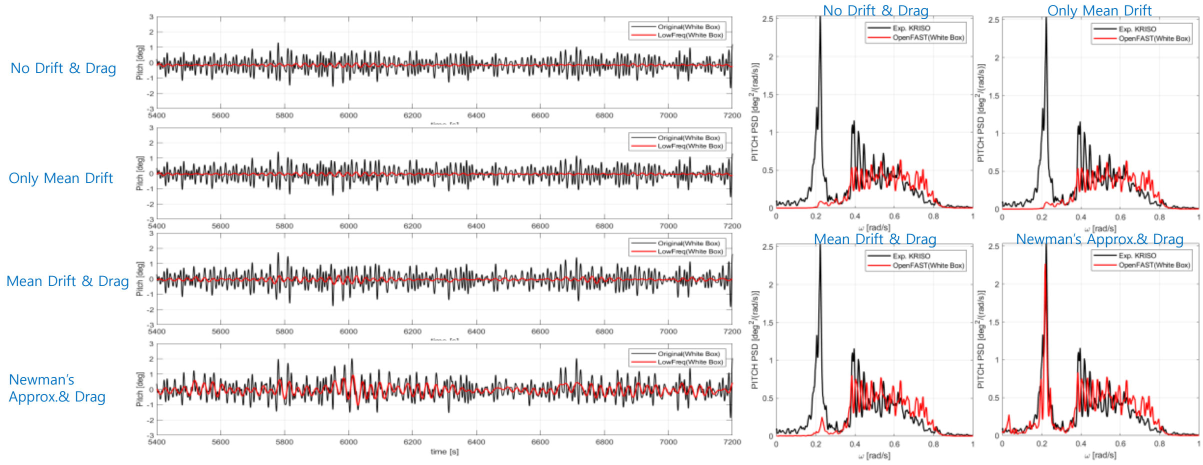


Figure 2 Low-frequency band-pass time series(left) and PSDs(right) of the pitch motion with various simulation models (LC19)

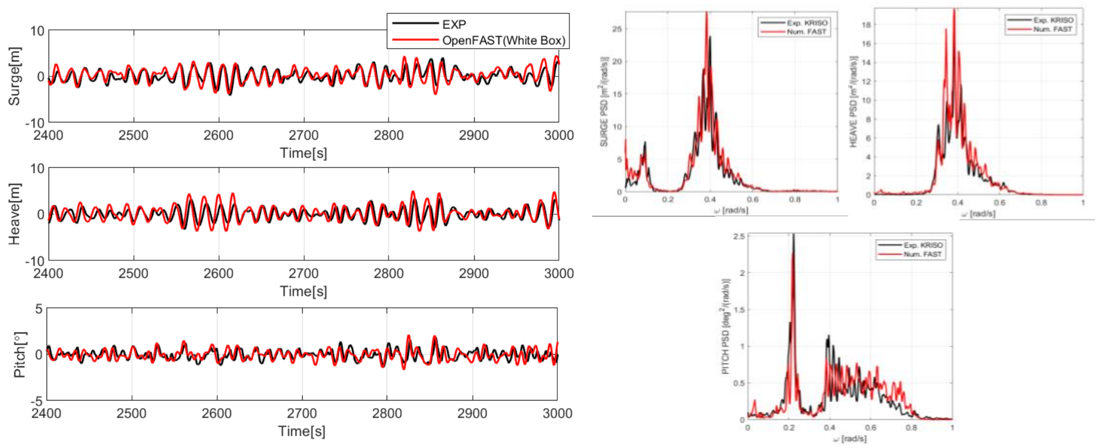


Figure 3 Time series(left) and PSDs(right) for motion responses under survival condition (LC19)

3.2 Prediction Results of Grey-Box Model

To enhance the white-box model, a grey-box model with a deep learning technique was constructed, combined with a GRU model. Total 80% of the dataset for LC15 (Hs:10.72m Tp:16.37s with 50m/s steady wind) was used for training the grey-box model. To validate the results in LC15, the motion time series between experiments and the prediction results from white-box and grey-box models are compared in Fig. 4. Overall, it is clearly observed that the grey-box model predicts more accurately rather than those of the white-box model, especially for the over-prediction time durations. The right figure in Fig. 4 also compares the motion time series regarding the irregular wave (LC16) of different seeds from the training dataset of LC15. This also demonstrate the enhancement of the grey-box model compared to the white-box model, even for different wave seed. Fig. 5 compares the motion prediction errors between the white-box and grey-box models under the wave conditions of LC14, LC15 and LC16. It should be noted that only 80% of data set of LC15 were used to train the grey-box model. Regardless of wave conditions, it is clearly confirmed that the motion prediction accuracy is significantly improved when using the grey-box model rather than the white-box model only. In particular, the prediction errors in heave and pitch motions reduce by more than half when using the grey-box model.

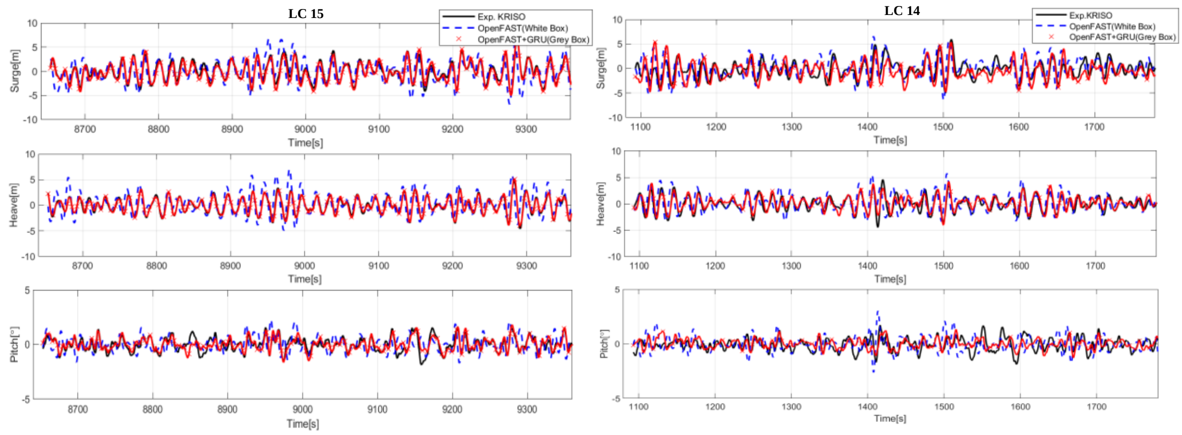


Figure 4 Comparison of motion time series between experiments and numerical simulation results (LC15 (left) and LC14 (right)

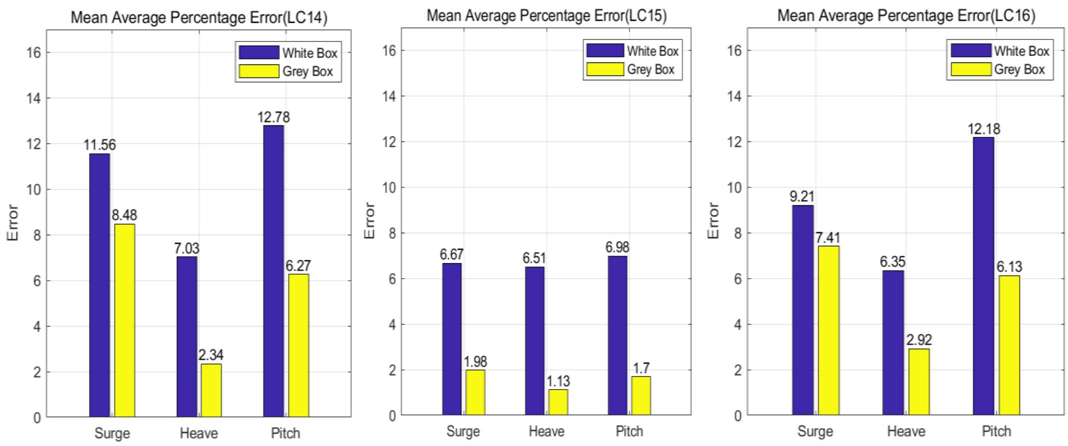


Figure 5 Motion prediction errors between white-box and grey-box models

4. Conclusion

In this study, a new grey-box model was developed to enhance the accuracy of motion prediction for a semi-submersible FOWT platform, utilizing the white-box model outcomes as inputs for a Gated Recurrent Unit (GRU)-based deep learning approach. To validate the results, the motion responses from white-box and grey-box models are directly compared with the experimental data. It is clearly found that the motion prediction accuracy is significantly improved when using the grey-box model rather than the white-box model only.

References

[1] Chakrabarti, S K (1994). Offshore Structure Modeling (Vol.9) world Scientific.
[2] F. Journee, J.M.J, & Massie, W.W. (2001). Offshore Hydrodynamics, Delft University of Technology.
[3] Jonkman, J. M. (2007). Dynamics modeling and loads analysis of an offshore floating wind turbine. University of Colorado at Boulder.
[4] Shi, W., Hu, L., Lin, Z., Zhang, L., Wu, J., & Chai, W. (2023). Short-term motion prediction of floating offshore wind turbine based on muti-input LSTM neural network. Ocean Engineering, 280, 114558.