Deep learning-based wind farm power prediction using Transformer network

Rui Li, Jincheng Zhang, and Xiaowei Zhao

Abstract—**Accurate wind farm power prediction is of vital importance for the performance improvement of wind farms and their grid integration. In this paper, a novel method based on the state-of-the-art deep learning model (i.e. the Transformer network) is developed to tackle this issue. Specifically, the prediction task is modeled as a segmentation problem and the powerful Vision Transformer (ViT) is employed to predict each individual turbine's power generation in a wind farm with wake interaction effects. The proposed method, called Wind Transformer (WiT), is evaluated by carrying out a set of numerical experiments. The results show that the proposed method achieves accurate and efficient wind farm power prediction and it outperforms other deep learning baseline models significantly. Particularly, the maximum mean absolute percentage error by the proposed method is only 1.030%, while they are 4.350% for LSTM and 3.510% for CNN models.**

I. INTRODUCTION

As one of the most important sustainable energy resources, wind energy has demonstrated tremendous potential and experienced a great surge in recent years [1]. Even though lots of efforts have been involved to reduce its cost and to make it more competitive with the traditional power generation, a lot of challenges still remain in order to further improve the performance of wind farms [2]. To this end, this work investigates the prediction of wind farm power generations, which plays a vital role in the design of wind farms, their efficient operations, and their integration into the grid [3].

`Wind farm wake models have been developed to predict wind farm power generations. The pioneering analytical wake model was proposed by Jensen [4] in 1983, which assumes that the wake expands linearly after a wind turbine. Thereafter, Larsen [5] constructed a semi-analytic wake model for the wake loading problem, while Frandsen [6] proposed a simplified model by conservation of momentum. The inherent weakness of these 1D models is the inaccurate assumption of velocity deficit profile. Hence, Bastankhah and Porté-Agel [7] proposed a two-dimensional (2D) Gaussian wake model. After that, Tian et al. [8] proposed the Cosine wake model and Gao et al. [9] developed the Jensen-Gaussian (J-G) wake model sequentially. Nevertheless, lacking the height dimension, the 2D model is still limited for practical application. To address this issue, Sun [10] proposed and verified an analytical three-dimensional (3D) wake model. Meanwhile, there are a series of works in analytical wind farm modeling recently, such as wind farm simulator [11] and bilateral Gaussian wake model [12], while certain surrogate modeling methods have also been introduced [13, 14] to enhance the efficiency.

Based on the analytical wake models, a series of works on wind farm power predictions are conducted. For example, M. Lydia et al. [15] proposed a hybrid power prediction method that combined the wind speed and wind turbine power curve models. M. Gaumond et al. [16] introduced a novel simulation post-processing method to tackle the wind direction uncertainty issue when measuring the Horns Rev offshore wind farm. Even though the post-processing technique boosted the consistency of the simulations for wake modeling, accurate wake predictions were required for the narrow wind direction sectors method. M. He et al. [17] proposed a general spatio-temporal analysis framework deriving from the finite-state Markov chain models to forecast the wind farm generation. Carlos et al. [18] introduced three Kalman filtering methods for wind speed prediction. Li et al.[19] built a physical approach for the wind power prediction based on the CFD pre-calculated flow fields.

On the other hand, as a data-rich industry, substantial detailed and reliable data are available. This opens opportunities for big data-driven machine learning (ML) models for wind farm power prediction [20]. For example, in [21], two neural network-based methods were investigated by A. Khosravi et al. [21] which directly and rapidly constructed the prediction intervals for short-term forecasts of wind farm power generation. H. Liu et al. [22] proposed and compared two-hybrid methods based on the Artificial Neural Networks and Kalman Filter for wind farm prediction. Z. Lin et al. [23] constructed a five-layer feedforward neural network to predict wind power outputs. In [24], six multi-objective prediction frameworks based on machine learning algorithms were evaluated for power generation and structural fatigue load prediction. Although these attempts have made encouraging progress in wind farm predictions, almost all of them are based on simple ML methods, limiting their potential for more complex scenarios such as predicting the power generation of each individual turbine in a wind farm.

Compared with simple ML methods, Deep Learning (DL) models, which usually stack multiple layers to extract nonlinear and hierarchical features, are more powerful and promising for power generation predictions. As an up-and-coming solution to data-driven modeling and projections, DL has brought amazing progress and evolution in many fields [25-27]. Considering what the DL algorithms require is the vast amounts of data instead of the explicit mathematical model of the farm operational process [28], the utilization of DL models for the data-rich offshore wind energy industry demonstrates the tremendous potential to highly enhance the accuracy and efficiency for wind farm predictions. This work, therefore, explores the use of the state-of-the-art deep learning architecture, i.e. the Transformer networks, for wind farm

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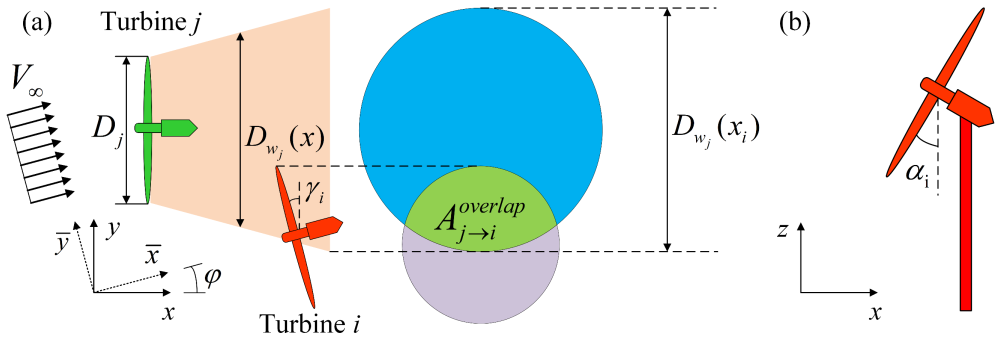


Fig. 1. The illustration of two turbine model example. (a) The wake expansion model of the turbines i and j (top view) (b) The tilt misalignment model of the turbine i (side view). In the Cartesian reference frame (x, y), the x-axis points downwind along the free stream inflow direction, the y-axis is orthogonal to the x-axis along the crosswind direction, and the z-axis is orthogonal to the x and y axis, and represents the altitude. The reference frame ($\bar{x}$, $\bar{y}$) is used to measure and represent the free stream inflow wind direction.

power predictions. Transformer, as a powerful and robust DL model, has shown strong capabilities to capture long-range dependencies and yield superb performances in a wide range of fields [29]. More recently, the tremendous success achieved in the language domain inspires researchers to explore the potential and adaptation of Transformer in the computer vision field [29]. Obviously, the successful application of Transformer will become the first and foremost step to integrate computer vision and natural language processing, thereby providing a universal and uniform artificial intelligence (AI) paradigm. Therefore, introducing the Transformer into the wind farm prediction will not only remedy the intricate forecast task but also integrate the aforementioned AI paradigm into the offshore wind farm prediction and control area.

Therefore, in this paper, we propose a novel framework to address the wind farm predictions. Particularly, we introduce the DL model, especially the state-of-the-art Transformer network for wind farm predictions. Different from the DL-based methods mentioned above which focused on the prediction of the whole farm or a single turbine, the proposed framework predicts the output of each individual turbine within an entire wind farm.

To evaluate the proposed method, numerical experiments for an example wind farm are carried out. In particular, we first build a wind farm with 16 turbines. Then, based on a wind farm simulation platform called FLORIS [30], the power generation of each turbine is simulated under 6 conditions with different wind speeds and wind directions. Finally, the accuracies of the Transformer model are evaluated on the simulated dataset and compared with two DL baselines, i.e., LSTM and CNN models.

The remainder of this paper is organized as follows. The problem formalization and methodology are presented in section II. Then the experimental setting and the prediction results are presented in section III. Finally, we conclude the paper in Sec. IV.

II. Methodology

A. Problem Formalization

Supposing an offshore wind farm comprising of N wind turbines denoted by the set $F = \{1,2,3,\cdots,N\}$, each wind turbine $i \in F$ is modeled by its rotor area, the inflow wind velocity, and a two-dimensional location (x_i, y_i) according to a common reference coordinate (x, y). As shown in Fig.1, the power generation of the downstream turbine i can be calculated by [31]:

$$P_{W_i} = \frac{\rho}{2}(A_i \cos\alpha_i)\, C_{P_i}(\beta_i, \lambda_i)\left(v_i(t)\cos^{\frac{1}{3}}\alpha_i \cos\gamma_i\right)^3, \quad (1)$$

P_{W_i} is the output power generated by the turbine i. ρ indicates the air density. A_i represents the rotor-swept area of the. α_i, β_i, γ_i, and λ_i denote the tilt misalignment angle, the blade pitch angle, the yaw offset angle, and the tip-speed ratio (TSR). $v_i(t)$ is the effective wind speed seen by the turbine i. C_{P_i} is the power coefficient. From equation (1), the power output of the individual turbine is dependent on the turbine operational parameters, the inflow wind speed, and direction. However, the overlapping turbine wake interactions aggravate levels of turbulence and shear, leading to the complicated dynamic loads of the downstream wind turbines. Therefore, it is normally intractable to explicitly derive an accurate analytical expression for turbines on the wind farm. The wake interactions exacerbate with the increase of wind turbines, thereby weakening the power generations and the reliability of the overall wind farm. Also, the degree of the wake interactions relies on the operating point of each wind turbine, which is fairly complex to parametrize for a large wind farm. Therefore, instead of hammering out a detailed and complex analytical wind farm model with wake interactions, the wind farm prediction can be lightly represented by training a deep learning model based on big data of input parameters.

B. Wind Farm Power Prediction based on Transformer

Given a specific wind condition (i.e., wind speed and wind angle), we set the yaw angle of each turbine as the input of the wind farm while the output is the power generation of each turbine. Hence, considering the wake interactions between the turbines, the intuitive thought is to model the wind farm predictions as a sequence-to-sequence task. For sequence-to-sequence, as an improved variant of the recurrent neural network, the long-short term memory (LSTM) is an effective method that can learn the information contained in series data. However, the spatial location information will be lost when transferring the input and output to sequence information. Therefore, modeling the issue to a segmentation task that maintains the input and output in the 2D format is a more sensible choice.

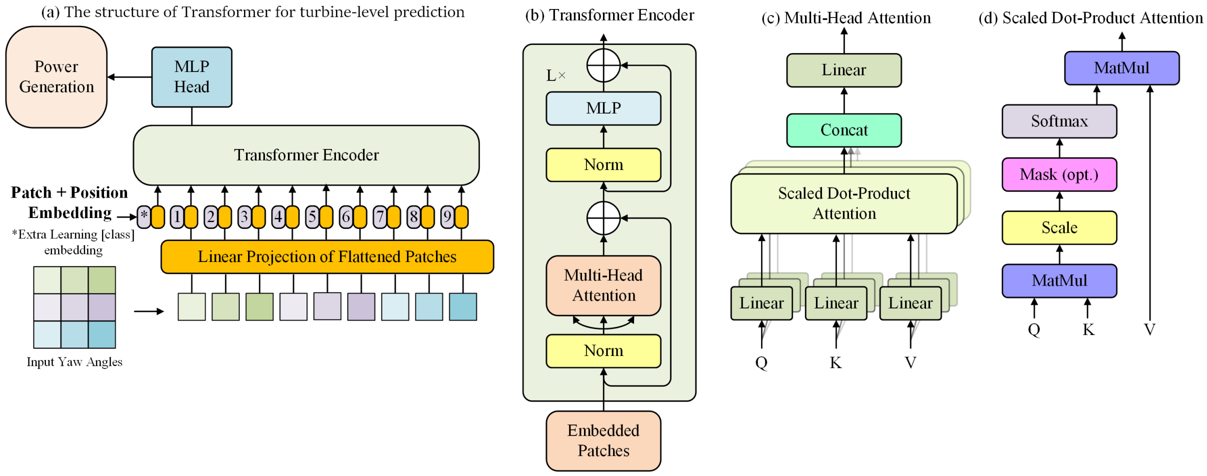


Fig. 2. The illustration of the Wind Transformer (WiT). (a) The structure of Transformer for wind farm prediction. (b) Transformer Encoder. (c) Multi-Head Attention. (d) Scaled Dot-Product Attention.

Semantic segmentation, which assigns definite categories to groups of pixels in an image [32], could help to scene understand or better explain the global context of an image [33]. Specifically, the input of segmentation is normally the natural image, while the output is in the same shape as the input while each pixel represents the category of the corresponding pixel in the input. Therefore, we can formally model the wind farm prediction task to a segmentation model. The major difference is that the segmentation is a classification task while the wind farm prediction is a regression task. Hence, the loss function utilized to measure the disparity between the predicted results and ground truth is Mean Squared Error (MSE):

$$MSE = \frac{1}{m}\sum_{i}(\hat{y}_i - y_i)^2, \tag{2}$$

while $\hat{y}_i$ is the predicted result, y_i is the ground truth, and m is the number of samples.

For the segmentation task, the convolutional neural network (CNN) is the frequently-used method, which is usually built by multiple blocks including convolution layers, pooling layers, and fully connected layers. However, the CNN is designed to extract local patterns and lacks the ability to model global information in its nature. Therefore, for wind farm prediction, we introduce the Wind Transformer (WiT) based on the Vision Transformer (ViT) [34] due to its powerful capacity to model the long-range dependencies of the input. As can be seen from Fig. 2, WiT first reshapes the input yaw angle $x \in \mathbb{R}^{H\times W}$ into a sequence of flattened patches $x_p \in \mathbb{R}^{N\times P^2}$, where $H \times W$ is the number of turbines in a wind farm, $N = H \times W$, P^2 is the resolution of each patch. To facilitate the understanding, we utilize the genuine picture to represent the input yaw angle in Fig. 2. Thereafter, the flattened patches are mapped to D dimensions with a trainable linear projection, which is named patch embeddings. Besides, a learnable embedding ([class] embedding) to the sequence of embedded patches is prepended whose state at the output of the Transformer encoder serves as the input representation.

After patch embeddings, position embeddings are operated to maintain positional information using the standard learnable 1D position embeddings. Then the resulting sequence of embedding vectors is fed into the Transformer Decoder. The main components of Transformer Encoder [35] include alternating layers of multi-headed self-attention and MLP blocks, which can be seen from Fig. 2(b), (c), and (d). Layernorm (LN) is applied before every block and residual connections after every block.

III. Experiments

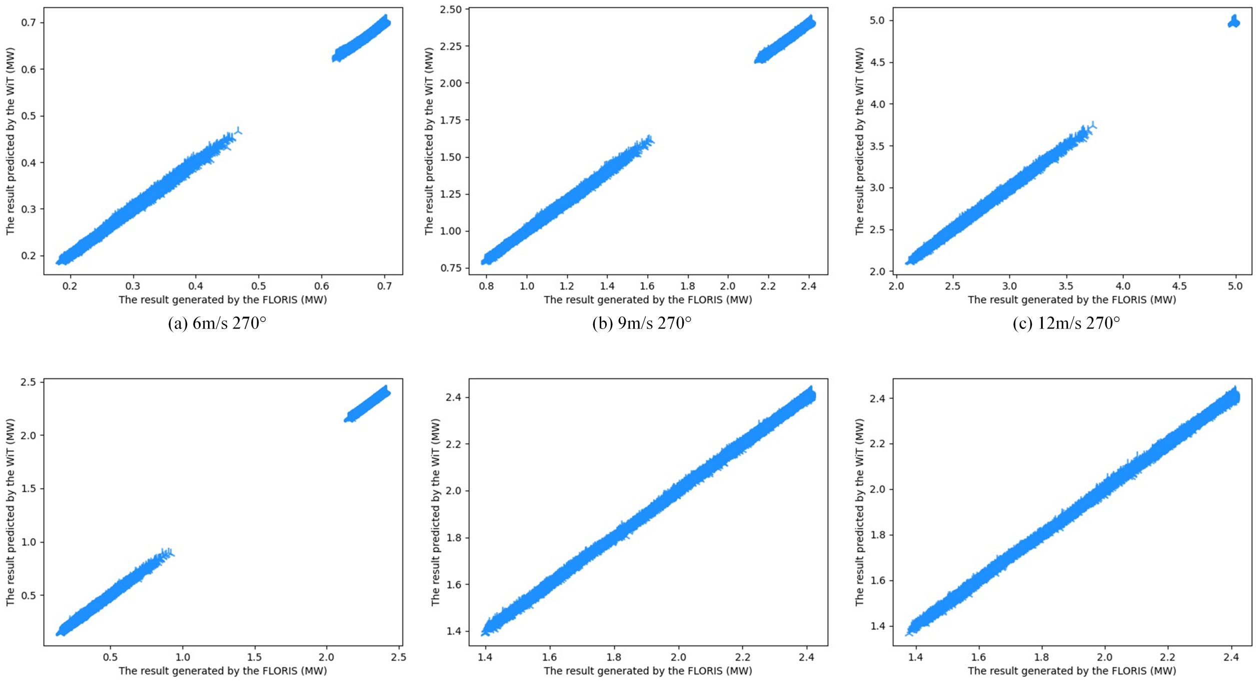
A. Dataset Generation

The assessment of the WiT has been conducted based on the wind farm simulation platform, i.e., FLORIS [30]. Concretely, 16 NREL 5 MW turbines were utilized to conduct a 4 × 4 layout wind farm with 7D (126m × 7) streamwise distance and 3D (126m × 3) spanwise distance. The power generation of each turbine is measured as the wind farm output and the yaw angle settings are fed into the model as inputs, while other input parameters such as the blade pitch angle, the tilt angle, and the turbine operational characteristics including the TSR and the rotor speed are kept constant.

For data generation, we considered six typical operating scenarios include diverse inflow wind speeds and directions: the mean wind speeds of 6 m/s, 9 m/s and 12 m/s with 270° wind direction, and the wind directions of 180°, 225°, and 315° with 9 m/s inflow wind speed. The input yaw angle for data generations in the FLORIS was randomly generated as a sample sequence consisting of 16 elements between -20° and 20°, and each yaw angle is fully distinguished from the previous one. For every scenario, 10000 samples are generated for training, 1000 for validation, and 1000 for testing. All case studies were carried out using Python 3.6.9 on an Intel Xeon(R) Platinum 8268 CPU.

B. Evaluation Metrics

We evaluate the performance of the proposed WiT as well as two baselines, i.e., LSTM and CNN, using the Root Mean Square Error (RMSE), Mean Absolute Percentage Error



(a) 6m/s 270°　(b) 9m/s 270°　(c) 12m/s 270°

(d) 9m/s 180°　(e) 9m/s 225°　(f) 9m/s 315°

Fig. 3. The qualitative comparison between the predicted result and the FLORIS data, while the horizontal axis represents the data generated by FLORIS and the vertical axis indicates the result predicted by the WiT.

TABLE I

THE EXPERIMENTAL RESULTS UNDER SCENARIOS.

Speed	Direction	LSTM			CNN			WiT		
		RMSE	MAPE	MARPE	RMSE	MAPE	MARPE	RMSE	MAPE	MARPE
6	270	0.015	3.417	1.471	0.014	2.633	1.293	0.003	0.660	0.251
9	270	0.025	1.288	0.524	0.022	1.354	0.537	0.007	0.396	0.113
12	270	0.042	1.047	0.454	0.050	1.262	0.526	0.011	0.282	0.102
9	180	0.038	4.350	1.812	0.019	3.510	1.504	0.005	1.030	0.372
9	225	0.029	1.060	0.430	0.016	0.588	0.227	0.004	0.207	0.066
9	315	0.028	0.998	0.352	0.023	0.846	0.289	0.006	0.224	0.074

(MAPE), and Minimum Absolute Relative Percentage Error (MARPE):

$$RMSE = \sqrt{\frac{1}{m}\sum_i (\hat{y}_i - y_i)^2}. \tag{3}$$

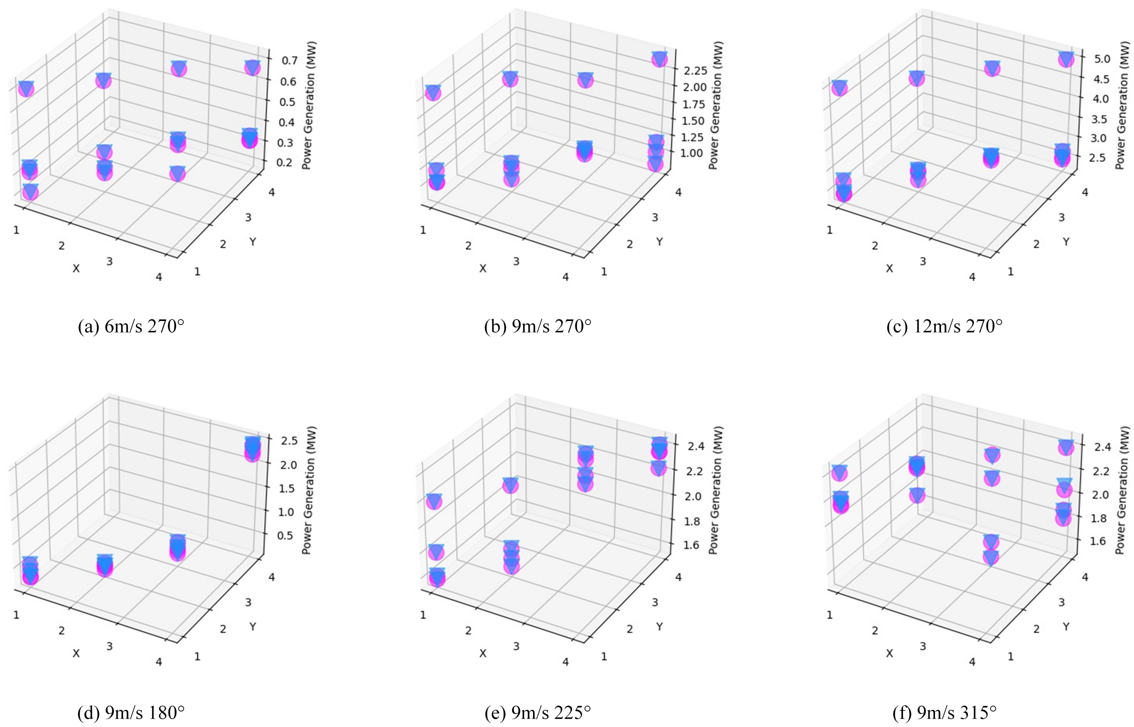
$$MAPE = \frac{1}{m}\sum_i \left(\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\%\right). \tag{4}$$

$$MARPE = min\left(\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\%\right). \tag{5}$$

C. Experiment Results

To evaluate the accuracy of the proposed method, we trained and verified the WiT as well as LSTM and CNN baselines on the six simulated datasets. All training and validation processes were implemented with PyTorch 1.8.0 on a single and Nvidia Quadro RTX 5000 GPU with 2048 batch size, and the optimizer was set as AdamW with a learning rate of 0.0003 and a weight decay value of 0.0025. For the learning rate scheduler, we adopted available ReduceLROnPlateau in PyTorch with the patience of 5 and the learning rate decrease factor as 0.5. If the loss on the validation set did not decrease for more than 10 epochs, the training procedure would be stopped, while the maximum iteration period was 1000 epochs. For LSTM, the input shape was in 1D sequence format, while in 2D format for CNN and WiT.

As can be seen from Table I, calculated by 100%-MAPE, the relative accuracy for all models can achieve at least 95%. But the performance between different methods has obvious differences. Concretely, the performance of CNN is better than that of LSTM most of the time, due to the spatial relationships between wind turbines being better retained by CNN. For WiT,



(a) 6m/s 270° (b) 9m/s 270° (c) 12m/s 270°

(d) 9m/s 180° (e) 9m/s 225° (f) 9m/s 315°

Fig. 4. The qualitative comparison between the predicted result and the ground truth. The magenta circle indicates the ground truth generated by the FLORIS, the dodger blue triangle denotes the result predicted by the WiT, and horizontal and vertical coordinates represent the spatial position of the corresponding turbine.

the maximum MAPE (%) for wind power prediction is 1.030%, which indicates that the relative accuracy of wind farm power can achieve at least 98.970%. Meanwhile, the minimum MAPE (%) is merely 0.207%, signifying a 99.793% relative accuracy.

For qualitative comparison, we illustrate the 2D scatter diagram for whole test samples and 3D scatter diagram for a specific test sample between the predicted result and FLORIS data in Fig. 3 and Fig. 4.

In Fig. 3, the horizontal axis represents the data generated by FLORIS and the vertical axis indicates the result predicted by the WiT. As can be seen in Fig. 3, the dots are mainly located near the diagonal line, which means predicted results precisely match the FLORIS data. In Fig. 4, for each scenario, we choose a random yaw angle input and then visualize the ten turbines' outputs generated by the FLORIS and WiT, where the magenta circle indicates the ground truth generated by the FLORIS, the dodger blue triangle denotes the result predicted by the WiT, and horizontal and vertical coordinates represent the spatial position of the corresponding turbine. As can be seen from Fig. 4, the predicted wind farm power generations of each turbine coincide highly with the values generated by FLORIS, which strongly demonstrates the effectiveness of the WiT.

IV. Conclusion

In this paper, we proposed a novel deep learning based method for the prediction of wind farm power generation. The proposed method, called Wind Transformer (WiT), was developed by first modeling the prediction task as a segmentation problem and then taking advantage of the powerful Vision Transformer (ViT) developed in computer science. The proposed prediction approach was designed to forecast the power output of each individual turbine in a farm instead of taking the whole farm as a black box and just predicting a total generation. Thus, it can provide detailed power generation information for each individual turbine. To evaluate the proposed method, substantial experiments were conducted, where six typical operating scenarios include diverse inflow wind speeds and directions widely were considered. Experiments conducted on simulated datasets demonstrated that the accuracy on MAPE of the proposed WiT can achieve at least 98.970%, significantly exceeding the LSTM and CNN baselines.

In summary, for this article, we not only introduce the DL model for wind farm predictions but also model the issue as a segmentation task, thereby utilizing the Transformer network to address it. Our future work is to train the network and validate its effectiveness of the proposed WiT on real running records of the wind farm instead of the simulated data, thereby further enhancing the fidelity of the predicted results.

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