Response to the Review on the Paper wes-2022-13

A WaveNet-Based Fully Stochastic Dynamic Stall Model

J.P. Küppers, T. Reinicke

We thank the reviewer for his detailed evaluation of our manuscript. Below we respond to his comments and explain the changes resulting from his comments. Please note that in the revised version of the manuscript, all changes related to reviewer #1's comments are highlighted in red if uploading a revised version is possible.

1. Please describe the basis of the window sampling size in the revised paper as well. What happens if the sampling is less than one period of dynamic stall? It would be interesting to add the initial studies in the paper. Note that in real case dynamic stall is never ever periodic especially for turbulent case, thus the model should be relatively independent of the sampling width, knowing the limit will be of importance. From what we observed in our studies, there is a certain limit of the window width needed be followed, for timeseries prediction of the turbine wake we adopted autocorrelation for finding that, but here perhaps relate that with the dynamic stall parameters as you feel more convenient.

   The data of the "initial studies" were not kept. This was an optimization process that was automated and always saved only the best models. However, even small windows sizes could give acceptable results in my experience. We found that smaller receptive fields can still provide robust solutions but maybe miss flow behavior caused by earlier events, resulting in a worse overall score. The base for the sampling size was therefore simply the best score for this particular dataset.

2. I believe the silhouette plot adds a good value in the clustering analysis.

   Perfect, we will add it to the paper.

3. Indeed we can feed the data for different airfoils and different Reynolds number. However, what about the weights obtained in the present studies? Should it be calibrated? What if we have no dynamic stall data for calibration for that airfoils? Note that in real wind turbine design load cases, manufacturers have to run more than 1000 load cases where most of the time they have no data to compare with and to re-train the models.

   If we simply do not have data for a particular wing profile, a data-driven method is obviously not to be used. Otherwise, most load cases should be within the experimental data parameter range. For extreme parameters that were not mapped in experiments, one could possibly extend the data set with LES-Simulations or artificial data.

4. No, unfortunately lift coefficient amplitude as high as 40 is totally incorrect. Just see on the raw data, the amplitude of the fluctuations is not even greater than 1. Have you checked in the FFT if you have divided the amplitude with the sampling number points in the FFT calculations?

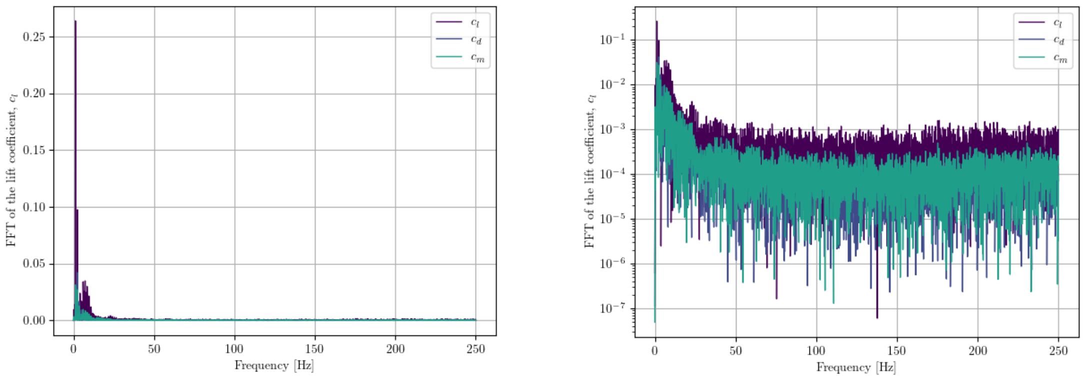

Figure 1. Frequency response in normal and log representation with correct amplitude

Great observation! I actually missed to divide the amplitude by the number of sample points and was confused about the figure number you were talking about. Now it is correct.

5. The problem with a fixed time step is the real usage in wind turbine design tools. Do we need to re-train the model every single time we modify the time step? I still see this as a drawback compared to well established model like Beddoes Leishman where we do not need to bother with time step and work without any training data. Please justify this in the revised paper.

   As mentioned in the first answers, it would be no problem to adapt the model to work with a variable time step. Another solution is to run the dynamics stall code asynchronously to the flow solver. One could simply take the most recent value for the lift coefficient etc. or extrapolate intermediate values for the BEM to work with.

6. As mentioned above, the problem with its generality is that the weights should be recalculated for different airfoils. For example, only for one blade we could have more than 7 different airfoils. What if we need to simulate several turbines at various inflow conditions? Coupling this with real wind turbine design tools will be a huge challenge and this should be properly mentioned in the paper.

   Ideally, the whole community creates an ever growing pool of openly accessible high-resolution unsteady data (LES and experiments). Then more sophisticated models could be trained to deal with all kinds of airfoils. Another, less sophisticated solution would be to train the neural network on the difference between the experimental data and the Beddoes-Leishman model. Then the WaveNet model could be applied on top of BL for more airfoilds already. However, the question of how meaningful the data obtained in this way is still to be answered.

7. Moreover, when simulating the real turbine, we have “no initial value” to look back by 128 steps as done in the paper. I also believe this poses a challenge to use in wind turbine design tools and it is not as simple as just enabling TensorFlow as the tool. This has to be mentioned as well.

   For initialization, the array was filled with artificial data. Then a short transient process takes place (see also the figures in the answers to Reviewer #2). Mostly, all parameters were simply set to "0", except for the Reynolds number.