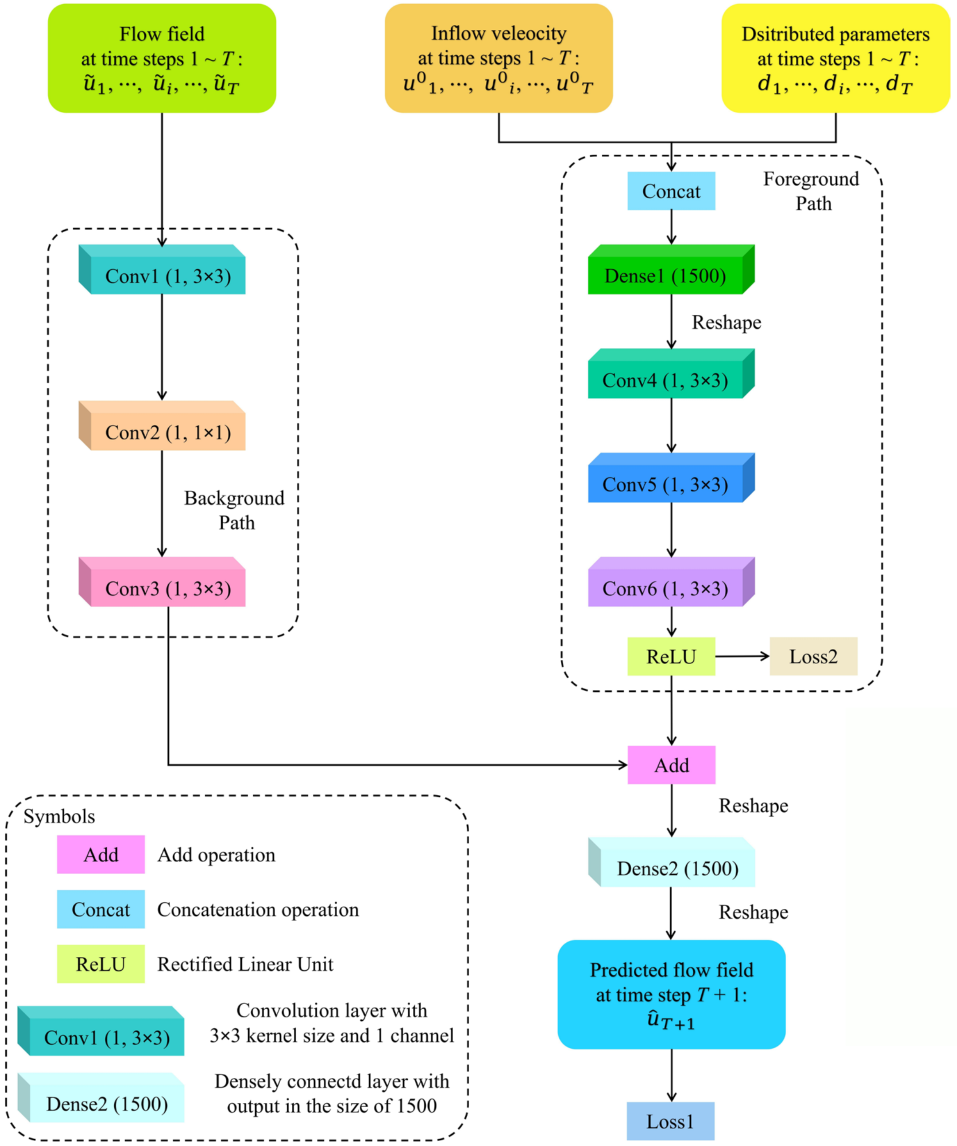
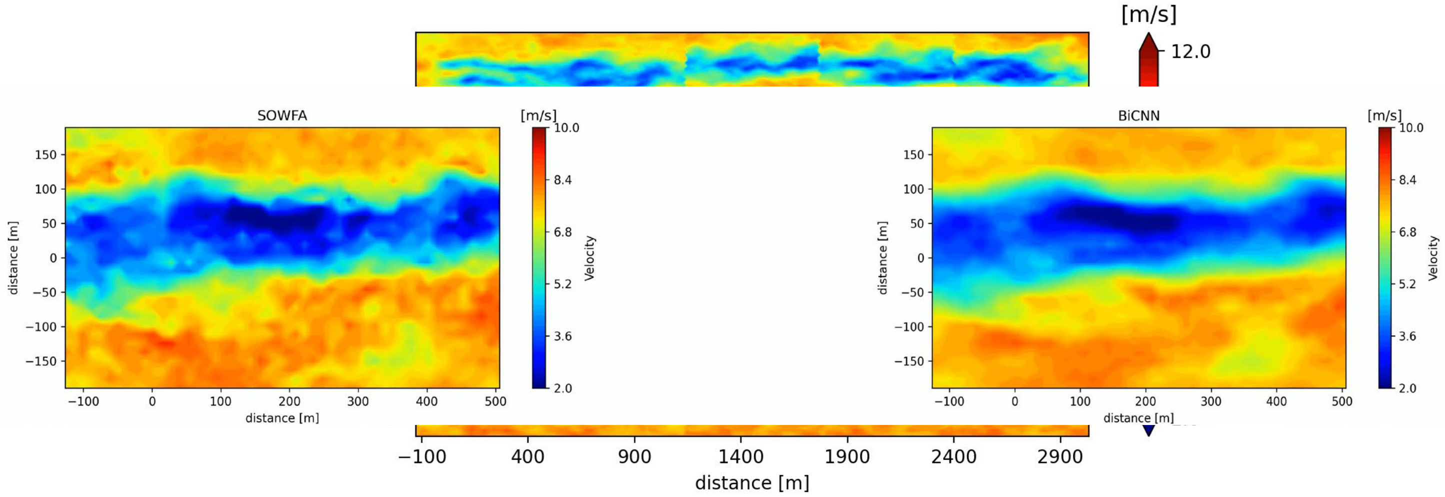
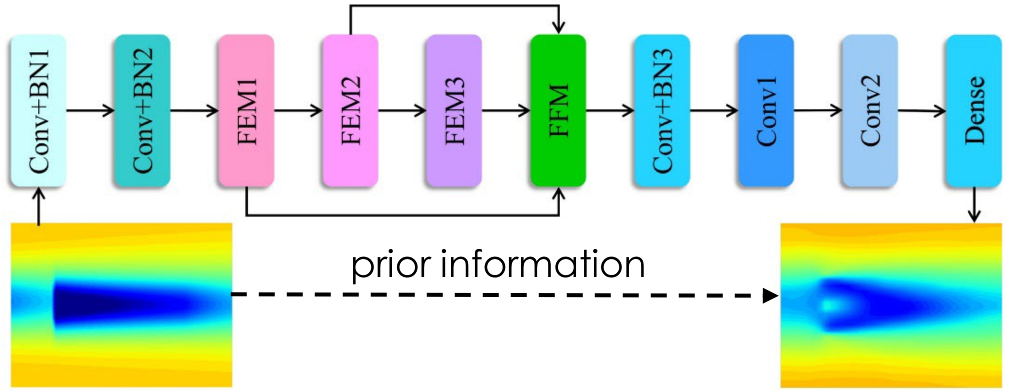


An accurate and efficient dynamic wake model (including turbulence, transport delay, time-varying mean wind speed and direction, and potentially floating platform motion) is essential for the design and evaluation of the wind farm control strategy. In this study, we propose a deep-learning-based wake model which achieves a great balance between efficiency and accuracy.

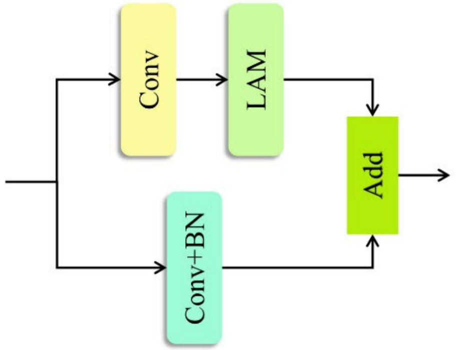
We design our Bilateral Convolutional Neural Network (BiCNN) based on the following observations: generally, the basic status of the flow field is contiguous and stable along the adjacent time steps, while the change of inflow velocity and distributed control parameters are the main external factors that cause the variations.

Rui Li, Jincheng Zhang, and Xiaowei Zhao. "Dynamic wind farm wake modeling based on a Bilateral Convolutional Neural Network and high-fidelity LES data." Energy 258 (2022): 124845.

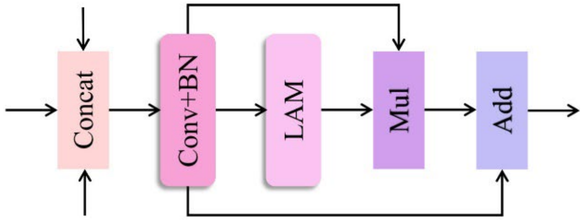




(a) Super-Fidelity Network (SFNet)



(b) Feature Extraction Module (FEM)



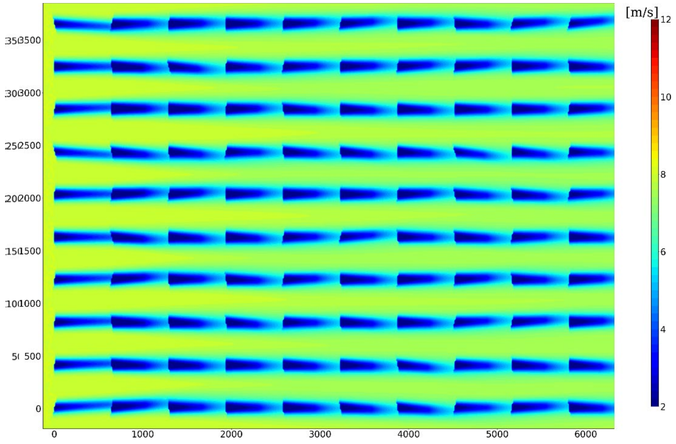
(c) Feature Fusion Module (FFM)

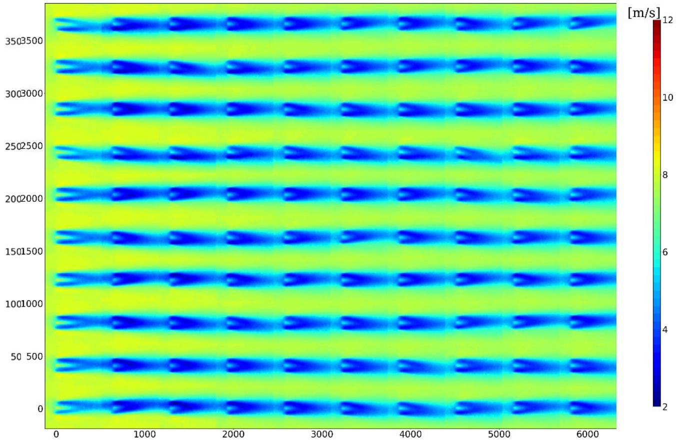
An overview of the super-fidelity Network, (a) network architecture, (b) the Feature Extraction Module (FEM), and (c) the Feature Fusion Module (FFM).

Although the flow fields generated by the low-fidelity analytical models do not contain detailed flow features, the general features (such as the yaw effects and wind speeds) are well captured, which can serve as the prior information for high-fidelity flow fields.

In summary, the analytical models can provide the basic status while the numerical models can supply precise details of the flow fields. Therefore, by fusing the information from both low-fidelity and high-fidelity models, a novel wind farm wake model with strong generalizability may be formed balancing the accuracy and the efficiency. The Super-Fidelity Network (SFNet) is then designed based on the above considerations.

Rui Li, Jincheng Zhang, and Xiaowei Zhao. "Multi-fidelity modeling of wind farm wakes based on a novel super-fidelity network." Energy Conversion and Management 270 (2022): 116185.





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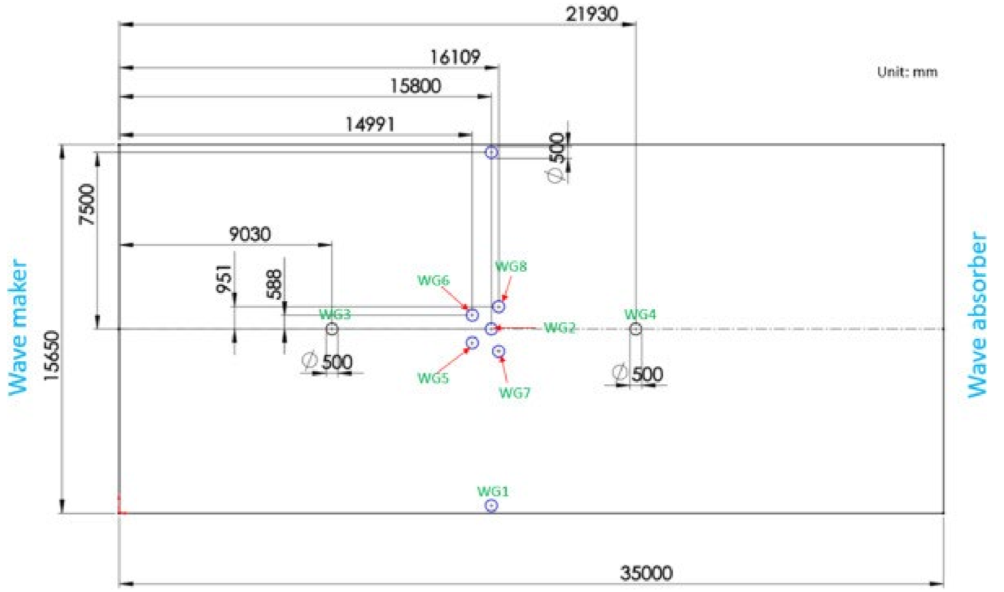
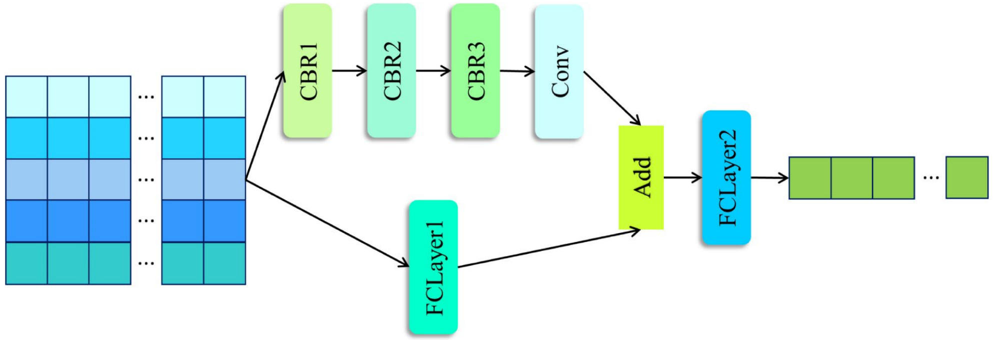


The layout of the wave basin experiments (provided by the University of Plymouth team), where WG2, WG5, WG6, WG7 and WG8 constitute the pentagonal gauge array.

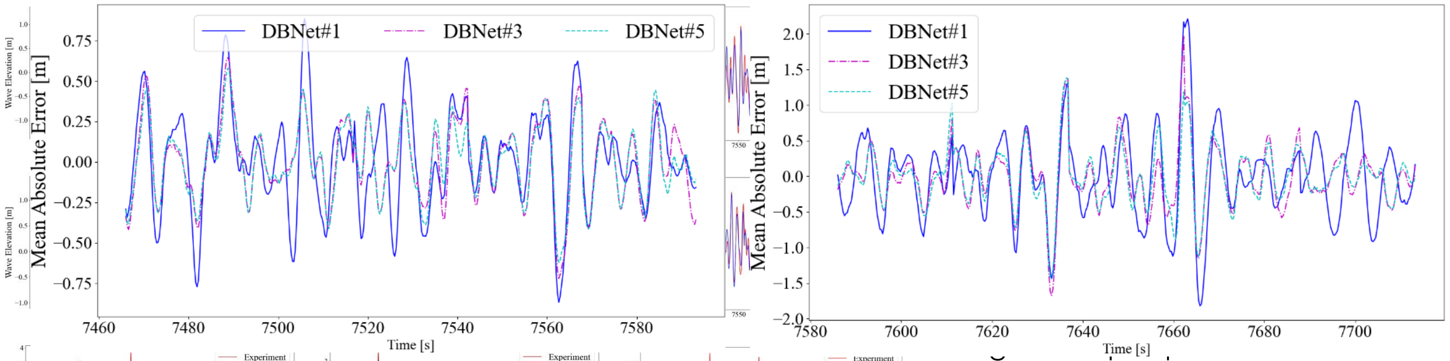


The structure of the proposed DBNet, where FCLayer means the fully connected layer and CBR represents the convolutional layer with the BN operation and the ReLU activation function.

Existing works for ML-based wave prediction have two major limitations, i.e. the generalization of the model to diverse sea states and the prediction of 3D waves. In our study, we investigate, for the first time, the phase-resolved real-time prediction of 3D waves using ML methods for multiple sea states.

The performance of four frequently used machine learning methods, including GRU, LSTM, MLP and CNN, are investigated and verified for the phase-resolved forecasting of 3D waves. Moreover, a novel DBNet is proposed to further enhance the accuracy of ML-based methods which can take advantage of both MLP and CNN.

Rui Li, Jincheng Zhang, Xiaowei Zhao, Daming Wang, Martyn Hann, and Deborah Greaves. "Phase-resolved real-time forecasting of three-dimensional ocean waves via machine learning and wave tank experiments." Applied Energy 348 (2023): 121529.



We gradually reduce the number of input gauges, while the prediction errors indeed increase accordingly. With only a single gauge as the input, i.e., without directional information, the prediction errors are significantly higher than in other scenarios.

(90 s in full scale) and 85 for output (25.5 s in full scale)

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