Tackling control and modeling challenges in wind energy with data-driven tools

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1 Introduction

Driven by the abundance of data, new paradigms have lately emerged in science and engineering fields. Wind energy makes no exception and an increasing number of data-driven methods are used to tackle one of today's biggest challenges in the wind community: reduce the levelized cost of energy. Many underlying themes are concerned, ranging from wind turbine and wind farm control for power maximization and fatigue reduction to wake modeling.

We present a couple of efforts into exploiting such data-driven paradigms to address important matters in wind energy. At the turbine scale, we focus on the detrimental effects of atmospheric boundary layer and turbulence on structural components. We propose an individual pitch controller based on a neural network (NN) trained with reinforcement learning (RL) [1, 2]. As for the wind farm scale, wake interaction is a big challenge as it generates major power losses. We investigate wake redirection strategies under the lens of RL. The investigations reveal the need for low-cost yet accurate wake modeling, which leads us to bring data assimilation and physics together and develop an online dynamic wake meandering model [3, 4].

2 Reinforcement-learned individual pitch control for load alleviation

The controller is based on the separation of low-level control tasks from high-level ones. The pitch angles are generated by oscillators (low-level) that are modulated by a NN (high-level). The latter is trained with RL based on the upstream flow conditions, which are sensed through a novel load transformation strategy. The learning environment comprises a synthetic model of sheared and waked inflows and the blade element momentum theory for the loads computation. The trained controller is further deployed in large eddy simulations (LES) to assess its performances in turbulent and waked flows. Results show that the NN learns how to reduce fatigue loads and to exploit that knowledge in complex turbulent flows.

3 Coordinated learning for wind farm power production maximization

First, a parametric wind farm model with simplified wake dynamics is used to develop and test a set of learning algorithms in a variety of layouts and wind conditions. The turbines can vary their yaw angle and power induction factor. Second, the initial learning methods are coupled with a more realistic wind farm model, i.e. LES in which the rotor is modeled by an advanced Actuator Disk [5]. This approach has the advantage to accurately capture the unsteady wake behavior and the rotor dynamics. However, the long delays between action and reward related to the wake propagation can be prohibitive. This clearly hints at more complex predictive wake models as a way to enable more reactive control schemes.

4 Physics- and data-based dynamic wake meandering model

A framework was then developed to bring together flow sensing and wind farm wake modeling. The flow sensing module relies on physics-based Kalman Filter and a NN for the estimation of the upstream flow features. This information, evaluated at the machine location, is then discretized as a series of information carrying particles shed at successive time steps. The latter are then propagated downstream, thereby incrementally reconstructing the freestream flow field across the wind farm. A similar approach is used for the turbines wakes, which are modeled as a series of simplified analytical wake deficits fed by the measured information. The wake is finally advected downstream based on the estimated freestream velocity field which subsequently allows to capture wake advection mechanisms such as wake meandering. The resulting framework is validated against the LES of a small wind farm.

5 Conclusions

This work gathers results related to three topics of interest, namely wind turbine load alleviation, wind farm power maximization and dynamic wake modeling. It shows the introduction of data-driven methods in these fields, whether it is to learn control schemes or to model complex physics. While such methods bring another perspective to the investigations, they come along with challenges such as the generation of the data, which can be quite costly when it comes to fluid mechanics. This has led to make compromises, such as (1) learning in a low-fidelity environment for the load alleviation problem before being able to bring the knowledge to realistic complex flow fields or (2) developing an online wake model to ease and accelerate the learning of wake mitigation strategies to pursue power production maximization.

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