Proceedings of the 1st international Symposium on AI and Fluid Mechanics
Abstract No S5 A7

On training of data-driven and physics driven neural networks for wind farm planning

[1]Zahra Lakdawala*; [1]Hassan Kassem; [1]Waasif Nadeem

[1]*Fraunhofer Institute for Wind Energy Systems, Kuepkersweg 70, 26129 Oldenburg*

Abstract

Accurate estimation of wind energy production and forecasting wind farm performance are challenging due to the unpredictable nature of wind and the need for extensive computational fluid dynamics (CFD) simulations, which are resource-intensive and time-consuming. For a quantitative understanding of wind and energy in complex terrains, a detailed site assessment is done, most often using mesoscale and/or microscale computational fluid dynamics (CFD) based approach. Typically, one would require multiple scenarios/case for a CFD simulator to incorporate the influence of a parameter on variability of wind speed and energy production. Traditional methods, like Monte Carlo simulations, become impractical for large-scale evaluations. This study explores the potential of two neural network approaches—data-driven and physics-informed neural networks—for improving wind resource assessment. One network is data-trained where the data is generated using CFD simulations, while the other integrates physical equations such as the RANS and Navier-Stokes models using NVIDIA's Modulus framework. Both networks utilize feed-forward convolutional architectures with a custom loss function incorporating residuals from either simulation data or governing physical equations. The L-BFGS optimization algorithm is employed to minimize the loss and optimize the networks' hyperparameters. The performance of these networks is compared to CFD simulations in two test scenarios: flow over complex terrain with varying canopy foliage and flow over a hill with varying hill sizes. The evaluation of the multi-objective loss function, accounting for both data and physical equation errors, reveals the accuracy and limitations of these models. Results indicate that these trained networks can effectively simulate wind resource assessments, potentially reducing the computational burden associated with CFD simulations. Our work lays the foundation for AI-driven methods that can complement and accelerate traditional CFD workflows, while also demonstrating how one can potentially incorporate parameter and model uncertainty estimates in site assessment workflows.

Keywords: Wind resource, site assessment, data-driven neural network, physics-informed neural network, Navier-Stokes, machine learning.