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WIND ENERGY SCIENCE DISCUSSIONS

Interactive comment on "Real-time optimization of wind farms using modifier adaptation and machine learning" *by* Leif Erik Andersson and Lars Imsland

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Thank you for the response to our article. I believe most of the comments can be addressed in a discussion section of the final version of the paper. We investigated some of the questions in a LES study. However, as the nature of these studies the data and test tests are limited by computational constraints. The other referee pointed also out that some parts of the paper can be condensed especially the explanation of the algorithms. I will follow these recommendations in the revised version of the article. I have added my response also in the supplement.

Please see below a more detailed response to your questions:

Questions in comment 1 Can this approach work in truly dynamic environment? Will the approach work with varying wind directions and wake propagation delay?

These are extremely interesting and important questions. It was also pointed out by the other referee. If the approach would not be applicable to such environments it would be inapplicable to wind farm control. In our LES study that we plan to present at the TORQUE 2020 we simulated a nine-turbine plant with quasi-static wind conditions. The wind direction did not change, but we applied a turbulence intensity of 5%. We filtered the power output with an averaging filter. The approach was able to improve the power production compared to the Gaussian model (with tuned parameter via parameter estimation) about 2-3%. How a complete dynamic case with uncertainties in wind velocity, direction and yaw angle will affect the approach is difficult to say. The approach will require more data to cope with the variance in the training data. The performance will decrease like in robust approaches, which consider uncertainties explicitly. Nevertheless, we expect the approach will still improve the performance of the wind farm.

Questions in comment 2 Could the problem to solve large layouts be addressed by decomposing the large wind farm into manageable subsets according to wake interactions?

One way is to separate the farm into subsets according to wake interactions. Park and Law (2016) proposed such an approach. The other approach is to include the power measurements of each wind turbine in the model identification. Currently, we use a MISO approach approximating the total power production of the plant. A more efficient use of the available measurements is to identify the power production of each turbine and combine these N models in the optimization to optimize the total power output. It is a distributed learning strategy. In simulation studies we were able to show that this distributed (MIMO) approach scales much better for large wind farms. It needs much less data to achieve the same performance as the MISO approach. The distributed learning approach can be combined with the subset approach. Even thought, the GP learning can identify these subsets it can be helpful to specify them explicitly. The disadvantage of the distributed approach is the requirement to identify N models (which can be parallelized). The disadvantage of the subset approach is the inflexibility it introduces. Depending on the wind directions and the resulting different subset structures x models would have to be identified for each of these structures.

Questions in comment 3 How would the approach handle a non-input-output dependency, like turbulence, which varies on day/night basis? If in the extreme two models for stable and unstable atmospheric conditions are needed, is there a possibility of modeling hidden confounders?

It depends heavily on the influence of the non-measured input to the output. The approach can work without measuring every input. However, if for example turbulence is not explicitly considered in the GP model's inputs its influence will be averaged (over the training data set). In addition, it will increase the variance of the output of the GP. Conditions like stable and unstable atmospheric conditions where the response of the wind farm can differ drastically have to be approached by separate models. If approximated by one model the model will again average the output of these two conditions. This might decrease performance of the control approach. I would propose to differentiate in the data collection of the training data between atmospheric conditions and create several models. It would not be necessary to consider the atmospheric condition as an explicit input to the model. During operations it should be possible to estimate which model is most accurate in the current situation and hence estimate the atmospheric condition. The most accurate model would be used in the optimization. Another way would be a multi-model approach in which each model is weighted: Power =\phi_1 M_1 +\phi_2 M_2+(1-\sum \phi_i) M_3. The parameter \phi_i would be estimated using approach proposed in the literature about statistical learning. However, for the multi-model approach I am unsure if an interpolation between models for different atmospheric condition would be appropriate.

Again, thank you for all your comments. I hope I could answer some of your questions. I will try to include some of them in a discussion section at the end of the paper.

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Discussion paper

Please also note the supplement to this comment:
https://www.wind-energ-sci-discuss.net/wes-2020-18/wes-2020-18-AC2-supplement.pdf

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