Failure Avoidance for Wind Turbines through Fleetwide Control

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As a society, we recognize the effects of climate change. This reality urges us to increase the percentage of renewable power generation. Offshore wind is expected to play a large role. A major hurdle to the development and acceptance of renewable electricity sources is ensuring that they are cost competitive with fossil-fuel generation.

For long-term viability, offshore wind must significantly improve its cost efficiency. To reduce the costs for wind energy, reliability of turbines must rapidly be improved, even in harsh environments, and reduce operations and maintenance costs in general. Overdesigning is not a viable solution, as the capital cost of the turbine will increase too drastically. Therefore, we propose to improve the reliability of the entire wind farm by avoiding failure through farm-wide control strategies.

Although wind farm control research mainly focuses on static loads and power production, the reduction of dynamic loads through operational measures has received less attention. However, recent evidence suggests that dynamic loads induce failure. Preventing failures has a direct impact on the availability of the turbines and it reduces lifetime costs.

It is tempting to consider a wind turbine as a generic entity, and impose operational control from this perspective. However, in reality each individual mechanical unit is unique. Therefore, maximum reliability can best be achieved by treating the wind farm, or *fleet*, as a data-compiling collective, and capturing the similarities between turbines that exist on a statistical level, while acknowledging the uniqueness in their specific operational behavior. By investigating the links between operational behavior and dynamic loads, each turbine can learn optimized responses to avoid loading conditions that may lead to failure in real-time.

We propose a two-step fleetwide control method that (1) leverages the similarities between turbines to detect event-driven discrepancies in operational behavior, and (2) adequately initiate a data-driven control protocol, using reinforcement learning, for preventing potential failure caused by the dynamic event in the field [1].

To define the similarities between turbines, we use Bayesian Gaussian Mixture Models to cluster the operational parameters of the turbines (i.e., rotor speed and power production). Therefore, turbines that exhibit similar steady-state behavior are clustered together. Any significant discrepancies from this behavior can be investigated and used as an indicator for a dynamic event. Based on field data of a real-world wind farm, we showed that clustering the turbines reveals a geographical structure of operational regimes. In addition to the observation that neighboring turbines are similar, a pattern emerges where upstream turbines and downstream turbines are clustered separately. This is due to a known phenomenon, called the *wake effect*, which refers to the reduction in wind speed after passing through the upstream turbines, which affects the operating conditions of the downstream turbines. When we apply this method for each discretized environmental condition (based on wind speed and direction), we can profile the entire wind farm under nominal behavior.

Once the expected operational patterns are known, discrepancies from the nominal behavior of the fleet can be used to detect dynamic events, and a failure prevention control protocol can be initiated. However, the case of dynamically changing multidimensional loads of such great magnitude as found in wind turbines is uncommon with other industrial machinery, and generally underresearched. Therefore, it is challenging to manually develop a control mechanism that actively prevents failure-inducing dynamic loads. To this end, we use reinforcement learning to optimize a control policy in a data-driven manner. Specifically, we use the REINFORCE method, which performs online optimization of policy parameters by sampling control decisions stochastically and evaluating alternative policies according to the defined reward scheme. REINFORCE maintains a parametric representation of the policy, which allows control experts to incorporate domain knowledge in the policy structure. For example, it makes sense to have a systematic shutdown of subsets of turbines when a storm cascades through the wind farm. We demonstrate this by defining a row-based stochastic policy for a storm event in a real-world wind farm, where each row of turbines must learn to shut down after a specific time period after the detection of the storm event. The time period is sampled from a Gaussian independently per row, where the means per row need to be learned and the variances are used as an exploration parameter that decays exponentially over training episodes. A reward of 1 is given for each minute a turbine is operational before the storm arrived at its position, while a penalty is given for each minute the turbine is operational after the storm arrived. We observed that turbine rows learn to consecutively shut down while the storm passes through. Additionally, increasing penalty parameter makes the turbine rows shut down earlier, which allows control experts to choose between risky and conservative policies.

References

1. Verstraeten, T., Nowe, A., Keller, J., Guo, Y., Sheng, S., Helsen, J.: Fleetwide data-enabled reliability improvement of wind turbines. Renewable and Sustainable Energy Reviews **109**, 428–437 (2019). https://doi.org/10.1016/j.rser.2019.03.019