Response to Reviewers

The authors appreciate the valuable comments by the Reviewers and have carefully revised the manuscript to address these comments. A point-by-point response to the review comments and relevant updates to the manuscript are also marked below. All the changes have also been highlighted in yellow in the revised manuscript.

Reviewer #1's comments:

In this study, the authors presented an ANN model for standalone wake effect with a superposition model for predicting wake affect considering the turbine layout. The research content fits the journal scope and the presentation of the whole paper is easy to follow. Nevertheless, after a careful review, the reviewer does not recommend its acceptance in ECM. The main drawback is the limited novelty, as the authors only applied a well-known AI model to simulate the behavior of the dataset. In this regard, it is just a practice of implementing AI algorithm, and no new structure or findings are provided in this paper.

Reply: Thanks for the patience in reviewing our manuscript. We would like to explain more details about 1. why ANN is adopted in our wake model; 2. how do others use AI models in wind energy and what are our differences; 3. how are the current practice and its drawbacks; 4. research gaps; 5. how does this paper fill the gaps. We sincerely hope the reviewer could accept our idea and explanation.

1. Why ANN is adopted in our wake model

First of all, we cannot deny that the AI model used in this paper, a double-layer ANN model, is widely used. In the past few decades, advanced AI models have already been developed, such as CNN, RNN, LSTM, RL, SVM, etc.

A Convolutional Neural Network (CNN, or ConvNet) is most commonly applied to analyze visual imagery. It is used to capture a few features from a large amount of information, which does not match the problem framework in this paper.

A Recurrent Neural Network (RNN) is also a class of artificial neural networks. Long Short-Term Memory (LSTM) is an artificial RNN architecture used in the field of Deep Learning (DL), which is well-suited to classifying, processing, and making predictions based on time series data. For the power prediction of wind farms, the steady-state solution is used in this paper. Therefore, it is not suitable to use LSTM networks either.

Reinforcement Learning (RL) is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. Therefore, the model needs to be combined with the actual environmental conditions, which are not designed for a steady solution and are unrelated to the topic.

Support-Vector Machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. The aim of this model does not match the problem framework either.

A Deep Neural Network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. The number of layers is usually large in order to model complex non-linear relationships. However, for wind turbine wakes, the wake deficit is approximately in a gaussian shape. Therefore, the wake model does not require too many layers. In this paper, the double-layer ANN model is proved to be efficient and has a very high coefficient of determination (0.99).

In summary, those advanced AI models have their own design purpose, which is not suitable for this paper. On the other hand, the ANN model is adopted in this paper because it is easier to follow and more suitable to solve this problem. The problem we focused on has no relationship with classification or time series. Therefore, there is no need to do any convolution or time-related training. We have also stated in the paper as follows:

> 2.3 Machine learning technique
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> Machine learning has a lot of branches, among which ANN is a basic one. However, this model aims to predict velocity field and turbulence intensity field by using only two inflow parameters (wind speed and turbulence intensity at hub height). A steady solution is also required for power prediction. Therefore, it has nothing to do with convolution or time step. Hence, ANN is a primary machine learning model but the most suitable choice for this problem. This feature is also proved in Ti's previous work [23, 24].

2. How do others use AI models in wind energy, and what are our differences

In recent years, some AI applications have been initialized in wind energy. Its development is still in a preliminary stage. However, the idea is brand new in terms of wind farm layout optimization. From literature reviews about AI models utilized in wind energy, we can see that Zhang [1] simulates the velocity field around a wind turbine and trains the LSTM model to predict the next step. Sun [2] trained an ANN model to maximize the power output of five fixed wind turbines by controlling their yaw angles. Similarly, we use this ANN model to replace the traditional wake model for layout optimization. Although the classic AI models are developed by others, our work is to extend the application of the AI model to wake prediction in a wind farm, which is also the novelty and our contributions. Even if we both use the ANN model, the framework could be totally different between Sun's [2] and ours as we focus on different optimization problems. Guo [3] trained an AI model using the SCADA data based on an analytical wake model. However, the analytical models may not be so generic to suit high turbulence cases. Therefore, the correlation of Guo's model can only reach the coefficient of determination of 0.7~0.8. In contrast, our ANN model is based on fully validated CFD simulation data, which can fit a wide range of inflow conditions. Therefore, our methodology is not based on a priori model so that it can have a very high coefficient of determination of 0.99.

3. How are the current practice and its drawbacks

In current practice, commercial software and packages are adopted widely, usually equipped with an analytical or CFD simulation model. However, the latter ones are too computationally expensive to apply in optimization. Therefore, the mainstream layout optimization still cooperates with analytical models.

Even if the efficiency of the mainstream methodology based on analytical models is good enough, the accuracy is insufficient to adapt to the wake under various inflow conditions. As a consequence, the inaccuracy of the model may lead to "fake" optimal solutions and significant errors in power evaluation (up to 15%), as mentioned in this paper. High-fidelity CFD simulation models are high in accuracy but unaffordable for large-scale wind farms. In this case, this paper successfully seeks to balance efficiency and accuracy. By introducing the AI model, the framework can simultaneously improve accuracy and efficiency.

It is noted that the accuracy of the proposed framework using machine learning is around 4-15% higher than the framework with the analytical model. Without AI, we can hardly reach the accuracy of CFD simulation. The trend of layout optimization is also balancing efficiency and accuracy. To the authors' best knowledge, the competitor we chose is one of the most accurate analytical models involving the formulation of ambient turbulence intensity, as briefly introduced in 2.1.

4. Research gaps

This paper provides a new choice for layout optimization of a large-scale wind farm. As far as known by the authors, the research gaps can be summarized as follows:

(1) Layout optimization of large-scale wind farms is mainly based on analytical models and is infeasible with CFD simulations.

(2) No similar AI-based framework has been proposed for layout optimization of large-scale wind farms.

(3) Lack of numerical verification of large-scale wind farms with a large number of wind turbines.

5. How does this paper fill the gaps

This paper brings an AI model driven by well-validated simulation data into layout optimization for the first time. A double-layer ANN wake model is successfully established and trained with a very high coefficient of determination (0.99). The power prediction framework using machine learning is successfully built and proved accurate and efficient.

The critical point is that the proposed framework successfully balance efficiency and accuracy. In this way, the power prediction in every trial of layout optimization of large-scale wind farms can be as accurate as CFD simulation, which is a brand new idea or framework.

Besides, we have also provided CFD validation for a wind farm with nine wind turbines, which can be challenging without the application of overset mesh technique. Furthermore, the overset mesh scheme is compared with the traditional mesh method in the paper and proved to be far more efficient.

Thank you for considering our response. We sincerely hope that the novelty can meet the standard of ECM.

[1] J. Zhang, X. Zhao. A novel dynamic wind farm wake model based on deep learning. Applied Energy. 277 (2020) 115552.
[2] H. Sun, C. Qiu, L. Lu, X. Gao, J. Chen, H. Yang. Wind turbine power modelling and optimization using artificial neural network with wind field experimental data. Applied Energy. 280 (2020) 115880.
[3] G. Nai-Zhi, Z. Ming-Ming, L. Bo. A data-driven analytical model for wind turbine wakes using machine learning method. Energy Conversion and Management. 252 (2022) 115130.

Reviewer #2's comments:

1-seciton2.1.1. Does the mesh size have any effect on the model analysis? How to verify the validity of the simulation model of the paper?

Reply: Thanks for the reviewer's question. The mesh size should be fine enough to gain sufficient accuracy. When the computational domain becomes large, it may require a huge number of elements. However, if the related density of mesh is too small, the characterization of turbulence intensity will be inaccurate. In ANSYS Fluent, the model will not report any error if a coarse mesh is applied. Therefore, it is essential to verify the simulation results. To verify the simulations, the results are compared with more accurate LES simulation and experimental measurements in the previous study [4, 5]. In this study, the velocity and turbulence intensity profiles are also compared. A comparison of one of the cases is attached below. (Vertical wind speed profile, z_0=0.5) However, we decided to remove these repeated verifications in this paper for brevity.