Deep Learning for Wake Modeling of Wind Turbines

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Abstract: In this work, we explore an application of a composite neural network framework to learn the wake model from large samples of low-fidelity data along with very few samples of high-fidelity data. We train a composite neural network using data generated from Gauss and Curl analytical wake models treated as proxies for low- and high-fidelity models, respectively. This works opens up possibilities for data-efficient construction of surrogate models for wake prediction that can be utilized to study the influence of wind speed, yaw angles, and layout configuration on wind farm power production.

Keywords: Deep learning, Wake prediction, Multi-fidelity modeling

1 Introduction

The optimization and control of fleets of wind farms comprising hundreds of wind turbines is one of the grand challenges in realizing the widespread use of wind energy [1]. Within the wind farm, the wind speed does not recover to its freestream value once the kinetic energy is extracted by the first row of turbines, and therefore, subsequent turbines encounter a wind speed lower than the freestream speed. The strong wake interactions between turbines is one of the major factors that cause a significant power loss in wind farms. There are hierarchies of models to predict fluid flow in the wake of a turbine ranging from approximate but computationally cheap analytical models to highly accurate but computationally expensive large eddy simulation (LES). Despite the plethora of analytical wake models [2], the accurate and real-time prediction of the wakes in a wind farm is still an open problem due to spatio-temporal variability of wind speed, the unsteady nature of interactions of turbine wakes with other wakes, and atmospheric turbulence. This has spurred the interest of wind energy researchers to exploit machine learning models for wake prediction [3], and in this work, we propose a novel deep learning (DL) framework that can learn the wake model through integration of information from low- and high-fidelity models.

2 Problem Statement

If the DL framework is to be developed for wake prediction, the data should include accurate information for a comprehensive set of parameters which would require running high-fidelity models for a large set of parameters. This can be computationally very expensive. We leverage composite neural networks [4] coupled with dimensionality reduction methods that can exploit the correlation between low- and high-fidelity data to tackle the problem of dense parameter spaces for the efficient construction of a surrogate model for wake prediction. We utilize Gauss and Curl models as proxies for the low- and high-fidelity data, respectively.

The composite neural network is comprised of three components as shown in Figure 1. The first one is the low-fidelity neural network $\mathcal{NN}_L(\boldsymbol{x}_L;\boldsymbol{\theta})$ that is utilized to approximate the low-fidelity data. The second and third neural networks, $\mathcal{NN}_{H_i}(\boldsymbol{x}_H,\boldsymbol{y}_L;\boldsymbol{\theta}_{H_i}), i = 1,2$, are used for approximating the linear and nonlinear correlation between low- and high-fidelity data, respectively. The output from the linear and non-linear network are combined through a summation operation at the output layer. To establish a viable parametric surrogate model for wake prediction, the data obtained from numerical simulation for the whole domain is split into multiple training samples. Specifically, the learning map is given by

$$\mathcal{NN}_L : \{C_T, \phi, x\} \in \mathbb{R}^3 \to \{\boldsymbol{y}_L\} \in \mathbb{R}^n, \tag{1}$$

$$\mathcal{NN}_H : \{C_T, \phi, x, \boldsymbol{y}_L\} \in \mathbb{R}^{n+3} \to \{\boldsymbol{y}_H\} \in \mathbb{R}^n, \tag{2}$$

where C_T is the thrust coefficient, ϕ is the yaw angle, x is the stream-wise location, $\boldsymbol{y}_L$ and $\boldsymbol{y}_H$ are prediction from the low- and high-fidelity model, respectively.

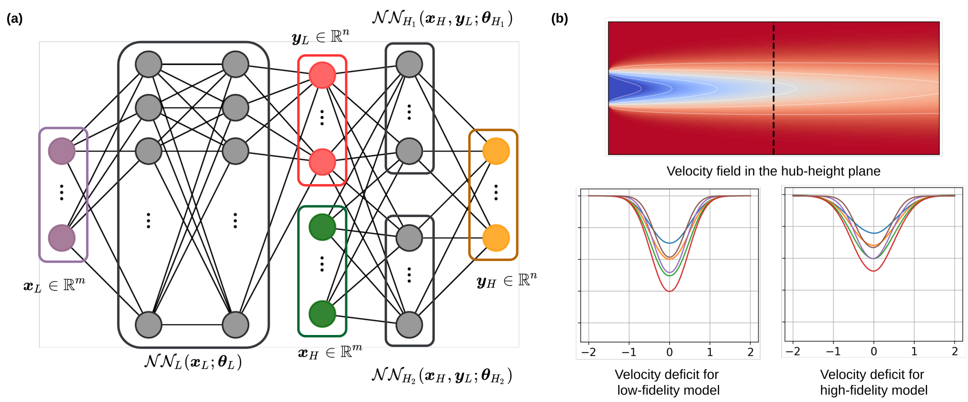

Figure 1: (a) Illustration of the composite neural network architecture used in the present study. The purple color is for input features to low-fidelity model, red color for low-fidelity model output, green color for input features to high-fidelity model, yellow color for high-fidelity model output, and gray color for hidden layers. (b) Data pre-processing stage which demonstrates that the composite neural network is trained to learn the velocity deficit in the span-wise direction.

3 Full Paper

The full paper will present the details of data-driven wake modeling including:

- The composite neural network that exploits the low-fidelity information obtained from the Gauss model along with the Curl model as a proxy for high-fidelity data for wake prediction.
- Feature extraction using an application of principal component analysis (PCA) for dimensionality reduction of three-dimensional wake field.
- Discussion on physics-based metrics to analyze the wake prediction recovered from the data-driven wake model.

References

[1] Veers, Paul, et al. Science 366.6464 (2019).

[2] Stevens, Richard JAM, and Charles Meneveau. Annual review of fluid mechanics 49 (2017).

[3] Ti, Zilong, Xiao Wei Deng, and Hongxing Yang. Applied Energy 257 (2020): 114025.

[4] Meng, Xuhui, and George Em Karniadakis. Journal of Computational Physics 401 (2020).

[5] NREL. Floris. version 2.4, 2021