Physics-Informed Machine Learning for Wind Energy Applications

Jincheng Zhang and Xiaowei Zhao
The University of Warwick, UK

Abstract

Wake interactions in wind farms significantly impact power production and structural loads on wind turbines. Current numerical tools for wake prediction mainly fall into two categories: computational fluid dynamics (CFD) models, which are accurate but computationally expensive, and analytical wake models, which are fast but lack accuracy. Despite their limitations, analytical wake models remain the primary tool in practical applications. To bridge the gap between accuracy and computational efficiency, the first part of this work focuses on developing machine learning (ML)-based wake models capable of real-time evaluation, capturing high-fidelity flow features, generalizing well to unseen flow scenarios, and scaling effectively for large wind farms.

The proposed ML-based framework consists of static and dynamic wake modeling approaches. Static wake modeling frameworks developed include the use of dimensionality reduction combined with neural networks, deep convolutional neural networks (CNNs) augmented with generative adversarial networks (GANs), and a multi-fidelity modeling approach based on a novel super-fidelity network. These methods ensure accurate wake representation with reduced computational costs. On the other hand, dynamic wake modelling frameworks developed include the use of dimensionality reduction alongside sequential prediction techniques, as well as a Bilateral Convolutional Neural Network (BiCNN) to capture the temporal evolution of wake structures efficiently.

The second part of this work focuses on digital twining of wind farm flows based on physics-informed machine learning approaches. Existing tools in wind energy can only provide wind measurements at sparse locations, while low-fidelity analytical models and high-fidelity CFD models often focus on standalone simulation of wind farms. These tools often lack the capability to integrate both physical principles and real-time measurement data. To address this limitation, this work introduces a digital twin of the wind farm flow system, a data-driven, physics-informed ML model capable of predicting the unsteady flow field in front of a single wind turbine. It is then extended to flow fields across the wind farms capturing wake interactions. The developed digital twin integrates data from LIDAR and turbine sensors with physics-based constraints derived from NS equations and actuator modelling of turbine rotors, forming the first system capable of in situ spatiotemporal wind farm flow field

prediction. Case studies are conducted under different operational scenarios and the results show that the developed digital twin can achieve accurate predictions of the dynamic flow fields, bringing brand new opportunities for wind farm control with full awareness of its wind environment. For future works, a Physics-Informed Sequential Deep Operator Network (PI-S-DeepONet) is under development, eliminating the need for retraining.

1. AI-based modelling of wind farm wakes

The proposed framework is illustrated in Figure 1. It leverages AI-based modelling to develop a fast and scalable wind farm wake simulation system. It begins with high-fidelity numerical simulations of wind turbine wakes, generating flow field data that captures wake dynamics over time. This data is then used to train machine learning models, which learn complex wake interactions and develop a data-driven fast simulator. The trained model can efficiently predict wind farm flow fields in real-time, significantly reducing computational costs compared to traditional CFD-based methods. The resulting fast wind farm simulations retain high-fidelity flow features, generalize well to unseen flow conditions, and enable scalable predictions for large wind farms, supporting optimization and control strategies.

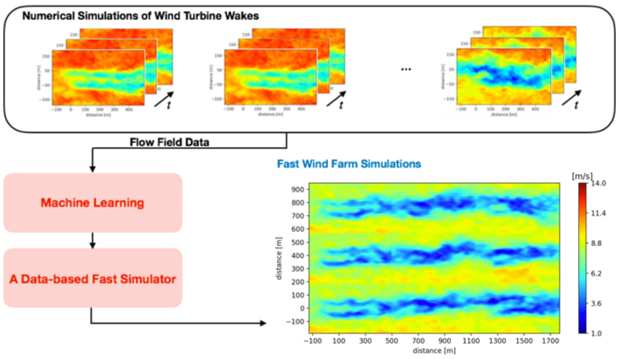

Figure 1: The overall framework of AI-based modelling of wind farm wakes.

A set of machine learning models have been developed and tested within the framework as shown in Figure 1. For static modelling, the customised machine learning models developed include the combination of dimensionality reduction techniques with neural networks [1], a deep convolutional conditional generative adversarial networks (GANs)-based framework [2], and a multi-fidelity modelling approach based on a novel super-fidelity network. A sample result is shown in Figure 2, which shows that the ML surrogate model achieves great accuracy for both spanwise and streamwise velocities.

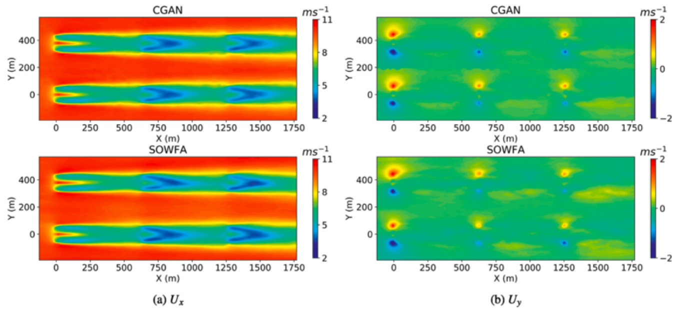

Figure 2: *Case study of a six-turbine wind farm using the ML-based static wake model.*

For dynamic wake modelling, the machine learning models developed include the combination of dimensionality reduction techniques with LSTM [3], as well as a customised convolutional network structure called Bi-CNN [4]. A sample result is shown in Figure 3, which shows that the ML model accurately captures both the front turbine's and the rear turbine's wake flow fields and at different time instants, demonstrating its usefulness as a control-oriented wind farm wake model.

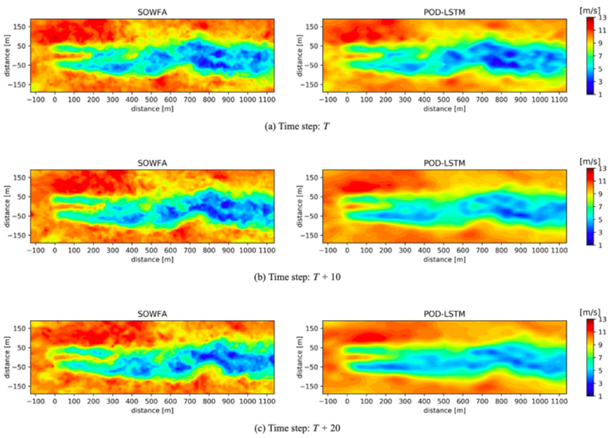

Figure 3: *Simulation of a three-turbine case using the ML-based dynamic wake model.*

2. Digital twin of wind farm flows

The proposed digital twin framework is illustrated in Figure 4 [5-6], which integrates real-time LIDAR measurements, turbine modelling, and physics-informed neural networks (PINNs). Specifically, from the physical system, measurement data, including wind data using LIDAR sensors and turbine parameters (e.g., location, yaw angle, and thrust), are collected to inform the PINN model about the real-time flow states. The Navier-Stokes (NS) equations, along with the actuator modelling of wind turbines, are used to enforce physical consistency. By fusing data and physics, after training, the model can predict wind field dynamics in real-time, enabling accurate digital mirroring of the physical system.

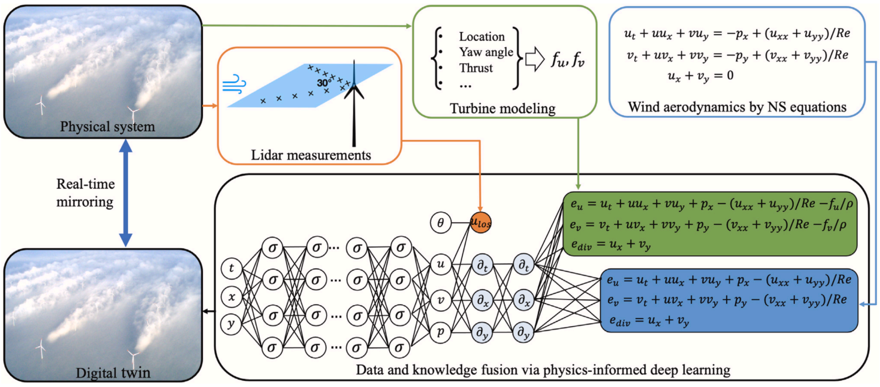

Figure 4: The overall framework of wind farm digital twin via physics-informed ML.

Three case studies have been carried out to test the performance of the digital twin, including a greedy case, a wake-steering case, and a partially-operating case. The results for the greedy case are given in Figure 5. The results show that flow characteristics, including the speed variations of incident wind, wake development in the downstream direction (including its deficit, deflection and expansion), and meandering in the crosswind direction, are all captured very well by the digital twin, demonstrating its value for improving wind farm monitoring and control.

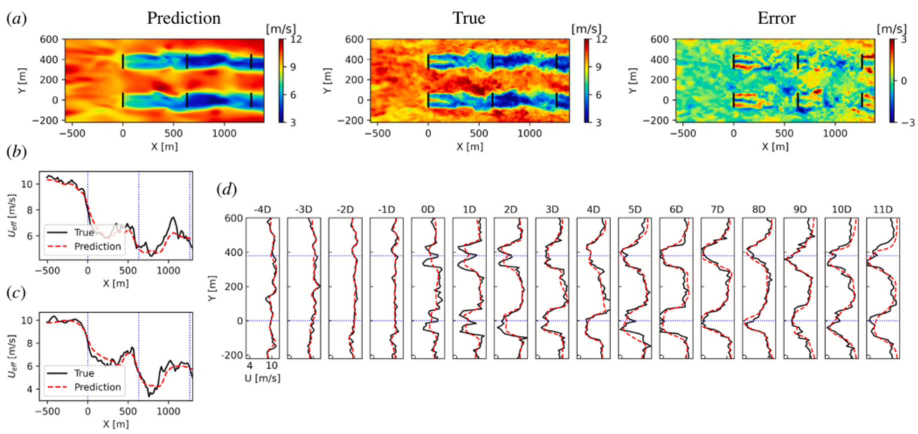

Figure 5: The DT predictions for the greedy case. (a) the full field; (b-c) the rotor-effective speed for the upper-row and the lower-row turbines; (d) the speed profiles.

3. References

[1] J. Zhang and X. Zhao, 2021, AIAA Journal, 59 (3) 868-879. **[2]** J. Zhang and X. Zhao, 2021, Energy, 238, 121747. **[3]** J. Zhang and X. Zhao, 2020, Applied Energy, 277, 115552. **[4]** R. Li, J. Zhang, and X. Zhao, 2022, Energy, 258, 124845. **[5]** J. Zhang and X. Zhao, 2021, Applied Energy, 288, 116641. **[6]** J. Zhang and X. Zhao, 2023, Energy Conversion and Management, 293, 117507.