Machine Learning in Wind Turbine Wake Modeling

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As wind energy continues to be a crucial part of sustainable power generation, the need for precise and efficient modeling of wind turbines, especially under yawed conditions, becomes increasingly significant. Addressing this, the current study introduces a machine learning-based symbolic regression approach for elucidating wake dynamics.

wind energy optimization | symbolic regression | wind turbine wake deflection | wind turbine velocity deficit | machine learning

1. Background

As global energy consumption continues to rise in the face of dwindling fossil fuel reserves and escalating climate change concerns, the search for sustainable and clean energy sources has become a pressing imperative. One such source, wind energy, has rapidly become prominent in the global energy landscape. Recognized for its renewable nature and significant potential for reducing carbon emissions, wind energy has positioned itself as a viable and critical solution to the energy conundrum [1].

The translation of this potential into practical energy production at scale has been realized through wind farms, which are large arrays of wind turbines designed to convert the kinetic energy of wind into electricity. Scattered across both land and sea, these towering structures have become symbols of the pursuit of renewable energy, embodying the commitment to a sustainable future [2].

However, despite the apparent simplicity of their operation, wind turbines are governed by complex dynamics that pose considerable challenges to their efficiency and longevity. A central element in these dynamics is the 'wake' that each turbine generates as it extracts energy from the wind [3]. These wakes—areas of turbulent airflow and reduced wind speed, or 'velocity deficit', behind the turbines—pose significant challenges to harnessing wind energy effectively. The turbulence within the wake not only leads to efficiency losses but also results in increased fatigue loads, which can reduce the operational lifespan of turbines [4][5].

The intricacies of wake effects are magnified within wind farms, where the close positioning of turbines creates an interplay of wakes that can lead to a cascading effect of power loss across the installation. When multiple wakes intersect, the downstream turbines face lower wind speeds and increased turbulence, leading to a substantial drop in energy production and heightened structural stresses [6]. Moreover, when turbines are not aligned directly with the incoming wind—a condition known as 'yaw'—the wake characteristics become even more complex. Yawed conditions induce changes in wake structure, which complicate the prediction and management of wakes and introduce additional efficiency and load challenges [7].

Given these challenges, modeling wind turbine wakes is of paramount importance in the pursuit of efficient wind energy harvesting. Traditional methods of wake modeling often employ Computational Fluid Dynamics (CFD) simulations. Techniques such as Large Eddy Simulation (LES) and Reynolds-Averaged Navier–Stokes (RANS) equations have been widely used to simulate and study the dynamics of wakes. While these methods provide valuable insights, they are computationally intensive and require significant time to complete, rendering them impractical for large-scale or real-time applications [8].

Additionally, the wake dynamics of yawed turbines present unique challenges that current analytical models do not fully address. Despite the crucial role of yaw in real-world wind turbine operation, the body of research on yaw-induced wake behavior is notably sparse. Existing models often fall short in accurately representing wake behavior under yawed conditions, leading to significant gaps in the understanding and prediction of wake dynamics in these scenarios [9]. A comprehensive understanding of yawed wake dynamics is critical not only for improving individual turbine performance but also for optimizing the design and control strategies of wind farms. It can provide pathways for increasing overall energy yield and reducing mechanical loading on turbines, thus enhancing the durability and efficiency of wind farms [10].

With its ability to recognize patterns and learn from data, machine learning offers a promising alternative to traditional wake modeling. Leveraging machine learning techniques, such as symbolic regression, allows for the generation of models that can accurately predict wake behavior under various operating conditions, including yaw misalignment [11]. Particularly, symbolic regression provides the added advantage of producing transparent and interpretable models, a significant departure from the 'black-box' nature of many conventional machine learning methods [12]. Consequently, the development and refinement of machine learning-based symbolic regression models for predicting yawed wind turbine wakes represent a promising and emerging field of research. This approach holds significant potential for enhancing wind energy production and shaping the future of the wind energy sector.

2. Wind Turbine Wake Aerodynamics

Understanding the intricacies of wind turbine aerodynamics, specifically wake phenomena, plays a critical role in enhancing turbine performance and, consequently, the overall efficiency of wind energy systems [3][13]. Wind turbines, by their very nature, interact with wind flow, causing disruptions and giving rise to a wake—a region characterized by reduced wind speed and increased turbulence.

The fundamental principles underpinning wake aerodynamics in wind turbines are firmly grounded in the broader discipline of fluid dynamics and, specifically, the study of turbulence and vorticity [14][15]. As wind interacts with the turbine's rotor, a momentum deficit ensues in the immediate downstream region. This deficit translates into a change in velocity, often marked by a velocity deficit in the wake compared to the free stream wind speed [16].

The formation and propagation of wind turbine wakes are contingent upon many factors. From a meteorological perspective, atmospheric stability, wind speed, and turbulence intensity are major influencing factors [5][17]. Meanwhile, parameters related to turbine design and operation, such as rotor diameter, tower height, blade pitch, and turbine control strategies, can significantly modulate wake characteristics [18][19]. Understanding these factors is paramount for predicting wake behavior and optimizing wind farm performance.

Wake effects have a significant bearing on both individual turbine performance and the overall efficiency of wind farms. Owing to wake interference, downstream turbines (i.e., turbines located behind other turbines relative to the prevailing wind direction) often face reduced wind speeds, leading to lower power output [4][5][19][20][21]. Furthermore, the wake's turbulent nature increases the wind load's variability on the turbine structures, potentially resulting in increased structural fatigue and reduced component life [22][23].

To mitigate these detrimental wake effects, various strategies have been proposed and implemented. Wind farm layout optimization, for example, seeks to arrange turbines to minimize wake interference and maximize overall power production [24][25]. Similarly, active wake control strategies such as deliberate yaw misalignment and adaptive blade pitch control can redirect wakes away from downstream turbines [26][27].

Empirical research and computational modeling have been invaluable in extending the understanding of wind turbine wake aerodynamics. Real-world measurements of wake effects using advanced technologies such as LIDAR and SODAR provide critical insights into wake behavior under varying operational and environmental conditions [6][19][28][29][30]. Concurrently, computational studies utilizing methods such as Computational Fluid Dynamics (CFD) and Large Eddy Simulation (LES) have provided a platform to simulate and study wake dynamics in controlled conditions, enabling researchers to isolate and understand the influence of specific factors [8][31][32]. It is worth noting that Large Eddy Simulation (LES) is a computational technique frequently used for turbulence modeling and is often deemed advantageous for capturing a wide range of turbulent flow scales. However, it has its limitations. One of the primary constraints is computational expense, as LES demands significant computational resources and time, especially for high Reynolds number flows [33][34]. Additionally, the accuracy of LES is highly dependent on the quality of subgrid-scale models employed to represent unresolved scales, and inadequate modeling can lead to erroneous results.

The understanding and characterization of wake aerodynamics continue to evolve as researchers harness new technologies, adopt innovative modeling techniques, and continue to collect and analyze field data from wind farms operating worldwide. Through continued research and development, the wind energy sector hopes to overcome the challenges posed by wake effects and move closer to realizing the full potential of wind power.

The analysis of wind turbine wakes under normal operating conditions is a pivotal component in designing and optimizing wind farms. Over the years, various analytical wake velocity models have been proposed, each bearing unique assumptions and simplifications derived from flow-governing equations.

Popular models for wind turbine wakes under axial inflow conditions from the existing literature include the Jensen model [35], the Katic Model [35][36], the Larsen Model [37], the Frandsen Model [38], the B-P (EPFL) Model [39][40], the Tian Model [41], and the Gao Model [42]. However, the modeling of wakes under yawed wind turbine conditions is not extensively covered in the existing literature, and this represents an area requiring further investigation [43].

3. Wake in Yawed Wind Turbines

Yaw in wind turbines pertains to the rotation of a turbine around its vertical axis in relation to the wind's oncoming direction [44][45]. This ability to adjust and control yaw angles ensures the optimal operation of wind turbines, balancing the maximization of power output against the minimization of structural loads [46][47]. The mechanical systems enabling yaw adjustments are central to the functional design of modern wind turbines, ensuring that they can respond adaptively to fluctuating wind directions [48][49].

When wind turbines operate under yawed conditions, as shown in **Figure 1**, distinct changes occur in the downstream wake characteristics. The misalignment introduced by yawing the turbine causes a deflection and skewness of the wake, effectively steering it away from its normal trajectory [50][51]. Additionally, this yaw misalignment increases turbulence within the wake, leading to a more chaotic and diffuse wake structure [52].

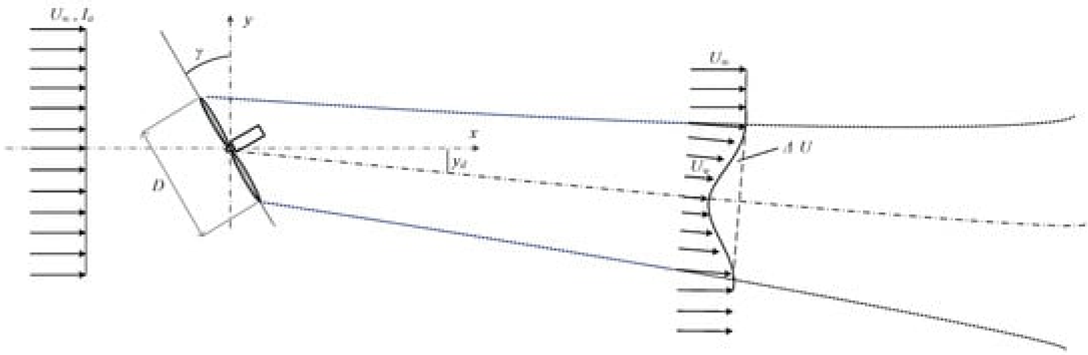

Figure 1. Schematic representation of a wind turbine yawed by the angle γ, illustrating the resulting wake deflection characterized by the wake deflection yd. Adapted from [9].

The phenomena involved in yaw-induced wake redirection have broad implications for wind farm operations. While the altered wake can influence the performance of downstream turbines, potentially leading to power losses and increased turbulence loads [44][52], strategic yaw misalignment can also be beneficial. By actively controlling the yaw angle of turbines, operators can effectively steer the wake away from downstream turbines. This active wake control method can potentially increase the overall power output of wind farms [53][54].

Comprehensive research has to be conducted to further characterize wind turbine wakes under different yaw conditions. Planned future studies, which will involve comparative analyses of wake features under various yaw angles, are anticipated to illuminate the complex dynamics of yaw-induced wakes [7][52][55][56][57].

4. Analytical Models for Yawed Wind Turbines

In 2016, Micallef and Sant [44] noted in their study on wind turbine yaw aerodynamics that, regrettably, no empirical models had been put forth to characterize the wake deformation in yaw. A handful of analytical models for predicting the wake characteristics of yawed turbines have been put forward in recent years [43]. These models and their limitations are discussed below.

4.1. Jiménez et al. [52] Wake Model for Yawed Conditions, 2010

Introduced in 2010, the wake model by Jiménez et al. [52] adopts a “hat-shaped” approach to predict the wake characteristics in yawed conditions. The model is particularly known for its straightforward computational architecture but has several limitations that need to be addressed.

- Limitations
  - The model has a tendency to exaggerate the deflection of the wake [9][43][58][59][60][61].
  - Additionally, this model has a tendency to underestimate the maximum velocity deficit [61].

4.2. Bastankhah and Porté-Agel [58] Wake Model for Yawed Conditions, 2016

Developed in 2016, the wake model by Bastankhah and Porté-Agel utilizes Gaussian functions to better capture the characteristics of wakes in yawed conditions. The model excels in its computational efficiency but also presents challenges with respect to empirical parameter estimation.

- Advantages
  - A cost-effective analytical approach for computational prediction of wake characteristics in the far wake [62].
- Limitations
  - The estimation of two empirical parameters is necessary to figure out the initiation of the far wake zone. However, obtaining universal values for these parameters is challenging, as their forecasts heavily rely on computer simulations or experiments. Consequently, the practicality of the wake model is significantly constrained [61].
  - Wake is significantly impacted by turbulence intensity, which is not sufficiently taken into consideration in this model [62].

4.3. Qian and Ishihara [9] Wake Model for Yawed Conditions, 2018

The wake model by Qian and Ishihara, formulated in 2018, also employs Gaussian functions but with distinct improvements over the Bastankhah and Porté-Agel model. Specifically, this model accommodates varying conditions of ambient turbulence and thrust, enhancing its practical utility.

- Advantages
  - In contrast to the Bastankhah and Porté-Agel model, this model incorporates input parameters that are expressed as functions of ambient turbulence intensity and thrust coefficient. This consideration is believed to improve the practicality of the model [61].
- Limitations
  - The model has a tendency to underestimate the maximum velocity deficit in scenarios involving yaw angles of 10° and 20° [63].

- The underestimation of maximum velocity deficit is especially evident in the instances of yaw angles $\gamma=20^\circ$ and $\gamma=30^\circ$ [61].

- More validation studies are necessary to support the efficacy of this model [61].

4.4. General Limitations of Existing Analytical Models for Yawed Wind Turbines

There are several disparities included within the wake models pertaining to yawed turbines. In their study, Dou et al. [43] extensively elucidated the variations in the concept of wake center across various models. In general, experts regard the wake center as the spot where the foremost velocity deficit occurs at each subsequent downstream position. Therefore, the maximum velocity deficit is considered to be the wake center. Another crucial assumption is that the suggested models for downstream velocity distribution are based on a presumption of symmetry in the streamwise velocity distribution around the center of the wake. However, this assumption is seldom validated by experimental findings. The presence of asymmetry in the flow conditions may significantly impact the operation of the downstream turbine, perhaps resulting in inaccurate predictions of the wake [43].

5. Role of Machine Learning in Wind Turbine Wake Modeling

Machine learning (ML) has recently emerged as a transformative paradigm across multiple domains, bringing innovative solutions and improved efficiency to long-standing challenges. Wind energy, specifically in the context of wake modeling, stands as a conspicuous beneficiary of this technological influx. Although conventional approaches like the Blade Element Momentum (BEM) method and Computational Fluid Dynamics (CFD) provide valuable insights, their limitations in accurately capturing complex aerodynamic behaviors or high computational cost have led researchers to consider data-driven approaches [12].

It is salient to note that machine learning's active application in modeling yawed wake characteristics such as deflection or velocity deficit has been relatively minimal. Nevertheless, its potent influence in related areas of wind turbine wake modeling is irrefutable. For instance, machine learning algorithms like Support Vector Regression (SVR), Artificial Neural Networks (ANNs), and Extreme Gradient Boosting (XGBoost) have been applied to accurately predict wake velocity and wake turbulence intensity [11]. These algorithms have demonstrated their ability to be commensurate with CFD simulations while operating at speeds akin to those of low-fidelity wake models.

Similarly, Genetic Programming (GP), another machine learning technique, has been used to formulate new analytical models for predicting wake velocities and turbulence intensities [64]. This highlights machine learning's adaptability in generating models that accommodate the complex and non-linear nature of wake effects, including the Atmospheric Boundary Layer (ABL) impacts.

Moreover, machine learning algorithms have been integrated with physics-based models to yield hybrid methodologies that strive for increased generalization. The focus on the generalizability of these models has been a noteworthy avenue of investigation, aiming to ensure that machine learning-based wake models can predict properties across multiple turbines and varying operating conditions [65].

Data-driven approaches have proven effective not only in static models but also in dynamic wind farm wake modeling, utilizing sophisticated deep learning techniques like Long Short-Term Memory networks (LSTMs) [66]. In addition, reinforcement learning has been employed for optimizing the power output of wind farms through yaw-based wake steering, showcasing machine learning's potential in real-time applications [67].

Nevertheless, while machine learning brings forth numerous advantages, it is crucial to exercise prudence. The limitations in machine learning approaches, particularly in the context of training data and the need for advanced regularization techniques, still present challenges that warrant further research [65].

Although machine learning has yet to be actively applied in creating data-driven models for yawed wake characteristics, it has played a significant role in advancing wind turbine wake modeling. Not only has it improved the accuracy and efficiency of existing models, but it has also opened avenues for real-time optimization and control. The synergy of machine learning with traditional computational methods presents an exciting frontier for the wind energy sector, promising more robust and versatile wake models in the future.

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