SCIENTIFIC MACHINE LEARNING BENCHMARKS TO ADVANCE WIND ENERGY

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ABSTRACT

Meeting the Biden Administration's goals of decarbonizing the nation's electricity by 2035 will require an enormous deployment of renewable energy technologies, with targets of deploying 30 GW of offshore wind by 2030 and 110 GW by 2050 [1]. To accomplish this, improved computational tools that can accelerate the design optimization, real-time controls, and grid integration of wind energy deployments are crucial. Scientific machine learning (SciML) offers a wide range of approaches to building data-driven models for prediction, generation, and decision-making, but it is not always clear which particular SciML technique is best for wind energy applications. Wind energy considerations involve vast spatiotemporal scales (decadal wind patterns to subsecond power electronics), challenging multi-physics (turbulent boundary layer flow, large displacement fluid-structure interactions, floating offshore wind), and characteristically difficult datasets (sparse and noisy nacelle-mounted sensors, non-Euclidean lidar data or airfoil representations) that make it challenging to use 'off the shelf' SciML models. Additionally, the prevalence of proprietary data (turbine descriptions and controllers, observational data, manufacturing processes, etc) often makes it difficult to ensure reproducibility of SciML results across the wind energy community.

To accelerate the achievement of the wind deployment goals, we are developing an open source suite of benchmarks to assess the performance of emerging SciML techniques on canonical wind problems. These benchmarks will include a comprehensive description of relevant problem physics to allow for physics-informed learning, domain-relevant quantities of interest and corresponding error metrics to measure performance, and simulation and experimental datasets for training and validation. The library of benchmarks being developed include 1) wind plant fluid flow data to study techniques for data compression, inflow generation, and turbulence closures, 2) surrogate models for wind plant optimization and controls, 3) airfoil simulations to study unsteady aerodynamics and shape optimization, and 4) inverse problems for state or parameter estimation. Moreover, whenever possible, datasets from distinct physical models are also provided to enable the investigation and benchmarking of multifidelity approaches. For all the benchmark problems we will also include a baseline approach that provides a point of comparison to evaluate SciML solutions against in terms of computational cost, accuracy, and data efficiency. We expect this suite of benchmarks will accelerate the identification and development of impactful SciML techniques that help achieve national decarbonization goals.

REFERENCES

[1] https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/29/fact-sheet-biden-administration-jumpstarts-offshore-wind-energy-projects-to-create-jobs/