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Towards the development of a wake meandering model based on neural networks

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Abstract. In this work, we develop a neural network model for predicting the instantaneous wake position, which is crucial for a wake meandering model. The data used for training are from the large-eddy simulation of a utility-scale wind turbine. A neural network of four hidden layers with 128 units for each layer is found to be effective when training the model. Effects of different input features on the accuracy of the trained model are systematically tested. It is found that the input features including the downwind and crosswind velocities at two locations upwind of the turbine and the thrust and torque acting on the turbine are enough to guarantee the accuracy of the trained model. Without using the thrust and torque as the input features, the accuracy of the model is significantly worse.

1. Introduction

Wake meandering, which describes the large-scale, low frequency motion of turbine wakes, affects the power output and dynamic loads of downwind turbines. Turbine wake meandering is a complex flow phenomenon affected by incoming atmospheric turbulence, wind farm turbulence as well as turbine operating conditions [1, 2, 3, 4]. The dynamic wake meandering (DWM) model developed by researchers at the Technical University of Denmark [5] is one of the most widely used wake meandering models. In the DWM model, the wake meandering is modeled by considering wake deficits as passive scalars advected by incoming large-scale eddies of the atmospheric turbulence, for which the downwind variation is neglected based on Taylor's frozen flow hypothesis. Besides the large-scale eddy mechanism, the bluff body shear layer instability is also shown to be the cause for wake meandering based on wind tunnel experiments [6]. In a recent LES study of a utility-scale wind turbine [7] the authors found that the two mechanisms coexist in the meandering of turbine wakes. A literature review of wake meandering can be found in [8].

To develop site-specific wind farms with low levelized cost of energy (LCOE), effects of wake meandering have to be properly taken into account when designing and operating the wind farm. High-fidelity models, e.g., large-eddy simulation (LES), have shown to be able to predict wake meandering [9]. However, high-fidelity simulations are computationally expensive and cannot be directly applied to the design of utility-scale wind farms. Development of predictive engineering models [10] for turbine wake meandering is essential for bridging the gap between the academia research and the industrial practice. Machine learning has been widely used in many fields of fluid mechanics [11, 12, 13]. The neural network is one of the most widely used machine



learning techniques [14]. It also has been employed in wind farm applications. For instance, Li et al. [15] developed a model based on a neural network and measured wind farm data for predicting the produced power of each turbine. In [16] a neural network model is used to reduce the frequency fluctuation of wind farms. It is promising that the machine learning technique can pave the way for developing predictive wake meandering models accurately taking into account the complex meandering mechanism. As a key step towards predictive wake meandering models, the objective of this work is to develop a model for predicting instantaneous wake positions based on neural networks and the data from high fidelity simulations. Specifically, we will examine effects of input features including the spatially and temporally filtered incoming velocity at different locations upwind the wind turbine, and the thrust and torque acting on the wind turbine on the effectiveness of model training and the accuracy of the trained model.

2. Methods

2.1. Description of the simulation data

The computational data from the large-eddy simulation of the University of Minnesota EOLOS turbine [17, 18, 19] are employed for training the neural network model for predicting instantaneous wake positions. The rotor diameter and hub height of the EOLOS turbine are 96 meters and 80 meters, respectively. The Virtual Flow Simulator (VFS-Wind) code [20] with the actuator surface model for turbine blades [21], which has been successfully applied to simulate turbulent flows over utility-scale wind turbines and wind farms [22, 23, 24, 25], is employed for the large-eddy simulation of turbine wakes. In the simulation, the tip-speed ratio (which is defined as $\lambda = \Omega R/U_h$, where Ω is the rotor rotating speed, R is the rotor radius, and U_h is the incoming wind speed at turbine hub height) is 8.3 close to the optimal operating condition. Fully developed turbulent inflow obtained from a precursor simulation is applied at the inlet. The simulation data, which include the flowfield data on a horizontal plane located at turbine hub height and the turbine operational data, are saved for about 2000 rotor revolutions. The wake center location is obtained by finding the position of the minimum of the spatially and temporally filtered downwind velocity with the filter widths D (rotor diameter) and T (mean rotor revolution period) in space and time, respectively. It is noted that in this work we only consider the wake position at $7D$ (which is typical for turbine spacings in wind farms) downwind of the turbine on the horizontal plane located at turbine hub height without considering its position in the vertical location. Different combinations of the incoming velocity fluctuations and the turbine operation data are tested as input features. For the wake position at location x and time t , the turbine operation data at time $t - (x - x_t)/U_c$ and the incoming velocity at time $t - (x - x_{in})/U_c$ are taken as the corresponding input features, where x_t is the turbine coordinate and x_{in} is the location for the incoming velocity, respectively, and the convection velocity $U_c = U$ (where U is the time-averaged incoming wind speed at turbine hub height).

2.2. Setup of the neural network

The feed-forward neural network with fully connected hidden layers, which uses MSE (mean square error) as the loss function and ReLU (Rectified Linear Unit) without the dropout as the activation function, is employed in this work. The learning rate is set at 0.001. The training will stop when the maximum number of epochs is achieved or no improvement is observed after 10 epochs. A schematic of the employed neural network is shown in figure 1. The neural network model is implemented using TensorFlow [26]. To build the model, the simulation data are divided into two sets, in which the first 80% temporal series of the data are employed for training and validation, and the rest 20% data are employed for testing. The first 80% of the data are further randomly divided into 80% for training and 20% for validation. Before testing the effect of input features, we examine different neural network architectures of different number of hidden layers and different number of units for each layer in figure 2. As seen, the MAE significantly reduces

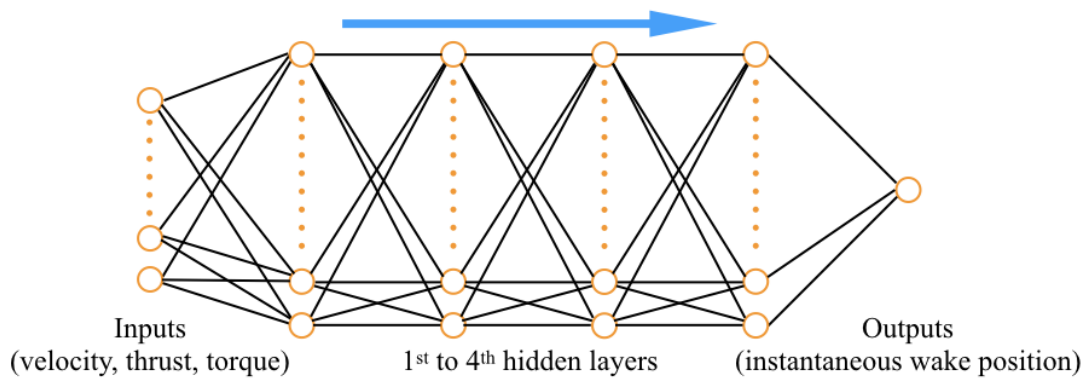


Figure 1. Schematic of the neural network model for predicting instantaneous wake positions.

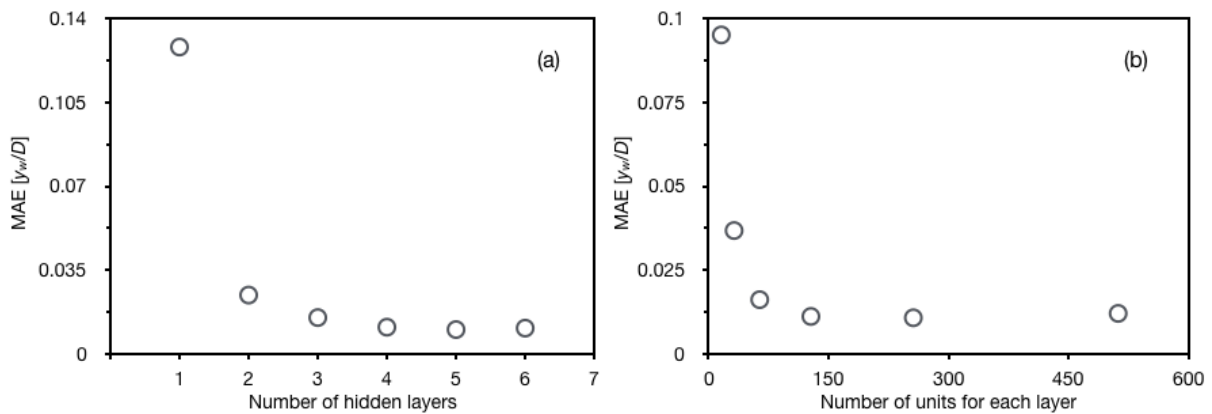


Figure 2. Variations of MAE (Mean Absolute Error) for (a) different number of hidden layers (with the number of units fixed at 128) and (b) different number of units for each layer (with the number of hidden layers fixed at 4). The case studied is c11 as shown in table 1.

as we increase the number of hidden layers from 1 to 2, while remains nearly the same as we further increase the number of hidden layers to 5 and 6. A similar trend is observed for different number of units in each layer. Based on this test, an architecture of four hidden layers with 128 units for each layer will be employed in all the cases for testing the effect of input features.

3. Results

We test the effect of different input features, including the spatially and temporally filtered velocity fluctuations at different upwind locations, and the thrust and aerodynamic torque coefficients, on the training effectiveness and the model performance. A complete list of the tests is shown in table 1. It was found that with only the velocity at one position upwind of the turbine, the training fails to converge (cases c1, c2 and c3). Using crosswind velocity and thrust or torque (cases c5 and c6), and only the thrust and torque (case c7) as input features, the training of the neural network also fails to converge. Using both downwind and crosswind velocity at one upwind location and the thrust or torque as the input features (cases c8 and c9), the neural network model is successfully trained. Having both the thrust and torque as input features in case c8 or c9 (case c10) the MAE of the trained model is decreased by about two times. Having the velocity at two positions, the trained model is also able to give some reasonable predictions (case c4). By adding the velocity at one more location to the input

Table 1. Model performance evaluated using the test data for different input features, where $u(-aD)$ and $v(-aD)$ denote the downwind and crosswind spatially and temporally filtered velocity fluctuations at aD upwind of the turbine, and C_T and $C_{\tau,aero}$ are the thrust coefficient and the aerodynamic torque coefficient of the turbine, respectively.

Case	c1	c2	c3	c4	c5	c6	c7
Input features	$v(-2D)$	$v(-2D), v(-1.5D)$	$v(-2D), u(-2D)$	$v(-2D), u(-2D), v(-1.5D), u(-1.5D)$	$v(-2D), C_T$	$v(-2D), C_{\tau,aero}$	$C_T, C_{\tau,aero}$
MAE	$0.200D$	$0.190D$	$0.169D$	$0.026D$	$0.161D$	$0.168D$	$0.172D$
Case	c8	c9	c10	c11	c12	c13	c14
Input features	$v(-2D), u(-2D), C_T$	$v(-2D), u(-2D), C_{\tau,aero}$	$v(-2D), u(-2D), C_T, C_{\tau,aero}$	$v(-2D), u(-2D), v(-1.5D), u(-1.5D), C_T, C_T$	$v(-2D), u(-2D), v(-2.5D), u(-2.5D), C_T, C_{\tau,aero}$	$v(-2D), u(-2D), v(-2.5D), u(-2.5D), v(-1.5D), u(-1.5D), C_T, C_{\tau,aero}$	$v(-2D), u(-2D), v(-2.5D), u(-2.5D), v(-1.5D), u(-1.5D), C_T, C_{\tau,aero}$
MAE	$0.049D$	$0.048D$	$0.022D$	$0.013D$	$0.013D$	$0.012D$	$0.023D$

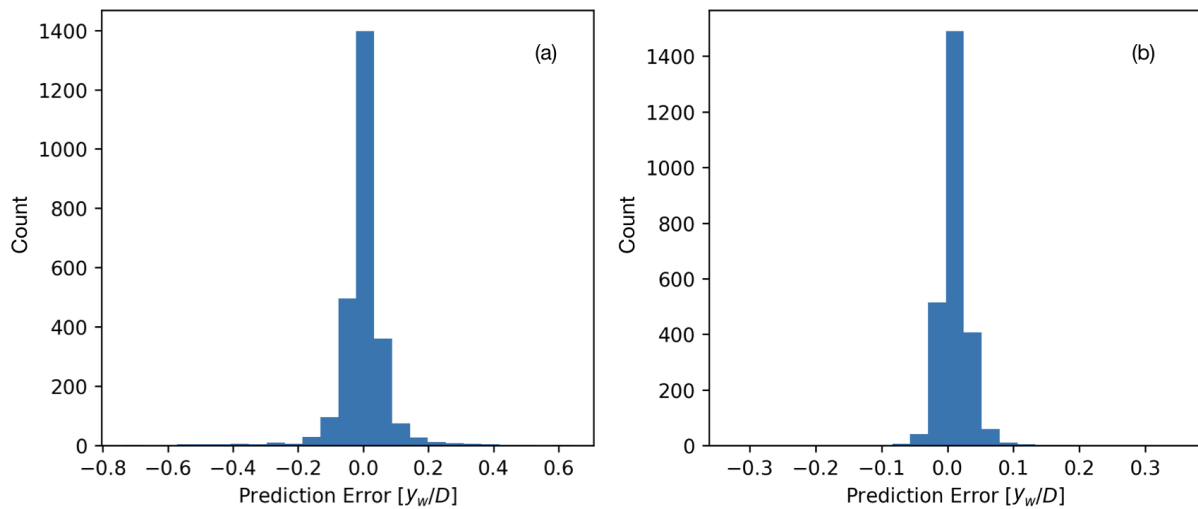


Figure 3. Histograms of error distributions for (a) case c4 and (b) case c11.

features of case c4 (case c14), no significant improvement is observed. On the other hand, by adding the trust and torque to the input features of case c4, the performance of the trained model is improved by about two times (case 11). Adding the incoming velocity at one more position as input features to case 11, no further improvement is observed (case c13).

Figure 3 compares the histograms of error distributions from two cases, i.e. case 4 and case 11. It is seen that the prediction error can be as high as $0.3D$ for case c4, which is approximately within $0.1D$ by adding the thrust and torque as input features. The predictions are compared with the true values in figure 4. As seen, the predictions agree with the true values for all the wake center locations for case c11. For case c4, on the other hand, the predictions deviate from

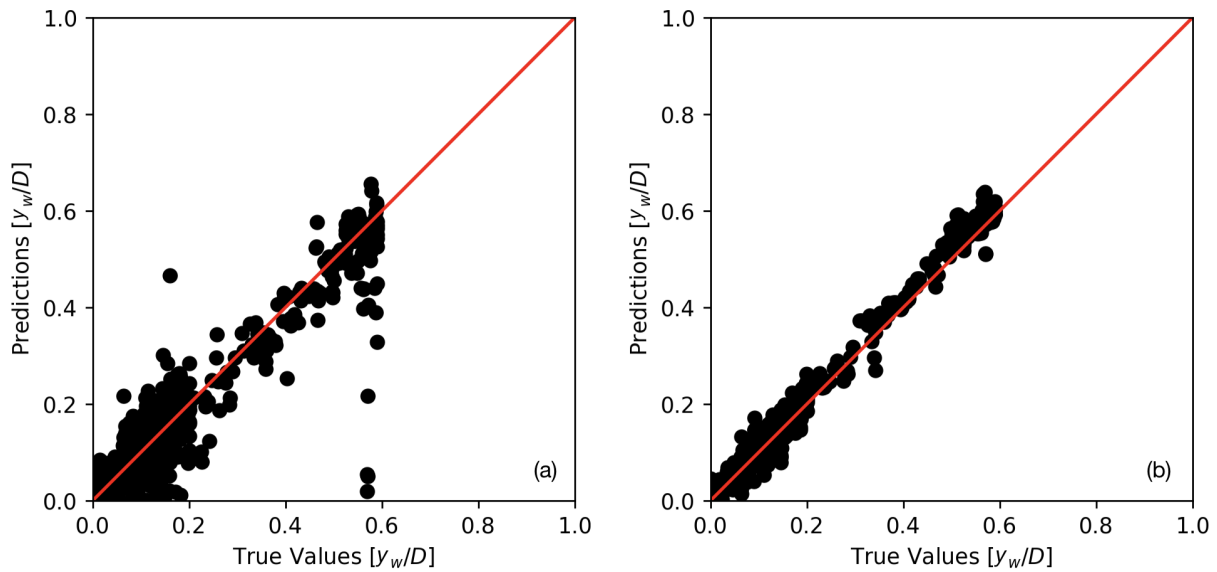


Figure 4. Comparison of model predicted wake center positions with true values (LES data) for (a) case c4 and (b) case c11.

the LES predictions (the true values) for $y_w/D < 0.2$, while slightly agree better with the true values for $y_w/D > 0.2$ but still with several outsiders significantly away from the true values for y_w/D close to 0.6. We now compare the predictions with true values for the whole dataset in figure 5. As seen, the predictions agree very well with the LES data for the time series used for train and validation. It is noticed that the train and validation data are randomly divided instead of dividing in time. For the times series for testing, the agreement between the predictions and the true values is still good but with some discrepancies observed for some instances.

4. Conclusions

We developed a neural network model for predicting wake positions and tested the effects of different input features on the model performance. We found that with only the incoming velocity at one location as input features, the trained model is not able to predict wake positions accurately. Using the incoming velocity at two positions and the turbine thrust and aerodynamic torque coefficients as input features, the predictions from the trained model show good agreements with the true values (LES data). A hypothesis explaining these results, which needs further study, is briefly described in the following. The velocity fluctuations at one upwind location tell the wake position at a “certain instant” based on Taylor’s frozen flow hypothesis. With the velocity fluctuations at two locations or adding the turbine operating conditions can help building the correlation between two locations and identify this “certain instant”.

The proposed model still cannot be directly applied to an operational environment. To build such a model, more effects have to be taken into account, such as the effects from upwind turbine wakes, complex terrain and ocean waves (for offshore wind). To provide a site-specific solution, a hybrid approach using both field measurements and high-fidelity simulations is preferred to provide the data for training the model. To apply the model to optimize a wind farm, the incoming velocity data in addition to the turbine operation data are needed as input features. It is suggested to take the incoming velocity upwind of the turbine as the input feature, which is not affected by the turbine itself. However, such wind speed measurement upwind of each turbine might not be available for each turbine in a utility-scale wind farm. In this case,

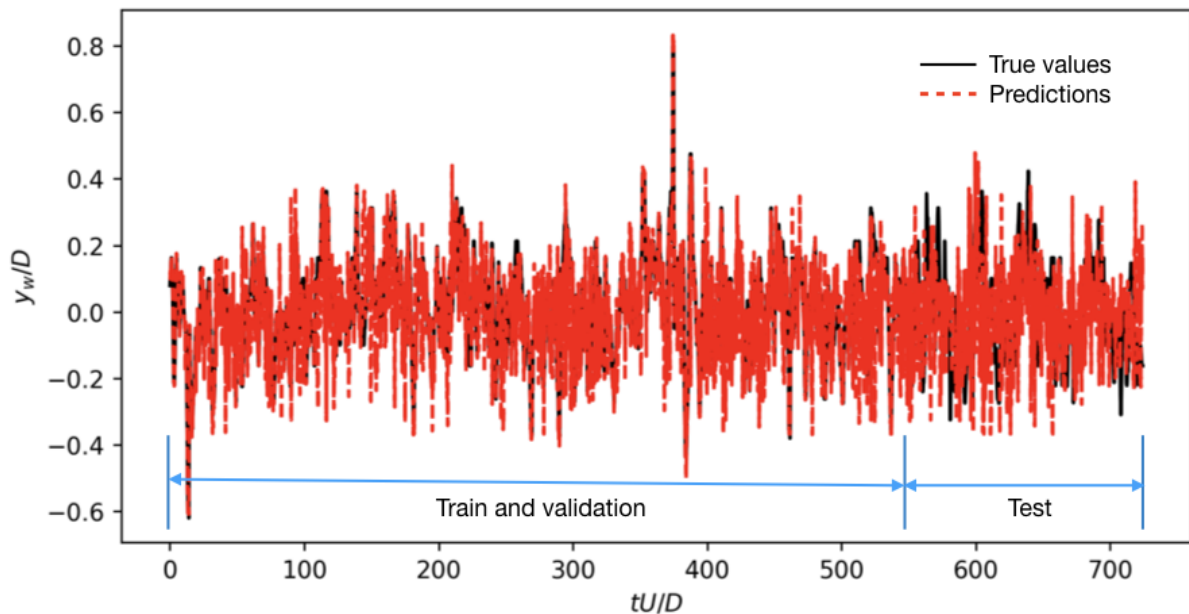


Figure 5. Time series of model predicted wake center positions (red lines) compared with true values (black lines) for case c11.

the incoming velocity can be obtained using the wind data collected at the turbine nacelle, constructed using the power data, or from upwind turbines. Additionally, the thrust coefficient and the aerodynamic torque coefficient might not be available from measurements. This can be solved by calculating C_T and $C_{\tau,aero}$ from the power coefficient C_P and the generator torque coefficient $C_{\tau,gen}$ based on some approximations, which are available from turbine's SCADA (Supervisory control and data acquisition) system, or training a new model based on input features including C_P and $C_{\tau,gen}$. Systematic study on these issues will be carried out in the future work.

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