I. RESPONSES TO RC1

A. The paper presents an analysis and different methods to predict the wake behavior of tilted wind turbines. The model proposed by Bastankhah and Porte-Agel for wind turbines in yaw is extended to tilted wind turbines. A deep learning approach is proposed as an alternative to solving the flow equations to calculate the detailed wake structure. The paper contains relevant information and indicates interesting approaches to study the wakes of tilted wind turbines. Nevertheless, there are significant aspects of the manuscript that require clarification.

B. As stated in line 68, the methodology proposed has been obtained for some specific conditions and is not generalizable to other ones. Nevertheless, a justification of why these conditions have been chosen is of interest, do they correspond to the more usual or representative working conditions?

1. Yes, these conditions are fairly representative of normal working conditions (wind speed of 8.0 m/s and turbulence intensity of 0.08). I have now included the following sentence:

   ”The additions and adjustments were calibrated on data representative of normal working conditions with a wind speed of 8.0 m/s and a turbulence intensity of 0.08”

C. Besides, these working conditions should be more clearly specified; some information is given in line 100, but I miss other relevant parameters dealing with wakes, like the thrust coefficient, ambient turbulence and other inflow conditions. Also, the main machine characteristics and dimensions should be also included without needing to consult bibliography.

1. Good catch - this needs to be clarified for reproducibility. I have now included the relevant parameters used. However, the physical dimensions of the NREL 5MW can be lengthy to include. I have included the hub-height and the rotor-diameter, however, for more detailed dimensions the reader can see the citation. Here is the portion of the paper that I have edited to include these details:

   “A 5-MW NREL reference turbine was simulated in SOWFA over varying degrees of tilt at a wind speed of 8 m/s, low turbulence intensity of 0.08, coefficient of thrust (CT) of 0.8, shear of 0.15, and a neutral atmospheric boundary layer (Churchfield et al.105 (2012)). The flow field results were averaged over the run time of 2,500 seconds where the flow converged. The turbine hub-height was set to 90.0 meters with a rotor diameter of 126.0 meters.”

D. It is not clear what data are you using to train the additional optimization and deep learning approaches, and what data are you using for validation and checking the results. A similar comment can be made about the surrogate model of vertical deflection. A brief comment is made in line 285, but it is not clearly justified if the training and validation data sets, both belonging to the same working conditions, are really independent.

   1. I have included more details of the data used to train the additional optimization and deep learning approaches. The additional optimization uses the same training data as the local optimization approach. The local optimization approach helps define the required empirical additions and adjustments and then the additional optimization uses the same data to further calibrate the parameters of the newly defined empirical additions and adjustments. The deep learning approach uses the same dataset as the local and additional optimization approaches including additional data for additional turbine tilt angles because the deep learning approach isn't limited to a range of tilt angles. Here is the revision in the paper:

      "In order to thoroughly train our neural net, we used 1,850 cross-stream slices from the SOWFA data velocity field over varying tilt angles ranging from -35° to 25°. The SOWFA data used holds the same turbine characteristics and flow field conditions as the data used to define the empirical relationships and implement the additional optimization step for the modified Bastankhah wake model. The 1,850 images were then randomized into separate training and validation datasets using PyTorch's randperm function, which implements the Mersenne Twister pseudorandom number generator (Imambi et al. (2021)). Although this data set is split into training and validation datasets it does not mean this model is generalizable. In future work, a more expansive training and validation data set that spans varying turbine types and flow field conditions would enable the model to be generalizable. However, for the purpose of comparing different approaches of analytical wake modeling we have limited the training and validation dataset to the working conditions detailed in section 2.1."

E. Besides, the usefulness of the proposed models is not clear, as you have to solve SOWFA first to get the training data for this particular situation. It may be that if in future work you are contemplating several different working conditions, the utility of the method would be more patent.

   1. It is true that the immediate usefulness of these models is limited due to the models being calibrated and trained on this particular situation. The

main purpose of comparing these models is to identify limitations and benefits of each approach. Future work can certainly include developing these models for a broader range of working conditions. However, we feel it is important to first understand which modeling approaches are more promising for developing complex wake modeling capabilities especially for floating offshore wind farms that deal with complex wakes due to the movement of the floating platform.

F. I think that the Bastankhah and Porte-Agel model was originally proposed for yawed wind turbines and its application to tilted wind turbines is not straightforward, and requires more than an improvement or modification, as seems to be suggested in the abstract and other parts of the paper.

    1. Good point - I have now included additional citations that address examples of previous additions and modifications to the Bastankhah and Porte-Agel model to justify our approach in the following portion of text:

       "The Bastankhah wake model has undergone several additions and modifications to account for varying yaw angles and turbulence intensities (Niayifar and Porté-Agel (2016); Bastankhah and Porté-Agel (2016)). This study introduces an improvement to the current approach of building the capabilities of the Bastankhah wake model (2016) as well as a novel deep learning approach to modeling complex wake dynamics."

    2. When the Bastankhah wake model was modified and adjusted to include yaw it also acknowledged limitations due to a kidney bean wake shape for large yaw angles. Our approach follows their derivation for wake deflection due to turbine rotor alignment but applies it in the vertical direction. Without the ground, the vertical deflection would follow trajectories similar to yaw deflection; however the presence of ground highly influences the wake recovery, wake deflection, and wake growth. Our local optimization approach was meant to demonstrate an approach used in the past to similarly add to and modify the Bastankhah wake model in order to expand its wake modeling capabilities.

G. In line 103, "SOWFA simulations confirm similar trends to previous studies of tilted turbines..." give references of these previous studies.

    1. I have now provided these references:

       "Overall, the results of the SOWFA simulations confirm similar trends to previous studies of tilted turbines (Annoni et al. (2017); Johlas et al. (2022); Bay et al. (2019))."

H. Figures 1a and 1b opposite of indicated in text.
    1. Thank you for catching that. I have not corrected it.

I. In figure 1 and following ones, it is difficult to see the contrast.
    1. I selected blue shades to ensure that the key aspects of the figures remain clear, even when printed in black and white. The focus is on observing the overall shape rather than analyzing specific velocity deficit values.

J. It is not clear how figure 2a is obtained. Bastankhah and Porte-Agel 2016 is for yawed wind turbines.
    1. I have now included in the description of Figure 2 that the stream-wise slice comes from a tilted turbine simulated in SOWFA.

       "Stream-wise slice of the velocity deficit centered at a 2.5◦ tilted turbine (simulated in SOWFA). z* represents the vertical position normalized with the hub height (90 meters)"

K. Figure 2b is not referred in the text
    1. Good catch - I have now removed figure 2b, and there are other figures that can be referenced instead of 2b.

L. Regarding line 114, cross stream slices should be symmetrical, but frequently they are not because of unavoidable errors. How do you deal with this asymmetry?
    1. This is a major limitation of the local and additional optimization approaches. They both assume the cross stream slice of the wake can be sufficiently estimated with a symmetrical shape. However, the local and additional optimization methods both account for vertical and horizontal deflection. Section 2.1.1 goes into how we account for some of the asymmetry.

M. In the caption of figure 3, how are the solid lines obtained, also from SOWFA?
    1. Good catch - the solid lines and points are both from SOWFA but the points assume the center of the wake moves vertically and horizontally and the solid lines assume the wake only deflects vertically. I have now clarified in the figure description that both the solid lines and dotted lines come from SOWFA data:

       "Deflection of tilted turbine wakes as observed from cross-stream slices in SOWFA (marked with points) and the deflection observed from a stream-wise slice in SOWFA (marked with solid lines)."

N. In lines 141 to 145, text not very clear.
    1. I have revised lines 141 to 145 to the following:

“In order to focus on accurately estimating the upper portion of the vertical velocity profile the profile is split at the point of max velocity deficit, at the peak of the gaussian shape (see Fig. 4). Then the upper portion of the velocity profile is mirrored across the point. For example, observing Figure 4, this would entail removing the portion of the SOWFA data that is less than a $z*$ value of around 0.81. Then mirroring the remaining SOWFA data across $z* = 0.81$. This forms a normal Gaussian shape where a normal Gaussian fit is used to find σz.”