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# Wind turbine wakes modeling and applications: Past, present, and future

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A R T I C L E I N F O

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A B S T R A C T

In the past few decades, wind energy technology has undergone rapid development, with large-scale wind farms bringing about significant wake effect. Since the wake effect can have a serious impact on wind turbine (WT) performance, the development of accurate WT wake models is essential for the optimal design and control of wind farms. A comprehensive review of wake modeling in WT will provide an understanding the strengths and limitations of wake models, leading to the development of more accurate and cost-effective models that are better suited to meet the operational challenges of wind farms. This review investigates the whole evolution process of WT wake models, focusing on the modeling process and application prospects. The review analyzes different wake modeling methods and explores the evolution laws of wake models. On this basis, the evolution, categorization and comparison of wake models are discussed based on the environmental characteristics of mountainous and deep-sea complex wind farms and the structural characteristics of WT, along with the prospects and potential improvements of WT wake models for complex environments. In addition, it discusses the latest research on the practical application of WT wake models, emphasizing the importance of the wake effect in the design of WT and in the construction and application of wind farms. Finally, it summarizes the limitations inherent in wake-related studies of WT, proposing potential strategies to overcome these challenges. Through systematic analysis, this review aims to deepen the understanding of WT wake effects and promote the further development of wind power technology.

Nomenclature

| Abbreviations: | | | |
|---|---|---|---|
| Two-dimensional | 2D | Navier-Stokes | NS |
| Three-dimensional | 3D | Field Operation and Manipulation | OpenFOAM |
| Three-dimensional cosine shape | 3D-COTI | Open-source Simulation Tool for Advanced Wind Turbine Systems | OpenFAST |
| A 3D super-Gaussian wake model | 3DJSG | Polynomial expansion | PE |
| Atmospheric boundary layer | ABL | Proportional integral | PI |
| Actuator disc model | ADM | Proportional integral differential | PID |

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(*continued*)

| Abbreviations: | | | |
|---|---|---|---|
| Actuator line model | ALM | Proper orthogonal decomposition | POD |
| Alternating direction method of multipliers | ADMM | Power related | PR |
| Absolute error | AE | Pattern search | PS |
| Annual energy production | AEP | Particle swarm optimization | PSO |
| Average error variance | AEV | Reynolds-averaged Navier-Stokes | RANS |
| Artificial intelligence | AI | Random forest | RF |
| Actuation method | AM | Root mean square error | RMSE |
| Adaptive model predictive control | AMPC | Reduced order model | ROM |
| Artificial neural network | ANN | Random search | RS |

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(*continued*)

| Abbreviations: | | | |
|---|---|---|---|
| Blade element momentum | BEM | Simulated annealing | SA |
| Backpropagation neural network | BPNN | Sequential Least SQP | SLSQP |
| Computational fluid dynamics | CFD | Sequential quadratic programming | SQP |
| Convolution neural network | CNN | Sum of squared residuals | SSR |
| Cost of energy | COE | Sum of the squared deviation of testing data points | SST |
| Cost per energy | CPE | Simulator for Wind Farm Applications | SOWFA |
| Double-Gaussian | DG | Technical University of Denmark | DTU |
| Dynamic mode decomposition | DMD | Technical University of Berlin | TUB |
| Direct numerical simulation | DNS | Variance normalized root mean square error | VNRMSE |
| Dynamic wake models | DWMs | Weather research and forecasting model | WRF |
| Evolutionary algorithm | EA | Wind Turbine | WT |
| Extended DMD | EDMD | Wind Atlas Analysis and Application Program | WAsP |
| Extended pattern search -Multi agent system | EPS-MAS | Wind Simulation | WindSim |
| Finite element | FE | Wind Systems Engineering | WindSE |
| Free vortex wake | FVW | Xie and Archer | XA |
| Fatigue, Aerodynamics, Structures, and Turbulence | FAST | | |
| FLOw Redirection and Induction in Steady-state | FLORIS | Notations : | |
| Genetic algorithm | GA | The synthetic wake velocity of ith WT | $u_i$ |
| Generative adversarial network | GAN | The wind speed of the ith WT under the influence of the jth WT | $u_{ij}$ |
| Gaussian wake model proposed by Bastankhah and Porté-Agel | GaussBPA | The velocity when the jth WT operates in isolation | $u_j$ |
| Gaussian wake model proposed by Ishihara | GaussISH | The synthetic turbulent intensity of ith WT | $I_i$ |
| Gauss-Curl hybrid | GCH | The turbulent intensity of the ith WT under the influence of the jth WT | $I_{ij}$ |
| Gaussian process | GP | The turbulent intensity when the jth WT operates in isolation | $I_j$ |
| Global search | GS | The free inflow turbulent intensity | $I_0$ |
| Global Wind Energy Council | GWEC | The predicted value | $\widehat{U}_{.}$ |
| Levelized cost of energy | LCOE | The measurement value | $U_{.}$ |
| Large eddy simulation | LES | The mean value | $\overline{U}_{.}$ |
| Levelized production cost | LPC | The observed value | $\overline{U}_{.,obs}$ |
| Local search | LS | The number of predictions that represent a standard deviation of the mean observed value | $N_{out}$ |
| Long short-term memory | LSTM | The sample size | $N$ |
| Mean absolute error | MAE | The standard deviation | $\delta_p$ |
| Mean absolute percentage error | MAPE | The simulated wind speed ratio | $R_s$ |
| Mass flow conservative superposition | MFCS | The measured wind speed ratio | $R_m$ |
| Mass flow and thrust conservative superposition | MFTCS | R-square | $R^2$ |
| Model predictive control | MPC | Line correlation coefficient | $\rho$ |
| Multi Start | MS | Number of times the predicted value of a model exceeds the standard deviation of the mean observed value | $Out$ |
| Net present value | NPV | Relative error | $E_R$ |

## 1. Introduction

The global climate crisis is escalating, prompting countries to intensify their efforts in promoting a transition to cleaner energy sources to combat rising temperatures. Despite the entrenched dominance of fossil fuels such as coal, oil, and natural gas in the global energy consumption landscape, the share of renewable energy is steadily on the rise (Murdock et al., 2021). Recent years have witnessed a rapid reduction in the cost of renewable energy on a global scale, driven by supportive low-carbon policies, resulting in continuous growth in the deployment of new energy generation technologies. However, the current growth rate of renewable energy is still insufficient to meet the requirements of the Paris Agreement for achieving “net zero emissions” by 2050 (Van Soest et al., 2021). Therefore, shifting from major fossil fuels to cleaner, renewable forms of energy and expanding the scale of renewable energy generation are essential for the decarbonization of the world’s energy system (Liu et al., 2022a). Wind energy, as a mature and competitive renewable energy source, plays a pivotal role in reducing carbon emissions (Sadorsky, 2021; Guo et al., 2022a; Liu et al., 2023). According to estimates from the Global Wind Energy Council (GWEC), the global assembly of wind turbine (WT) will need to triple its current growth rate over the next decade to meet the 2050 net zero emissions goal and avoid the severe impacts of climate change (Global Wind Energy Council G, 2021). Wind energy is at the forefront of the clean energy revolution, and the wind power industry is poised to experience substantial growth and development (Wang and Wang, 2022).

To maximize the utilization of wind energy resources and ensure economic feasibility, the construction of wind farms is increasingly trending towards centralization and large-scale development. In large-scale wind farms, numerous WTs are typically installed. Through large-scale development, wind farms can reduce initial land use, infrastructure costs, and subsequent operational and maintenance expenses. However, due to the presence of wake effects, this centralized layout can also result in a certain amount of energy production loss. Studies indicate that the wake effect can lead to power losses of 10∼40% in wind farms and significantly increase the fatigue load on downstream WTs (Fei et al., 2020; Cai et al., 2021). To mitigate the negative impact of the wake effect, it is crucial to understand their nature. Fig. 1 illustrates a schematic diagram of the WTs’ wake structures. The wake effect refers to the phenomenon where natural wind, after passing through a WT, converts part of its energy into mechanical energy, resulting in reduced wind speed, increased turbulence, and wind shear. In other words, as the airflow passes through the blades of the WT, a part of the wind energy is converted into electrical energy. According to the principle of conservation of energy, the energy of the airflow is reduced. In fact, the blades of the WT act as a wind speed blocker, creating wake effect of downwind WTs similar to that of a ship. In this region the wind speed is lower than the incoming wind speed, the turbulence degree is high and there are complex structures, various scales and structures of vortices, which reduces the output of downstream WTs to a certain extent. However, the increase in turbulence will increase the fatigue load of downstream WTs, resulting in consequences such as vibration and mechanical damage (Ivanell et al., 2020). Firstly, the evolution of wake is usually influenced by several factors, including ambient turbulence, rotor yaw and tilt. As the blades rotate, vortices are generated at the trailing edge, forming spiral tip vortex and a central vortex, which are dominant features in the near-wake region. However, in the far-wake region wake evolution is affected by the interaction with the atmospheric boundary layer (ABL).

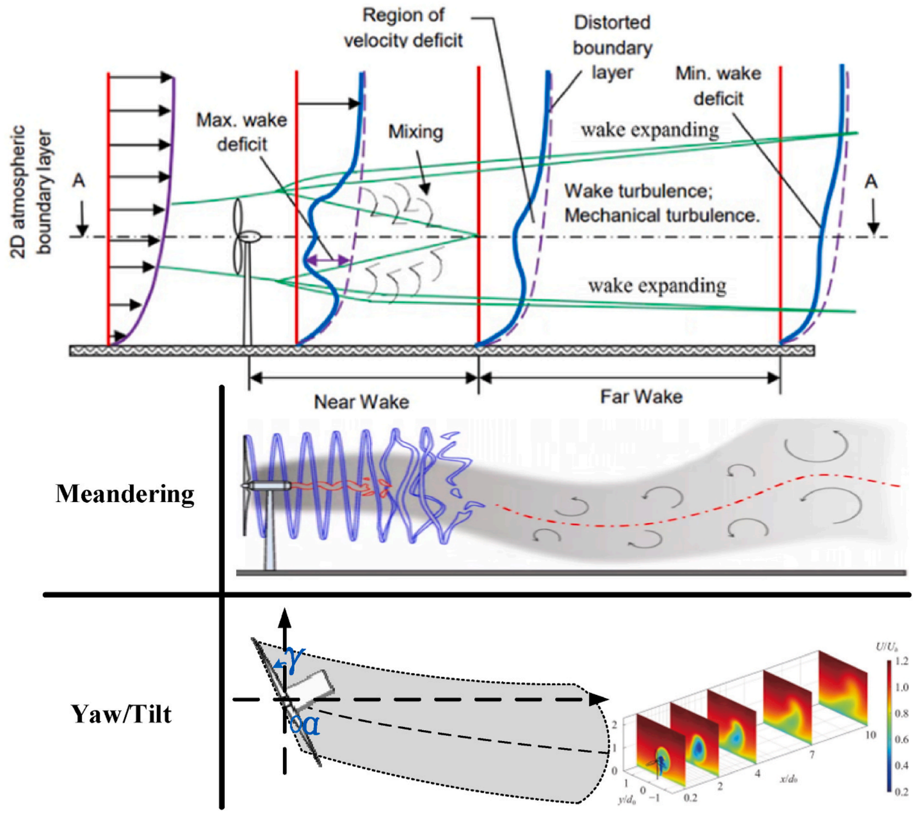



**Fig. 1.** Schematic diagram of the wake structure of WT (Kabir and Ng, 2019; Porté et al., 2020; Rak and Santos Pereira, 2022; Zong et al., 2020a).

Higher turbulence in the ABL increases the turbulent mixing effect leading to earlier breakup of the blade tip vortices and faster recovery of the mean velocity in the wake, which affects the structure of the wake and reduces the wake length (Neunaber et al., 2020). In addition, a turbulence phenomenon called meandering exists in the far-wake region, which represents larger-scale turbulence. Meandering increases the mixing of the wake with the surrounding high-velocity flow and accelerates wake recovery, thereby increasing the power output of downstream WTs. At the same time, meandering causes downstream WTs to switch between the free flow and wake of upstream WTs, thus increasing the fatigue loads on downstream WTs (Larsen et al., 2020). Secondly, the motion of the rotor has a significant impact on the evolution of the wake. When the rotor is yawed or tilted, it generates counter-rotating vortices that alter the path of the wake evolution. The change in rotor orientation introduces asymmetry to the flow field, which changes the conventional shape of the wake. The altered flow field dynamics can result in a curled or kidney-like shape of the wake stream (King et al., 2020).

Therefore, it is essential to reduce the influence of the wake effect. Existing studies suggest that the wake effect can be mitigated by focusing on three aspects :

1) The aerodynamic characteristics of the rotor are optimized to reduce wake effect during WT design process.
2) Before the construction of wind farms, the influence of the wake effect should be fully considered for the site selection of wind farms and the layout of WT.
3) During the operation of wind farms, the control strategy of WT should be adjusted according to the real-time wake characteristics to reduce the influence of the wake effect.

In summary, the wake effect is a critical factor affecting the operation of wind farms. This effect must be considered during WT design, wind farm construction, and operation (Boorsma et al., 2020; Castellani et al., 2015; Cao et al., 2022). A direct solution to the wake effect is to increase the space between WTs and restore the wake to an undisturbed free-flow state. The construction of wind farms usually requires a balance between a variety of factors, including environmental, ecological, land constraints, airspace use, and economic considerations. Given the trade-offs between these factors, the vast majority of WT in service operate under the influence of wake (He et al., 2023a). Therefore, it is important to study WT wakes propagation laws and the development of high-precision engineering wake models to improve wind energy utilization.

Fig. 2(a) shows the trend in the number of articles on wake-related research obtained from keyword search. The number of published articles related to wake research has experienced a significant increase since 2008, with over 50 articles published every year. This indicates that the studies of WT wakes have become a popular topic in the wind power industry. Fig. 2(b) shows the network visualization of the distribution of related studies with WT wakes as the search term. It can be demonstrated that in wake research, numerical modeling of wakes, studies of wake characteristics, and research on wind farm performance are closely related. Although a great deal of results has been achieved at home and abroad in the study of WT flow fields, there is still an increasing demand for more efficient, accurate and reliable WT wake models for wind farm design and optimization. More research and development work needs to be invested to clarify the evolution of modern WT flow fields.

To accurately describe the complex aerodynamic behaviors of WT, researchers have continuously proposed and refined WT wake models (Lundquist et al., 2019). Wind tunnel experiments and field measurements constitute the primary methods for wake investigations. Wind tunnel experiments, based on similarity theory, reveal the flow field dynamics of WT and wind farms, providing critical insights into the flow field structure of WT in boundary layer flows (Bottasso et al., 2020). Numerous field measurements using anemometers and LiDAR

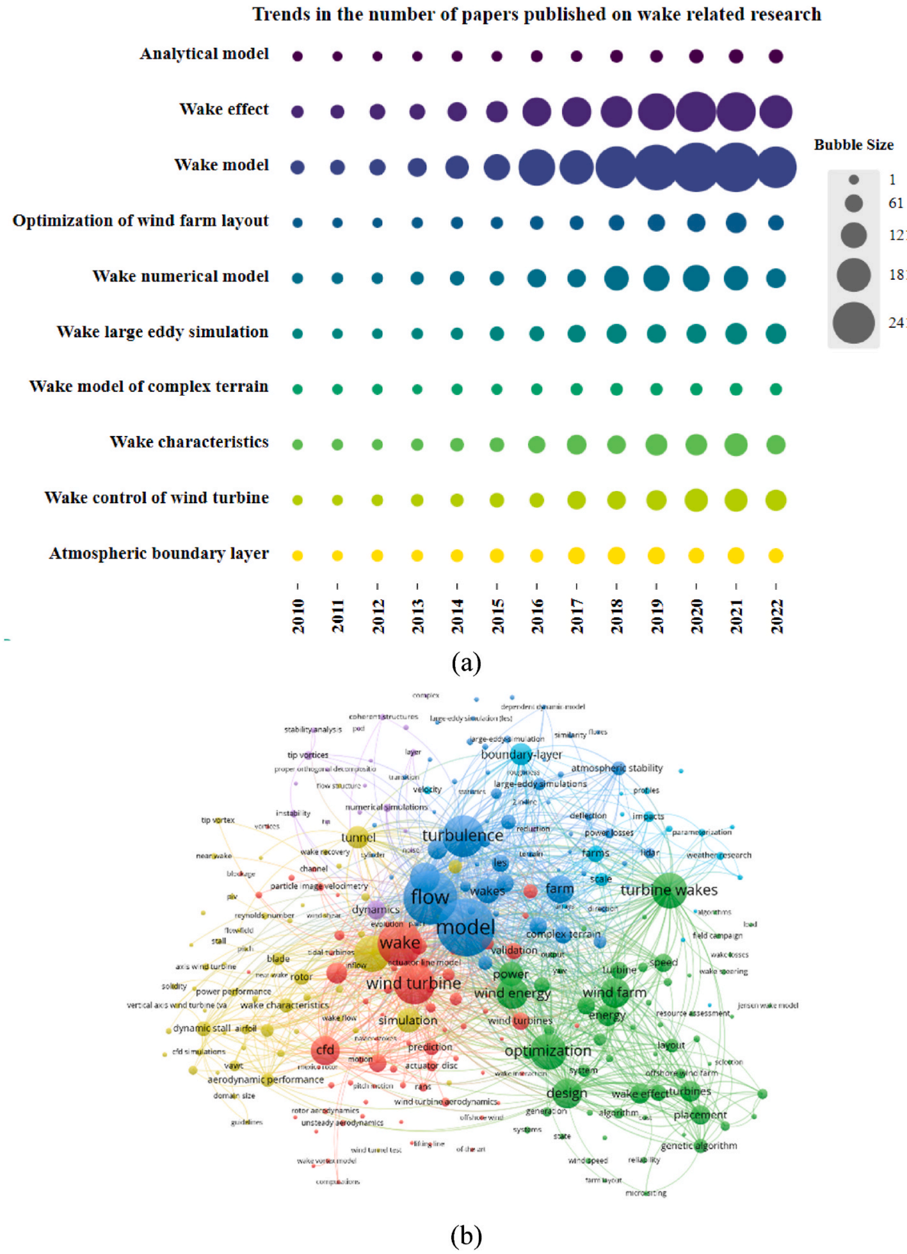



**Fig. 2.** Statistics of WT wake-related studies. (a) Trends in the number of articles published on wake-related research. (b) Network visualization of relevant research distribution with WT wakes as a search keyword.

instruments have been conducted to study the real insights into the flow field dynamics of wind farms (Gottschall et al., 2020). However, the lengthy measurement times and high equipment costs have limited the development of wake measurement experiments. With the advancement of computational technology, a variety of numerical methods have emerged (Sanderse et al., 2011). The computational fluid dynamics (CFD) method for solving the Navier-Stokes (NS) equations has been proposed. The direct numerical simulation (DNS) method, which directly solves the NS equations, consumes a large amount of computational resources and has not yet been applied in flow field research. To address the challenges of Reynolds-averaged unsteady turbulence, a large eddy simulation (LES) technique has been proposed to simulate large-scale turbulence to obtain dynamic information within the solvable scale range. Based on the assumption of isotropy, the Reynolds-averaged Navier-Stokes (RANS) method has been proposed to simplify the wake analysis calculations by treating the unsteady turbulent motion as a steady state problem. However, the CFD methods based on LES and RANS still require millions of grid levels, which are computationally and memory intensive and cannot meet engineering needs in terms of timeliness. Subsequently, based on the principle of mass and momentum conservation and the assumption of self-similarity in the wake velocity distribution, an explicit relationship between the aerodynamic coefficient of the WT and the wake velocity deficits can be established, leading to the proposal of a semi-empirical engineering wake model (Schmidt et al., 2020). New wakes modeling architectures combining CFD to obtain flow field data and machine learning are booming (Kabir et al., 2020). In the context of the rapid development of the wind power industry, a review of techniques and methods for flow field simulation is necessary to guide the design and operation optimization of new wind farms in the future. Table 1 summarizes past reviews on wake research. These reviews can be categorized into four perspectives:

The first aspect is the aerodynamics and wake structures of WT wakes. Aerodynamic studies of the WT have made a significant

**Table 1**
Review of wake-related research.

| Aspect | Ref. | Year | Country | Wake model | Focus on |
|---|---|---|---|---|---|
| Wake aerodynamics/ structures | Vermeer et al. (2003) | 2003 | Netherlands/ Denmark/Spain | Wind tunnel experiments/Field experiments/Numerical modeling | ● Near-wake and far-wake region. ● Far-wake decay laws. |
| | Stevens and Meneveau (2017) | 2017 | Netherlands/USA | Numerical modeling/analytical modeling | ● Wind tunnel experiments, field measurements, and numerical and theoretical developments. ● Interactions and coupling between wakes and the ABL. |
| | Porté et al. (2020) | 2020 | Switzerland/UK | Analytical modeling/CFD/wind tunnel experiments/Field experiments | ● WTs wake and its interaction with ABL. |
| | He et al. (2022) | 2022 | China | Wind tunnel experiments | ● Dynamic wake behavior. ● Potential for active yaw control. |
| Wake modeling | Koren et al. (2011) | 2011 | Netherlands | Actuation method (AM) | ● The generalized AM and the direct modeling. |
| | O'Brien et al. (2017) | 2017 | Ireland | CFD | ● Near wake. ●Wake predictions by commercial CFD codes. |
| | Breton et al. (2017) | 2016 | Sweden/Canada/ Denmark | LES | ● Best practices for high-fidelity LES of wind farms under various atmospheric and terrain conditions. |
| | Göç et al. (2016) | 2016 | Denmark | Wake models developed at DTU | ● How to best utilize six wake models. |
| | Yang and Sotiropoulos (2019) | 2019 | USA/China | LES | ● Origin, characterization and computational modeling of wake meandering. |
| Wake data measurements | Sun et al. (2020a) | 2020 | China | – | ● Validation of the wake models. |
| Application of wake modeling | Shakoor et al. (2016a) | 2016 | Malaysia/Pakistan/ China | Jensen model | ● Wind farm layout optimization problem. |
| | Nash et al. (2021) | 2021 | USA | 3D wake model | ● Active wake control strategies. |

contribution to the achievements of modern wind energy. By reviewing early experimental work on near-wake and far-wake, Vermeer found that near-wake focuses on the performance and physical processes of power extraction, whereas far-wake flow studies focus on the interactions of WTs placed in complex fields (Vermeer et al., 2003). He also summarized the behavior of the dynamic wake models (DWMs) from the perspective of the near-wake and far-wake (He et al., 2022). Stevens discussed the mean velocity distribution and turbulence characteristics of large wind farms, with an emphasis on the interactions and coupling between wake and ABL (Stevens and Meneveau, 2017). Subsequently, Porté-Agel also reviewed the interaction of ABL with WTs and wind farms, discussing the role of atmospheric turbulence in the main wake region (Porté et al., 2020). By reviewing theoretical, experimental and computational studies of WTs and wind farm flows, the nature, characteristics and effects of the wake region are analyzed and understood.

Secondly, from the aspect of WT wakes modeling, Sanderse summarized the research progress of generalized actuators based on aerodynamic theory and direct models for calculating WT wakes (Koren et al., 2011). O'Brien analyzed the commonality of the WTs' near-wake by studying commercial CFD and finite element (FE) modeling strategies (O'Brien et al., 2017). Breton summarized the wake variation laws of LES for WT under different configurations, and proposed guidance suggestions for the problems existing in the LES method (Breton et al., 2017). Göçmen compared six wake models developed by the Technical University of Denmark (DTU) at Sexbierum onshore and Lillgrund offshore wind farm (Göç et al., 2016). Yang reviewed the DWMs in terms of the mechanism of wake meandering generation (Yang and Sotiropoulos, 2019). These studies provide a reference for wind power research to understand and use wake models.

Thirdly, regarding wake data measurements, Sun reviewed the full-scale measurements of the wind farm full-wake (Sun et al., 2020a). Based on the operational characteristics of different types of WTs, reference databases were established for various test points, technologies, procedures, challenges, economic control, and main results to provide data support for wake research.

Finally, in the application of WT wake models, Shakoor summarized the application of the Jenson wake model in wind farm layout optimization (Shakoor et al., 2016a). Subsequently, Nash reviewed the different active wake control strategies of WTs (Nash et al., 2021). These researches pointed the way out of the traditional thinking of directional solutions to the wake loss problem.

While these studies have played a significant role in the development of WT wakes, there is a lack of a comprehensive review and discussion the development and application of wake models. Moreover, although there are significant differences in the operating environments of offshore and onshore wind farms, a review of the experiences and results of research on onshore WT wakes can provide valuable scientific and technical support for the development of offshore wind power. Therefore, this study reviews recent research on WT wakes modeling and applications. It analyzes and summarizes the development of wakes modeling, optimization of wakes modeling for complex terrain, and the applications of wake models in detail. For this purpose, 270 papers related to WT wakes research were collected. Categorized and reviewed by wake modeling methods and applications, and summarizes the development trend of wake-related research on WT. The specific contributions of this study are as follows:

1) By reviewing the development process of WT wakes modeling, the advantages and disadvantages of different types of wakes modeling are summarized. Then, for the analytical/semi-empirical wakes modeling of WT under the influence of multiple WTs, the limitations of the existing wake superposition strategies are reviewed, and future development trends are analyzed. Next, the evaluation criteria for wake models are summarized, and suggestions for wakes modeling evaluation are proposed according to the characteristics of wake modeling. Finally, software for wakes modeling is reviewed.
2) An overview of WT wakes modeling under complex operating conditions is presented. It focuses on the analysis of WT wakes modeling under the influence of complex mountainous terrain and wind conditions, and puts forward suggestions for the development of wakes modeling for WT under complex onshore terrain. In addition, considering the influence of the deep-sea environment and the structure of floating WT on the evolution of the wake, an outlook on the wakes modeling of floating WT is proposed from the perspective of the motion of floating platforms and wake characteristics.
3) Typical applications of wake models for WT are discussed. Three scenarios of wind farm layout optimization, WTs control and

resource assessment are discussed in detail, which are conducive to the understanding of the interactions between WTs clusters and the wake effects. Corresponding suggestions are made based on research issues such as model accuracy, model scale and model simplification, which indicate the research direction of the WT wake effect.

Fig. 3 shows the overall framework of this review. Section 2 describes the process of describing the WT wakes modeling. Section 3 reviews and summarizes the wake modeling of WTs in mountainous and deep-sea. Section 4 discusses and summarizes typical applications of wake models. Section 5 discusses the existing problems of the wake development from WT wakes modeling and applications, and indicates future directions. Section 6 summarizes this review. This paper can provide a meaningful reference for researchers working on the aerodynamics of WT and the impact of wake effects on performances of WT.

## 2. Approaches of wind turbine wakes modeling

The main work of this section is to review the development process of WT wakes modeling. Wakes modeling are description of the aerodynamic changes around the WT. It mainly consists of four parts: WT wakes modeling, wind farm wake superposition methods, wake models evaluations and simulation software.

### 2.1. Wind turbine wakes modeling

Understanding the flow field mechanism of WTs and wind speed distribution laws in the wake region are essential scientific challenges in the current utilization of wind energy. To enhance the speed and accuracy of capturing the wake evolution, WT wake models have been continuously improved. Fig. 4 shows the evolution of wakes modeling process. In recent years, the interaction between the ABL and WT has been studied through field measurements, wind tunnel tests and modeling analysis. These can be broadly classified into experimental methods, numerical modeling, analytical/semi-empirical modeling and data-driven modeling.

#### 2.1.1. Experiment methods

The experimental methods to study the wake evolution of WTs are divided into two ways: wind tunnel experiments and field measurements. Wind tunnel experiments utilize the principles of geometric similarity, flow similarity, and dynamic similarity to simulate the aerodynamic characteristics of WTs during operation, in order to provide realistic fluid dynamics information about vortex evolution, wake bending effects, and the interaction of the wake with complex terrain (He et al., 2022). Typically, realistic wake characteristics can only be simulated if the model's tip speed ratio and Reynolds number match those of full-size WTs. However, in wind tunnel experiments, it is difficult to satisfy both the similarity of the blade tip speed ratio and the consistency of the Reynolds number (Yang et al., 2022a). Nevertheless, wind tunnel experiments remain the basis of wake research, particularly in the studies involving complex terrain wake, floating WT wakes, and wake evolution under the influence of turbulence. Field testing involves full-scale measurements of wind speeds at wind farms using advanced sensor equipment to obtain highly reliable data. In the USA, the Rotor Aerodynamics, Aeroelastics, and Wake project and the American WAKE experimeNt use sensors, drones, and aircraft to collect atmospheric and wind data around and within wind farms. These efforts are aimed at analyzing and observing interactions between WTs, atmospheric interactions within wind farms (Letizia et al., 2023; Puccioni et al., 2023). Wind field measurements help to avoid limitations present in typical wind tunnel experiments, such as low Reynolds numbers and reduced geometries (Sun et al., 2020a). However, field measurements are time-consuming and the data quality is susceptible to the measurement equipment (Adaramola et al., 2011). Currently, typical wind farm wake measurements are available from all over the world, including the Goodnoe Hills wind farm in the United States, the Central Iowa wind farm, the Myres Hill wind farm in the United Kingdom, the Energy Research Center of the Netherlands test farm, the Sexbierum wind farm, the Nørrekær Enge wind farm in Denmark, the Vindeby wind farm, the Horns Rev wind farm, and the Middelgrunden wind farm in Denmark, as well as the Zhangjiakou wind farm, the Shiren wind farm, and the Longyuan Rudong Superjiantai wind farm in China, and the Alpha Ventus wind farm in Germany (Sun et al., 2020a). These available data contain wake data from onshore flat and complex terrain, as well as from offshore floating wind farms. And these data were used to realize the study of blade aerodynamic characteristics, wake flow field characteristics, ambient turbulence and floating platform motion.

#### 2.1.2. Numerical modeling

For carrying out numerical modeling studies of WT wakes, the first step is to model the WT. Currently, there are two main WT modeling approaches: the direct full resolution method and the generalized AMs. The direct full resolution method is to set up a grid directly on the blade geometry and calculate the entire wake from the blade boundary layer to the far-field boundary. In order to accurately resolve the blade

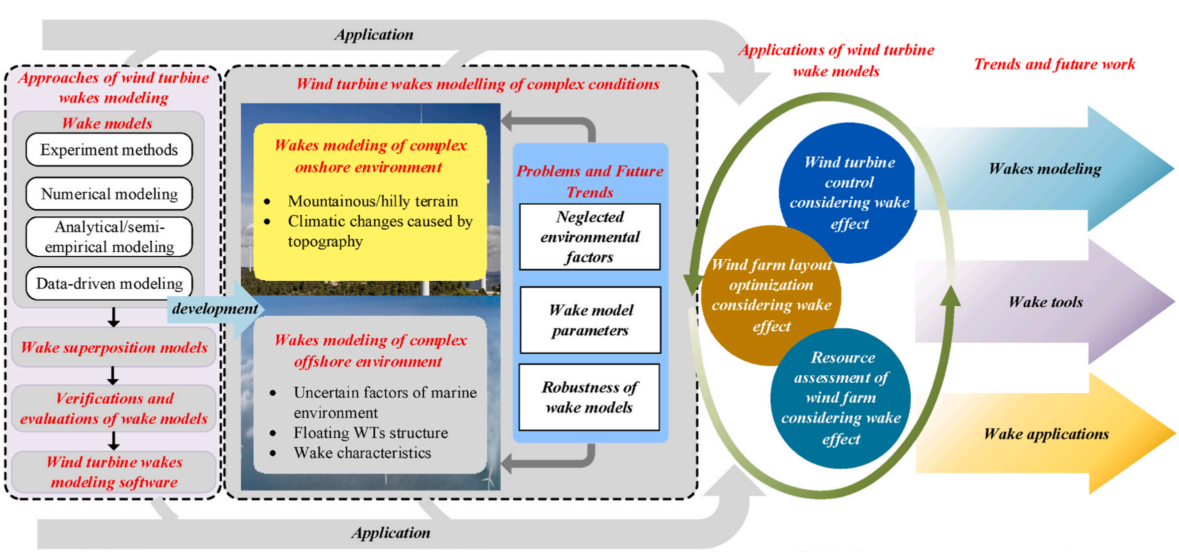



**Fig. 3.** Schematic diagram of this review.

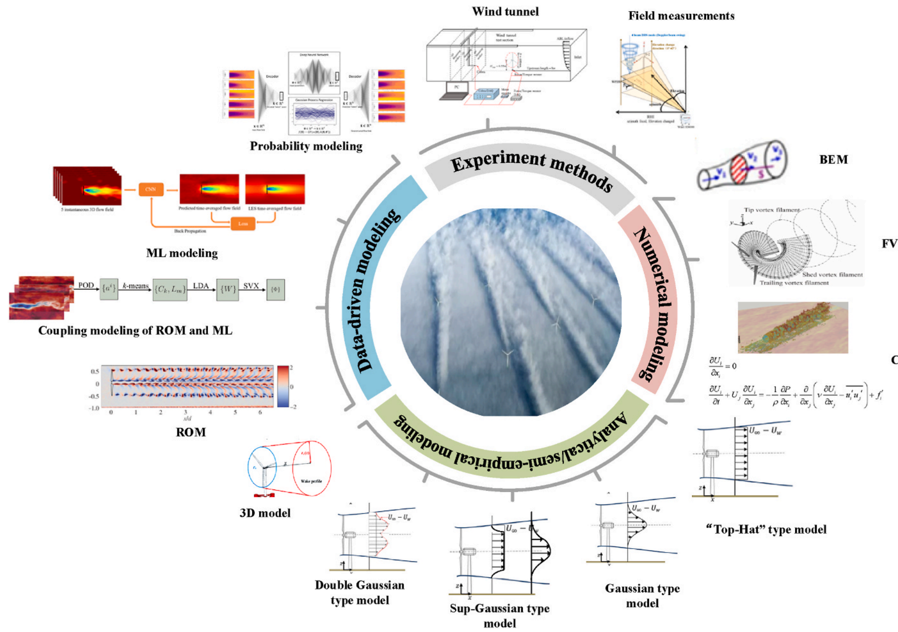



**Fig. 4.** Various methods of WT wakes modeling (Sanderse et al., 2011; Yang et al., 2022a; Wang et al., 2022; Bastankhah et al., 2014; Debnath et al., 2017; Ali et al., 2021a; Zhang et al., 2021; Renganathan et al., 2021).

geometry, a large number of meshes need to be computed. Therefore, this method is difficult to be used for flow solving in large-scale commercial WTs. The generalized AMs represent the effect of the WTs' blades on the flow by representing the volumetric forces of blade lift and drag. The method does not need to take into account the geometry of the WT, which is equivalent to simple geometries such as the actuation discs method (ADM) (Abraham et al., 2019), actuation lines method (ALM) (Abdelsalam et al., 2014) or actuation surfaces method (Ali and Cal, 2020), to reduce the difficulty of meshing. Firstly, the aerodynamic forces on each blade element are calculated using Blade element momentum (BEM) theory. Then, these aerodynamic forces are converted into volumetric force density and applied to the CFD grid. Finally, the calculated volumetric force density is added as a source term to the NS equations, which are then solved using CFD methods to obtain the flow field information. AM can obtain the same flow field information with relatively less time cost, and therefore it has been widely used in numerical simulation studies of wind farm wakes (Gao et al., 2021; Meng et al., 2020; Liu et al., 2021).

Aerodynamic analysis of WTs can be conducted using BEM, Vortex Method, and CFD. BEM is based on the static equilibrium wake assumption, which is superior in calculation time but sacrifices the accuracy of calculation. When the WT is in stall and yaw conditions, the BEM cannot be calculated accurately. Vortex method includes aerodynamic calculation of the blades and wake vortex calculation (Lee et al., 2022). The aerodynamics of the blades are simulated by lifting lines or lifting surfaces, which are highly accurate and computationally efficient. Vortex treatment commonly involves prescribed and free vortex wake (FVW) methods, where the FVW can simulate the transformation of vortex shapes and allows the vortex lines to move freely. This method is more accurate and physically consistent, suitable for simulating dynamic and complex conditions, and fully considers the mutual interference between the blades and wake (Sebastian and Lackner, 2012; Shi et al., 2014). However, the vortex method is based on the assumption of incompressible potential flow, it is unable to capture flow phenomena arising from viscous and compressible effects (Lee and Lee, 2019). Additionally, The CFD technology is widely used to describe the aerodynamic characteristics of WT blades, the flow characteristics of blades and wakes (Giahi and Dehkordi, 2016; Bai and Wang, 2016). The physical characteristics and flow of the fluid around the WT are restricted by three basic physical principles: mass conservation, momentum conservation, and energy conservation, which can be simulated by solving the NS equation (Daniele et al., 2020). Generally, the WT wake models established by the CFD method can be divided into the DNS method (Ohya et al., 2012), RANS (Abdelsalam et al., 2014)、 LSE method (Sedaghatizadeh et al., 2018; Uchida et al., 2021) and detached eddy simulation (DES) method (Spalart, 2009). The DNS needs to directly solve turbulent vortex structures at all scales, and thus its mesh scale must be smaller than the minimum vortex scale of the turbulent fluid, which must lead to the huge number of meshes to be solved using the DNS method (Li et al., 2020). LES requires fewer grids and lower computational cost when solving the average flow field in the eddy viscosity mode. However, a lot of computational resources are required to solve the flow field in detail (Porté and -Agel, 2004; PortÉ et al., 2000; Stoll et al., 2008; Wu et al., 2015). Compared with DNS and LES, RANS, which can solve the averaged processed NS equations with a coarse mesh, has been widely accepted for its small computational effort and has been widely used in engineering (Sanderse et al., 2011). Although the RANS method has many incomparable advantages, previous studies pointed out that the RANS method has some shortcomings in solving such complex flow problems as WTs wake, such as underestimating the deficit of wake velocity, delaying the recovery of wake and reducing the wake radius. To address the limitations of the LES and RANS models, researchers have attempted to integrate the advantages of both LES and RANS approaches into a single solving strategy, resulting in the development of hybrid models. The DES hybrid method, for instance, employs the RANS approach for near-wall regions and the LES approach for the remainder of the flow. This method is applicable to any turbulence model that has properly defined turbulence length scales and sufficient localization (Squires, 2004). The advantages and disadvantages of different numerical methods are shown in Table 2.

### 2.1.3. *Analytical/semi-empirical modeling*

Many studies have continuously improved the numerical modeling of WT wakes, and obtained expressions for the velocity deficit by idealized assumptions or fitting of experimental data to meet different boundary and wind conditions. According to the characteristics of the wake models, the analytical/semi-empirical modeling can be roughly divided into the "top-hat" type model, Gaussian type model and 3D

**Table 2**
Advantages and disadvantages of different numerical wakes modeling.

| Method | Advantages | Disadvantages |
|---|---|---|
| BEM | ● Fast calculation speed. | ● Unsuitable for dynamic wake simulations. |
| FVW | ● Suitable for dynamic and complex simulations. | ● Both the initial vortex core size and the relative total viscosity coefficient are difficult to determine.<br>● Inability to capture flow phenomena arising from viscous and compressible effects. |
| DNS | ● No assumptions or simplifications are made about turbulent flow, which results in accurate calculations. | ● It requires many computational grids, which cannot be applied.<br>● It is not suitable for the wake numerical simulation of large wind farms.<br>● Unsuitable for dynamic wake simulations. |
| LES | ● It can well predict the unsteady and non-linear characteristics of turbulence.<br>● Suitable for dynamic wake simulations. | ● Requires many computational mesh.<br>● The scene of the small eddy does not perform well. |
| RANS | ● Mesh requirements are relatively low, usually needing to meet wall-normal mesh density requirements. | ● Abandonment of modeling of non-constant turbulence.<br>● Nonlinearities make it extremely difficult to accurately characterize turbulence details by analytical methods.<br>● Unsuitable for dynamic wake simulations. |
| DES | ● Combining the advantages of RANS and LES.<br>● Higher accuracy. | ● Modeling complexity.<br>● Decreased accuracy or unstable values may occur in the transition region between RANS and LES. |

model. Table 3 shows the theoretical basis and characteristics of the WT wakes analysis/semi-empirical modeling.

“Top-hat” type wake models: Jensen and Katic first described the flow around the WTs. Based on the assumption that the wake width expands linearly with downstream distance and the velocity is uniformly distributed in the wake surface perpendicular to the axis of the WT, a relationship between the velocity deficit and the axial induction factor, known as the Jensen model, was established (Jensen, 1983). This model is based on the one-dimensional momentum conservation principle of an ideal WT and is only suitable for linear wake modeling on flat terrain. Larsen considered the flows to be stationary and incompressible. Larsen model was obtained by describing the wake region of the WT through the Prandtl turbulent boundary layer equation. In contrast to the Jensen model, the Larsen model is not only a function of the axial distance, but also of the radial distance. This eliminates the step problem in the Jensen model (Larsen, 1988). Subsequently, Frandsen based on the momentum conservation theory and assuming self-similarity of the wake expansion coefficients proposed the Frandsen wake model (Frandsen et al., 2006). The proposal of the “top-hat” type wake model has aroused the attention of wind power research on the wake.

Gaussian type wake models: The “top-hat” type wake models assume that the wake is only related to the downstream WTs’ position, and that the wake velocity is uniformly distributed on both the horizontal and vertical axes. This seriously underestimates the wake velocity at the hub height of the WT and overestimates the wake velocity at the wake edge. Moreover, through wind tunnel experiments and wind farm measurements, the wake velocity profiles in the far-wake region downstream of the WT is Gaussian type (Sun et al., 2020a). Bastankhah and Porté-Agel described the velocity profile of the far-wake using a Gaussian function, and derived the GaussBPA model from the momentum and mass conservation, which promotes the development of the Gaussian type wake models (Bastankhah et al., 2014). After years of development, these

**Table 3**
Theoretical basis and characteristics of WTs wake analytical models.

| Model | Wake width expression | Wake velocity profile | Theory | Near wake |
|---|---|---|---|---|
| Jensen model (Jensen, 1983) | Linear | “Top-hat” type | Mass conservation | × |
| Larsen model (Larsen, 1988) | – | “Top-hat” type | Mass conservation | × |
| Frandsen model (Frandsen et al., 2006) | Nonlinear | “Top-hat” type | Momentum conservation | × |
| GaussBPA model (Bastankhah et al., 2014) | Linear | Gaussian type | Mass conservation and momentum conservation | ✓ |
| XA model (Xie and Archer, 2015) | Linear | Gaussian type | Momentum conservation | ✓ |
| Jensen-2D model (Tian et al., 2015) | Linear | Cosine type | Mass conservation | × |
| Jensen-Gaussian model (Gao et al., 2016) | Linear | Gaussian type | Mass conservation and momentum conservation | ✓ |
| GaussISH model (Ishihara and Qian, 2018) | Linear | Gaussian type | Mass conservation and momentum conservation | ✓ |
| DG model (Keane et al., 2016) | Linear | Near wake: DG type<br>Far wake: Gaussian type | Mass conservation and momentum conservation | ✓ |
| DG model improved by Schreiber (Schreiber et al., 2020) | Fitting to the data | Near wake: DG type<br>Far wake: Gaussian type | Mass conservation and momentum conservation | ✓ |
| DG model improved by Keane (Keane, 2021) | Fitting to the data | Near wake: DG type<br>Far wake: Gaussian type | Mass conservation and momentum conservation | ✓ |
| Super-Gaussian models (Shapiro et al., 2019; Blondel and Cathelain, 2020) | Nonlinear | Transition from a “top-hat” to a Gaussian wake profile | Mass conservation and momentum conservation | ✓ |
| 3DJSG model (Zhang et al., 2023) | Linear | Transition from a “Top-hat” to a Gaussian wake profile | flow conservation | ✓ |
| Yaw wake model proposed by Qian (Qian and Ishihara, 2018) | Linear | Gaussian type | Momentum conservation | × |
| 3D model proposed by Li (Li et al., 2022a) | Linear | Z-axis: Gaussian type<br>Y-axis: DG type | Momentum conservation | ✓ |
| 3D model proposed by Sun (Sun and Yang, 2018) | Linear | Gaussian type | Momentum conservation | × |
| 3D model proposed by Peyman (Asad Ayoubi et al., 2022) | Linear | Gaussian type | Mass conservation and momentum conservation | × |
| 3DJG model (Gao et al., 2020a, 2022) | Linear | Far wake: Gaussian type | Mass conservation | × |
| 3D-COTI (Tian et al., 2022) | Empirical value | Dual-cosine distribution | Momentum conservation | ✓ |
| DWM (Larsen et al., 2008) | – | – | Momentum conservation | – |
| Wake meandering model proposed by Braunbehrens (Braunbehrens and Segalini, 2019) | Nonlinear | Gaussian type | The dispersion theory of Taylor | – |

(continued on next page)

Table 3 (*continued*)

| Model | Wake width expression | Wake velocity profile | Theory | Near wake |
|---|---|---|---|---|
| Yaw wake model proposed Bastankhah (Bastankhah et al., 2016) | Nonlinear | Gaussian type | Momentum conservation | × |
| Yaw wake models (Dou et al., 2020; Wei et al., 2021) | Linear | Gaussian type | Mass conservation and momentum conservation | × |
| 3DEG (He et al., 2021, 2023b) | Linear | Gaussian type | Mass conservation | × |
| GCH (King et al., 2021) | Linear | Gaussian type | Momentum conservation | – |

models have covered the influence of flow pressure gradient, vertical wind direction and other factors, and are becoming the standard wake models for wind farm capacity estimation (Lundquist et al., 2020). Xie and Archer proposed the XA model based on the discovery that the wake distribution is asymmetric under the influence of wind shear (Xie and Archer, 2015). Tian used a cosine shape function to describe the distribution of wake deficits in the lateral direction, and proposed a Jensen-2D model that can fully consider the variable wake attenuation rates of environmental turbulence and the turbulence generated by the rotor (Tian et al., 2015). Gao proposed a Jensen-Gaussian model by replacing the wake deficits of the "top-hat" type with Gaussian distribution based on the Jensen model (Gao et al., 2016). Ishihara proposed a GaussISH model based on the axisymmetric and self-similarity assumptions of wake deficits and turbulence intensity. The model can describe the flow field characteristics of the full-scale wake region of the WT (Ishihara and Qian, 2018).In addition, Aitken (Aitken et al., 2014) and Abraham (Abraham et al., 2019) have supported the development of a double Gaussian wake model by measuring WT wake data through LiDAR and high-fidelity experiments. Keane proposed a double-Gaussian (DG) model based on the mass and momentum conservation (Keane et al., 2016). Subsequently, Schreiber (Schreiber et al., 2020) and Keane (2021) modified the initial DG model to solve the problem that the initial DG model did not sufficiently take into account the physical processes or the relevant parameters. The modified DG model explicitly states that the model predicts a DG distribution for the wake deficits in the near wake region and a single-Gaussian distribution for the wake deficits in the middle and far-wake regions. However, the DG model is unable to simulate the variation of the very near-wake deficit. It has been observed both numerically and experimentally that the WT wake velocity profile evolves from a "top-hat" type in the near wake to a Gaussian type in the far-wake, Shapiro proposed the idea of redefining the wake velocity profile using super-Gaussian type functions (Shapiro et al., 2019). Subsequently, Blondel proposed a wake model based on super-Gaussian shape functions (Blondel and Cathelain, 2020). Once the super-Gaussian shape function is introduced, mass and momentum conservation can be ensured by choosing the order $n$. Zhang added the effect of wind shear to the superposition principle of energy loss and combined it with the super-Gaussian model to propose a wake model capable of characterizing the 3D wake velocity distribution over the full-scale flow field (Zhang et al., 2023). This model is different from the Bastankhah model proposed by Qian (Qian and Ishihara, 2018) and inclusion of a correction term in the XA model to predict the near wake velocity (Bastankhah et al., 2014), which violates the laws of mass and momentum conservation.

3D wake models: To understand and simulate the complex flow dynamics in wind farms, 3D models have been developed more fully. In 3D models, the wake expansion coefficients seriously affect the accuracy of the wake models. Recently, Li demonstrated the self-similarity of wake velocity and turbulence increase by LES experiments (Li et al., 2022a). Stein also found a high degree of self-similarity in the velocity deficit and Reynolds stress increased component of the lateral profile (Stein and Kaltenbach, 2019). Based on the axisymmetric and self-similarity assumptions of wake velocity deficits and turbulence increases, Ishihara derived a Gaussian-based 3D wake analysis model by fitting all parameters of the model using a large number of LES data (Ishihara and Qian, 2018). Sun (Sun and Yang, 2018) and Asad (Asad Ayoubi et al., 2022) improved the computational speed of the wake models by assuming the wake expansion coefficients isotropic to simplify the wake models, but the assumption of isotropy is only suitable for specific wind situations. However, Gao modified the wake expansion coefficient to improve the applicability of the 3D model by considering the anisotropic wake expansion rate caused by the turbulent intensity distribution characteristics (Gao et al., 2022). Considering the change of inflow wind in both horizontal and vertical directions, Gao (Gao et al., 2020a) introduced wind shear to improve the 3D Gaussian wake model, which effectively describes the wake spatial distribution. In addition, considering the influence of ambient turbulence intensity and the different interactions between near and far wake and ABL (Porté et al., 2020), a 3D model with coupled turbulence has also been proposed. Tian developed a 3D model considering turbulence and ground effect based on the Gaussian distribution and self-similarity property of wake velocity deficits (Tian et al., 2022).

Secondly, the simulation of WTs wake meandering through empirical knowledge or solving simplified equations is referred to as DWM (Yang and Sotiropoulos, 2019). The DWM was first proposed by Larsen (Larsen et al., 2008) and introduced into the revised IEC 61400-1 standard in 2019 (Commission, 2019). Larsen argued that it takes a turbulence length scale of more than twice the diameter of the wake to cause wake meandering (Larsen et al., 2008). Subsequently, Muller found that the wake position correlates well with the upstream lateral velocity when the characteristic length scale of the vortices is three times the diameter of the wake (Muller et al., 2015). Keck considered the effects of vertical wind shear and additional turbulence in the DWM (Keck et al., 2015). In addition, turbulence models based on Kemal spectral and exponential coherence models, the Mann spectral tensor model, and time-series inputs were used to vary the inflow conditions to investigate the effect of non-neutral atmospheric stability in atmospheric turbulence on the wake velocity and length (Rivera-Arreba et al., 2023). Braunbehrens applied particle dispersion theory to the cross-flow motion of wake meandering, revealing the physical mechanism of wake meandering (Braunbehrens and Segalini, 2019).

Thirdly, wake modeling with yaw/tilt modifications. Bastankhah and Porté-Agel revealed the cause of wake centerline deflection caused by the WT yaw through wind tunnel experiments, and derived the integral forms of flow and spreading RANS equations, thus establishing an analytical model of the far-wake under yawing conditions (Bastankhah et al., 2016). Martínez-Tossas directly linearized the NS equations to propose a 3D Martinez model, which successfully captures the yawed wake deflection (Martí et al., 2019). Dou proposed a 3D yaw wake model to estimate the non-centrosymmetric cross-sectional shape of wake velocity distribution and maximize the output power of wind farms (Dou et al., 2020). Wei adopted self-similarity assumptions of velocity deficits and hub height tilt to establish an analytical model for the yawing WTs' wake center and the average velocity of the far-wake (Wei et al., 2021). Considering the anisotropy of the wake expansion rate after the WT yawing, He modified the 3DEG model (He et al., 2021) to realize the capture of wake deflection using the momentum conservation to define the yaw angle (He et al., 2023b). In addition, the turbulence characteristics of the yawing WT are very important as it has a significant influence on wake development. Qian developed a wake model for the WT yaw conditions by considering the ambient turbulence, thrust coefficient and yaw misalignment effect. It is emphasized that wake curl models apply to the control of WTs, so it is very important to accurately describe the shape of the wake curl (Qian and Ishihara, 2018). King used the curl model to modify the Gaussian model, and the proposed Gaussian curl hybrid (GCH) model was able to simulate secondary steering and multiple WTs effects (King et al., 2021).

### 2.1.4. Data-driven modeling

The concepts of "smart wind power" have been proposed with the development of data science and AI technology. As it does not require complex mechanistic models, AI technology is widely used in wind power/wind speed prediction, fault diagnosis and WT control. In addition, there is an urgent to develop simple and accurate wake models for WT due to the high computational cost and poor compatibility between the numerical and analytical/semi-empirical modeling of WT wakes in the planning and control process of wind farms. Data-driven modeling solves these problems well. This type of approach does not need to explore the coupling mechanisms in the fields of aerodynamics, fluid dynamics, electricity and control. It only needs to utilize meteorological data related to wind farms to obtain the wake characteristics behind WT. Therefore, data-driven methods have been extensively investigated for wind farm wakes in recent years.

Fig. 5 shows the development of the data-driven method for wake modeling. Early data-driven modeling aimed to reduce the dimensional complexity of WT wake models by using reduced-order models (ROM). Then, the inability of lower-order models to accurately describe wake characteristics is addressed by capturing the high-fidelity flow field data. Dynamic mode decomposition (DMD) is the earliest technique used to build data-driven models of WT wakes. The DMD method, first proposed by Iungo for studies of the WT wake, achieved an accurate description of the main structure and dynamics of the wake (Iungo et al., 2015). Secondly, Bastine proposed the application of the proper orthogonal decomposition (POD) technique to WT wakes modeling (Bastine et al., 2015). Subsequently, Debnath solved the 3D wake velocity field of wind farms by combining the POD and DMD methods to obtain the main coherent structure. It was confirmed in real wind farms that the modal decomposition techniques were able to capture the main dynamic laws of the WTs' wakes very effectively (Debnath et al., 2017). Hamilton proposed a general framework for ROM of WT wakes using the POD technique (Hamilton et al., 2018). Zhang first used orthogonal decomposition technology to reduce the dimension of high-dimensional flow field data, and then predicted the dimension reduction coefficient by long short-term memory (LSTM). The model can quickly simulate WT wakes in large wind farms in seconds (Zhang and Zhao, 2020). Ali decomposed the flow field around the WT into linear and forced terms by using the Koopman operator, and then built the wake prediction model of the WT based on the DMD method to capture the evolution law of the flow field in the short term (Ali and Cal, 2020). In another study, Ali utilized a clustering model to link ROMs under different conditions to evaluate the optimal sparse sensor location downstream of the WT and used deep learning to predict wind speed fluctuations at the optimal locations (Ali et al., 2021a, 2021b). In the case of sensor location optimization, Chen proposed combining the Koopman operator and extended DMD (EDMD) method to model dynamic state-space WT wakes with physical states, which can reconstruct WT wakes with fewer velocity measurements and limited state determinations (Chen et al., 2021a). Data-driven models of the WTs' wake are no longer limited by the complexity of data dimensions with AI computing capability and speed increase. Wilson directly modeled the WTs' wake using machine learning. The timeliness and accuracy of four machine learning algorithms, linear regression algorithm, decision tree, random forest (RF) and fully connected neural network, were compared (Wilson et al., 2017). Ti used the turbulence intensity of wind speed and hub height to train the WTs' wake model based on a backpropagation neural network (BPNN) to accurately predict the spatial velocity deficits and additional turbulence in the wake region (Ti et al., 2020, 2021). Zhang used a generative adversarial network (GAN) under deep convolution condition network (CNN) to establish the wake model of wind farms, which is used to study the wake under different inflow conditions and yaw settings (Zhang and Zhao, 2022). Renganathan first introduced Gaussian process (GP) regression into the wake modeling of WTs, and realized the wake probability modeling with abnormal data and incomplete measurement data (Renganathan et al., 2021). Zhang developed a WT wake model based on convolution neural network (CNN), and verified the great potential of the CNN model for reconstructing the wake model on different datasets (Zhang et al., 2021).

It is worth mentioning that in the data-driven approach to modeling of WT wakes, research focus more on the computational cost and accuracy of the AI methods. The data-driven approaches based on ROM are techniques to reduce the complexity of mathematical models in numerical modeling. The ROMs obey the conservation properties and characteristics of the full-order model. By downscaling and data compression of hydrodynamic variables or structures, the state space is downscaled to achieve computational accuracy close to that of the full-order model. In addition, the ROMs typically use a small number of modal bases to represent the main features of the high-dimensional flow field, and thus the computational cost depends on the number of selected modal bases. The computational advantages of the ROMs over traditional numerical modeling methods are obvious. The wake models based on machine learning methods can learn wake features and patterns from a large amount of data to simulate and predict the wake evolutions. The computational cost and accuracy of this approach are affected by several factors, including the complexity of the model, data quality, and computational resources. Currently, the machine learning methods used can predict WT wakes in a relatively short period (typically within 1 min). The results are compared with high-precision CFD results, and the proposed data-driven models are effective in the WT and wind farm wake modeling. There is a trade-off between computational cost and accuracy in data-driven WT wake modeling. When selecting a model type, data quality, model complexity, and computational resources, trade-off decisions need to be made based on specific engineering needs to ensure that the predetermined accuracy standards are met and the development and maintenance of the models are accomplished within a reasonable cost range.

Table 4 shows the advantages and disadvantages of different wake modeling for WT. The flow field information is completely described by

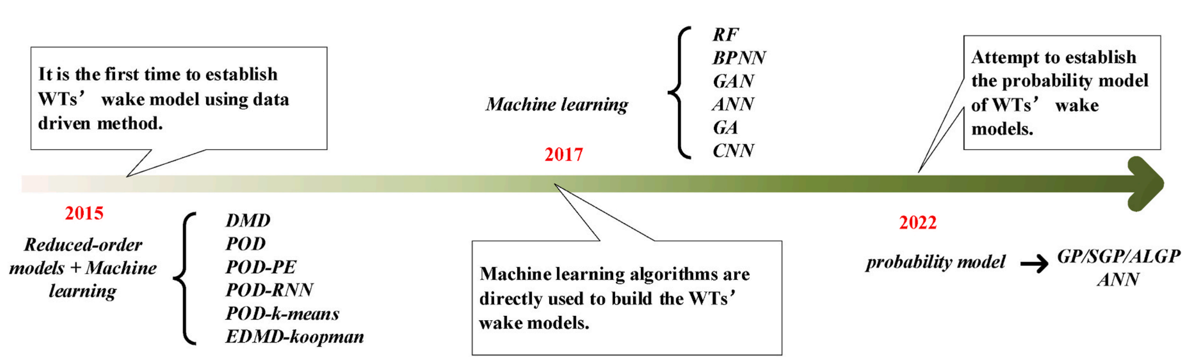



**Fig. 5.** The development process of data-driven wake modeling for WTs.

**Table 4**
Advantages and disadvantages of different wake modeling for WT.

| Classification of wake modeling | | Advantages | Disadvantages |
|---|---|---|---|
| Experiment methods | Wind tunnel experiments | ● Highly controllable for precise control of wind speed, direction and other environmental parameters.<br>● Ability to generate data in a shorter period than field measurements. | ● It is difficult to satisfy both the similarity of the tip speed ratio and the consistency of the Reynolds number at the same time.<br>● High cost of establishing and maintaining large wind tunnel facilities. |
| | Field measurements | ● Provides actual data in a real environment.<br>● Full-scale WT measurements for more realistic results. | ● Low temporal and/or spatial resolution.<br>● High cost. |
| Numerical modeling | | ● Describing accurately the wake of a WT or wake interaction of a few WTs.<br>● Reflecting exactly the development rules of the wake of the WT under complicated flow conditions. | ● Consuming a large amount of computing resources.<br>● In complex wind farms or wind farms, the lack of validation data may lead to uncertainty in numerical modeling results. |
| Analytical/semi-empirical modeling | | ● Simple models and low calculation costs.<br>● The model is highly practical and widely used in commercial software for wake analysis. | ● Detailed information on the mechanisms of wake generation and evolution is not provided.<br>● Based on different assumptions and empirical reference values, the use scenario of the models needs to be validated. |
| Data-driven modeling | | ● Accurate and efficient prediction of wake flow at all flow direction locations of WT near and far wakes.<br>● Model does not require prior knowledge.<br>● A good way to explore the non-linear relationship between wake characteristics. | ● A large number of data training models are needed, and dataset acquisition is difficult.<br>● The model is poorly interpretable. |

experiment methods and numerical modeling, which requires significant calculation time and resources. Neither the microscopic location of wind farms nor the wake control of WTs needs to pay attention to the details of the flow field, so that these modeling methods are not applicable in practical engineering (Talavera and Shu, 2017). However, the analytical/semi-empirical modeling is widely used in practical engineering and commercial wind power analysis software because of its high efficiency and easy operation. The analytical/semi-empirical modeling usually simplifies atmospheric conditions, boundary layers, etc., which leads to poor mobility. Data-driven modeling developed in recent years can accurately describe the WTs' wake evolutions without understanding the complex prior knowledge. Data-driven modeling integrates the advantages of numerical modeling and analytical/semi-empirical modeling, but the current research only stays at the experimental stage, lacking practical engineering applications to prove its superiority.

### 2.2. Wake models of multiple wind turbines

The wake evolutions of an individual WT can be obtained from the wake modeling described in Section 2.1. However, in actual wind farms, the arrangement of WTs is complex and there is a strong coupling relationship. As shown in Fig. 6, in typical wind farm layout, the downstream WTs will be affected by the full and partial wake of the upstream WTs. Among the four types of wake models mentioned in Section 2.1, the analytical/semi-empirical modeling can only model individual WT. So, when analyzing the wind farm wake effects by the analytical/semi-empirical modeling, a superposition model is needed.

Table 5 shows the wake superimposition model, which can be categorized into linear and square sum. The former considers that momentum loss is linearly proportional to the speed loss during WTs wake propagation, while the latter assumes that momentum loss is equal to speed loss. In 1979, Lissaman proposed that the average wind speed at the hub was approximately equivalent to the free-flow wind speed and utilized the linear superposition principle for the first time to analyze the impact of wake flow from adjacent WTs (Lissaman, 1979). Katic modeled the interaction of multiple wakes with a superposition of energy deficits instead of velocity deficits (Katic et al., 1987). However, Voutsinas rejected the weak wake hypothesis of Katic and proposed that the effective wind speed at each WT hub should be calculated from upstream to downstream sequentially in the wake superposition process (Voutsinas, 1990). Niayifar found that the Lissaman wake superposition model has the problem of overestimating the velocity deficits. A new wake superposition method based on the velocity deficits was proposed to reflect the interaction between the wakes of multiple WTs (Niayifar et al., 2016). For the wake superposition method, Zong pointed out that the kinetic energy of the mean flow is not conservative due to the turbulent dissipation during the wake propagation. The wake superposition operation based on square addition was negated. Furthermore, it was found that the wake superposition satisfying the condition of momentum conservation is a weighted linear superposition (Zong et al., 2020b).Where, $u_i$ is the synthetic wake velocity of ith WT; $u_{ij}$ is the wind speed of the ith WT under the influence of the jth WT; $u_j$ is the velocity when the jth WT operates in isolation; $u_0$ is the free inflow velocity; $I_i$ is the synthetic turbulent intensity of ith WT; $I_{ij}$ is the turbulent intensity of the ith WT under the influence of the jth WT; $I_j$ is the turbulent intensity when the jth WT operates in isolation; $I_0$ is the free inflow turbulent intensity.

In large wind farms, the calculation of WT wake superposition is generally categorized into two types: local superposition and global superposition. By local superposition, this means that superposition is only applied for multiple wakes impinging on a given WT, but with that WT's response computed serially based on that waked inflow. Specifically, firstly, the degree of overlap between the wheel surface of the target WT and the wake region of the upstream WT is determined, as shown in Fig. 6. Then, the proportion of the overlapped region to the target WT's wheel surface is calculated. Finally, adds the wake velocity of the upstream WTs multiplied by the proportion coefficient. This method is widely used in layout optimization, wake control, and resource assessment in wind farms (Chen et al., 2016; Yang et al., 2019; Ling et al., 2024). Global superposition involves solving for each WT individually and then adding the results together. The data-driven approach is a good way to obtain the wake evolution of the target WT based on the blades incoming flow information. And the data-driven model shows remarkable ability in dealing with complex fluid dynamics modeling problems. For instance, Barasa developed a mass flow

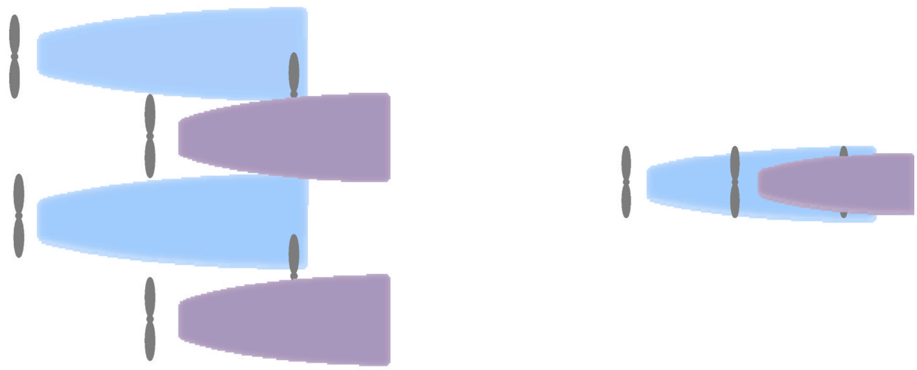



**Fig. 6.** Schematic diagram of two typical wind farm layouts.

**Table 5**
Principles and formulations of wake superposition techniques.

| Method | Summation Principle | Mathematical expression | Turbulent intensity superposition | Empirical basis |
|---|---|---|---|---|
| Geometric sum (Lissaman, 1979) | ● Mass conservation<br>● Empirical model based on iterative estimation of overall wake | $u_i = u_0 \prod_{j=1}^{n} \frac{u_{ij}}{u_j}$ | $I_i = I_0 \prod_{j=1}^{n} \frac{I_{ij}}{I_j}$ | Mass Flow |
| Sum of energy deficit (Katic et al., 1987) | ● Conserves kinetic energy<br>● Empirical model on the iterative estimation of overall wake | $u_i = \sqrt{u_0^2 - \sum_{j=1}^{n}\left(u_j^2 - u_{ij}^2\right)}$ | $I_i = \sqrt{I_0^2 + \sum_{j=1}^{n}\left(I_{ij}^2 - I_j^2\right)}$ | Energy |
| Linear superposition (Niayifar et al., 2016) | ● Mass conservation<br>● Semi-analytical model based on iterative estimation | $u_i = u_0\left(1 - \sum_{j=1}^{n}\left(1 - \frac{u_{ij}}{u_j}\right)\right)$ | $I_i = I_0\left(1 + \sum_{j=1}^{n}\left(\frac{I_{ij}}{I_j} - 1\right)\right)$ | Mass Flow |
| Sum of square (Voutsinas, 1990) | ● Conserves kinetic energy<br>● Empirical model on the iterative estimation of overall wake | $u_i = u_0\left(1 - \sqrt{\sum_{j=1}^{n}\left(1 - \frac{u_{ij}}{u_j}\right)^2}\right)$ | $I_i = I_0\left(1 + \sqrt{\sum_{j=1}^{n}\left(\frac{I_{ij}}{I_j} - 1\right)^2}\right)$ | Energy |
| Weighted linear superposition (Zong et al., 2020b) | ● Mass conservation<br>● Semi-analytical model based on iterative estimation | $u_i = u_0\left(1 - \sum_{j=1}^{n}\omega\left(1 - \frac{u_{ij}}{u_j}\right)\right)$ | $I_i = I_0\left(1 + \sum_{j=1}^{n}\varpi\left(\frac{I_{ij}}{I_j} - 1\right)\right)$ | Mass Flow |

conservative superposition (MFCS) model based on the linear momentum equation, and built a mass flow and thrust conservative superposition (MFTCS) model using a GP regression model to fit LES data. The experimental results demonstrated that MFTCS is more accurate than Katic and MFCS results (Barasa et al., 2022). The use of AI technology represents a new frontier in the research of WT wake superposition models.

### *2.3. Performance evaluation of wake models*

To evaluate the performance of established WT wake models, an effective method is to verify the models through field measurements or high-fidelity simulation data. These data are often difficult to obtain. Therefore, various evaluation indicators have been proposed in previous studies to quantitatively analyze the performance of wake models. Through a review of the work, evaluation indicators for performance of WTs wake models can be categorized into two types. The first type is the direct observation method, which directly determines the performance of the wake model by observing the output results of different profiles and the trend of the actual wake characteristics. The second type is indirect observation, which can be divided into traditional statistical evaluation criteria and wake-related evaluation criteria. The traditional statistical evaluation criteria are used to describe the degree to which the predicted results of the wake model deviate from the actual results. For example: absolute error (AE), bias, line correlation coefficient ($\rho$), the number of times the predicted value of a model exceeds the standard deviation of the mean observed value (*Out*), root mean square error (RMSE), variance normalized root mean square error (VNRMSE), R-square ($R^2$), mean absolute percentage error (MAPE), mean absolute error (MAE), relative error ($E_R$) a sum of squared residuals (SSR) and a sum of the squared deviation of testing data points (SST), and average error variance (AEV). Their calculation equations are shown in Table 6.

The wake-related evaluation criteria are to analyze the flow field around the WTs from different perspectives.

- Power related (PR) criterion: The power output of WTs can be affected by partial or full wakes.

$$PR = \int_{A_0} \frac{1}{2}\rho v^3 dA$$

- Fit-Full/Fit-DWM: Based on the evaluation criterion of RMSE, a fitness index is introduced to analyze:

**Table 6**
Expressions of traditional statistical evaluation criteria.

| Indicators | Mathematical expression | Indicators | Mathematical expression |
|---|---|---|---|
| Bias | $Bias = \frac{\sum_{i=1}^{N}(U_i - U_{i,obs})}{N}$ | MAPE | $MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{U_i - U_{i,obs}}{U_i}\right\rvert$ |
| $\rho$ | $\rho = \frac{\sum_{i=1}^{N}(U_i - \overline{U})(U_{i,obs} - \overline{U}_{obs})}{\sqrt{\sum_{i=1}^{N}(U_i - \overline{U})^2}\sqrt{\sum_{i=1}^{N}(U_{i,obs} - \overline{U}_{obs})^2}}$ | MAE | $MAE = \frac{\sum_{i=1}^{N}\lvert U_i - U_{i,obs}\rvert}{N}$ |
| Out | $Out = \frac{N_{out}}{N}$ | $E_R$ | $E_R = 100 \times \frac{\lvert R_s - R_m\rvert}{R_m}$ |
| RMSE | $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(U_i - U_{i,obs})^2}$ | SSR/SST | $SSR/SST = \frac{\sum_{i=1}^{N}(U_i - U_{i,obs})^2}{N\sum_{i=1}^{N}(U_i - \overline{U})^2}$ |
| VNRMSE | $VNRMSE = \frac{RMSE}{\delta_p}$ | AEV | $AEV = \frac{1}{n}\sum_{i=1}^{N} var(U_i - U_{i,obs})$ |
| $R^2$ | $R^2 = 1 - \frac{\sum_{i=1}^{N}(U_i - U_{i,obs})^2}{N\sum_{i=1}^{N}(U_i - \overline{U})^2}$ | | |

$$Fit - DWM = \left(1 - \sqrt{\sum_{t=1}^{k}\sum_{i=1}^{m}\frac{\lvert U_{i,t} - \widehat{U}_{i,t}\rvert^2}{\lvert U_{i,t} - \overline{U}_{i,t}\rvert^2}}\right) \times 100\%$$

$$Fit - Full = \left(1 - \sqrt{\sum_{t=1}^{k}\sum_{i=1}^{m}\frac{\lvert U_{i,t} - \widehat{U}_{i,t}\rvert^2}{\lvert U_{i,t}\rvert^2}}\right) \times 100\%$$

**Table 7**
Statistics of WT wakes modeling evaluation indicators.

| Ref. | Types of studies | Fit-Full/ Fit-DWM | bias | $\rho$ | Out | RMSE | VNRMSE | $R^2$ | MAPE | MAE | $E_R$ | $R_i$ | AEV | PR | SSR/ SST |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wang et al. (2022) | Analytical modeling | | | | | | | | | | ✓ | | | | |
| Debnath et al. (2017) | Data-driven modeling | | | | | ✓ | | | | | | | | ✓ | |
| Ali et al. (2021a) | Data-driven modeling | | | | | ✓ | | ✓ | ✓ | | | | | | |
| Zhang et al. (2021) | Data-driven modeling | | | | | ✓ | | ✓ | ✓ | ✓ | | | | | |
| Renganathan et al. (2021) | Data-driven modeling | | | | | ✓ | | | | | | | | | |
| Wu et al. (2015) | Wind power prediction | | | | | | | | | | | | | ✓ | |
| Bastankhah et al. (2014) | Analytical modeling | | | | | | | | | | | | | ✓ | |
| Tian et al. (2015) | Analytical modeling | | | | | | | | | ✓ | | | | | |
| Gao et al. (2016) | Analytical modeling and layout optimization | | | | | | | | | ✓ | | | | ✓ | |
| Keane (2021) | Analytical modeling | | | | | ✓ | | ✓ | | | | | | | |
| Shapiro et al. (2019) | Analytical modeling and WTs control | | | | | | | | | | | | | ✓ | |
| Blondel and Cathelain (2020) | Analytical modeling | | | | | | | | | ✓ | | | | | |
| Qian and Ishihara (2018) | Analytical modeling | | | | | ✓ | | | | | | | | | |
| Li et al. (2022a) | 3D analytical modeling | | | | | | | | | | ✓ | | | | |
| Sun and Yang (2018) | 3D analytical modeling | | | | | | | | | | ✓ | | | | |
| Asad Ayoubi et al. (2022) | 3D analytical modeling | | | | | | | | ✓ | | | | | | |
| Gao et al. (2022) | Wake modeling in complex terrain | | | | | | | | | | ✓ | | | | |
| Braunbehrens and Segalini (2019) | Wake meandering modeling | | | | | | | | | | | | | ✓ | |
| Dou et al. (2020) | Yawed wake modeling | | | | | | | | | | | | | ✓ | |
| He et al. (2021) | 3D analytical modeling | | | | | | | | | | ✓ | | | | |
| He et al. (2023b) | Yawed wake modeling | | | | | ✓ | | | | | | | | | |
| King et al. (2021) | Yawed wake modeling | | | | | | | | | | | | | ✓ | |
| Iungo et al. (2015) | Data-driven modeling | | | | | | | | | ✓ | | | | | |
| Hamilton et al. (2018) | Data-driven modeling | | | | | ✓ | | | | | | | | | |
| Chen et al. (2021a) | Data-driven modeling | ✓ | | | | | | | | | | | | | |
| Wilson et al. (2017) | Data-driven modeling | | | | | | | | | ✓ | | | | | |
| Ti et al. (2020) | Data-driven modeling | | | | | | | ✓ | | | | | | | |
| Ti et al. (2021) | Data-driven modeling | | | | | | | | | | | | | ✓ | |
| Zhang and Zhao (2022) | Data-driven modeling | | | | | ✓ | | | | | | | | | |
| Archer et al. (2018) | Layout optimization | | ✓ | ✓ | ✓ | | | | | | | | | | |
| Lopes et al. (2022) | Assessing wake models | | | | | | | | | | ✓ | ✓ | | | |
| Wang et al. (2016) | Assessing wake models | | | | | | | | | | | | | ✓ | |
| Dhiman et al. (2020) | Wind speed prediction | | | | | ✓ | | | | | | | | | ✓ |
| Japar et al. (2014) | Wind power prediction | | | | | ✓ | ✓ | | | | | | | | |
| Guo et al. (2022b) | Wind power prediction | | | | | ✓ | | ✓ | | | | | | | |
| Qian and Ishihara (2021) | Wind power prediction and wind farm control | | | | | | | | | | | | | ✓ | |
| Chen et al. (2022) | Wind farm control | | | | | ✓ | | | | | | | ✓ | | |
| Hegazy et al. (2022) | Assessing wake models | | ✓ | | | ✓ | | ✓ | | | | | | | |

Where, $\widehat{U}_{.}$ is the predicted value, "-DWM" indicates that this index calculates the fitness for the dynamic wake without the mean value, "Fit-Full" retains the mean flow.

Where, $U_{.}$ represents a measurement value, $\overline{U}_{.}$ represents a mean value; $\overline{U}_{.,obs}$ represents an observed value; $N_{out}$ is the number of predictions that represent a standard deviation of the mean observed value, $N$ represents sample size, $\delta_p$ is the standard deviation, $R_s$ as the simulated wind speed ratio and $R_m$ as the measured wind speed ratio.

Table 7 shows a review of the performance evaluations of the WT wake models. The analysis reveals that the RMSE, PR, $R^2$ and $E_R$ are widely used in the performance analysis of wake models, and that different types of wake models have different trends in selecting performance evaluation indicators. Since numerical modeling can fully describe the wake characteristics of WT, direct observation methods are often used to assess the difference between the output results of the wake models and the actual flow field. The analytical/semi-empirical modeling often focus on improving WT performance, and thus, the PR and $E_R$ become the main evaluation indicators. In the data-driven approaches, historical data of wind farms is used to train the model and extract wake characteristics. The learning ability of the model directly affects the accuracy of the wake prediction. Therefore, statistical indicators such as RMSE and $R^2$ become important criteria for evaluating the prediction accuracy of the data-driven wake modeling.

### 2.4. Wind turbine wakes modeling software

The development and application of WT wakes simulation software play a pivotal role in the wind energy industry, facilitating ongoing enhancements in wind farm design and operation. In recent years, there has been a growing interest among scholars and organizations in developing various numerical wake computation software (Neiva et al., 2019). This paper presents a collection of representative WT wake simulation software currently available: open source software: Open Field Operation and Manipulation (OpenFOAM), Qblade, Simulator for Wind Farm Applications (SOWFA), Open-source Simulation Tool for Advanced Wind Turbine Systems (OpenFAST), FLOw Redirection and Induction in Steady-state (FLORIS), Wind Systems Engineering (WindSE) and commercial software: Ansys, Wind Atlas Analysis and Application Program (WAsP), Wind Simulation (WindSim), STAR-CCM+. Specific information is shown in Table 8.

OpenFOAM, released in 2004, is an open source CFD toolbox that provides a variety of simulation and modeling tools for studying and solving complex fluid flow problems with a high degree of flexibility and customizability (Jasak, 2009; Stovall et al., 2010; Hoem and Kristoffersen, 2018; Ricci, 2024). In 2010, Technical University of Berlin

**Table 8**
The wakes modeling software of WT.

| | Developer/ country | Year | Wake models | Uses | Type | Operating systems |
|---|---|---|---|---|---|---|
| OpenFOAM | OpenFOAM/ UK | 2004 | ● CFD-based wake model | ● Wind turbine and wind farm simulation;<br>● Environmental impact studies;<br>● Generalized CFD applications. | Open source https://github.com/OpenFOAM | Linux, MacOS and Windows 10 |
| Qblade | TUB/Germany | 2010 | ● Lifting line free vortex wake method<br>● DWM | ● The aeroelastic simulation of WT | Open source https://sourceforge.net/projects/qblade/ | Windows and Unix |
| SOWFA | NREL/USA | 2011 | ● OpenFOAM-based CFD wake model | ● Ability to conduct performance and loading studies of wind turbines and wind farms under various atmospheric conditions and terrains. | Open source https://github.com/NREL/SOWFA | Linux, MacOS and Windows 10 |
| OpenFAST | NREL/USA | 2017 | ● Low-fidelity wake models<br>● High-fidelity wake models<br>● DWM | ● Wind turbine: load evaluation, control optimization and power generation calculation;<br>● Wind farm: wake calculation and wake control | Open source https://github.com/OpenFAST/openfast | Windows and Unix |
| FLORIS | NREL/USA | 2018 | ● Jensen model<br>● TurbOPark model<br>● Gaussian model<br>● GCH model | ● Optimal design methods for wind farm control and layout;<br>● Methods for the analysis of wind roses and annual electricity production;<br>● Methods for analyzing wind farm control field activities;<br>● Methods for coupling with other tools, including SOWFA and CC-blade;<br>● Simulation methods for non-uniform atmospheric conditions. | Open source https://github.com/NREL/floris | Windows and Unix |
| WindSE | NREL/USA | 2020 | ● CFD-based wake model | ● Simulation of atmospheric fluid flow in wind farm.<br>● Optimization of WT position or operational settings | Open source https://github.com/NREL/WindSE | MacOS and Linux |
| Ansys | Ansys/USA | 1970 | ● CFD-based wake model | ● Wind farm layout optimization;<br>● Detailed aerodynamic and structural analysis;<br>● Combine fluid, structural, electrical and other physical fields for comprehensive simulation. | Licensed https://www.ansys.com/ | Windows |
| WAsP | DTU/Denmark | 1987 | ● Park model | ● Empirical model-based wind resource assessment;<br>● Early project evaluation. | Licensed https://www.wasp.dk | Linux, MacOS and Windows 10 |
| WindSim | WindSimAS/ Norway | 2003 | ● CFD-based wake model<br>● Standard $k-\varepsilon$ turbulence model<br>● RNG $k-\varepsilon$ turbulence model | ● 3D wind farm simulation and wind farm optimization;<br>● High resolution wind resource and wake assessment;<br>● Ability to handle complex terrain, suitable for mountainous wind farms. | Licensed https://windsim.com | Windows |
| STAR-CCM+ | Siemens/ Germany | 2004 | ● CFD-based wake model | ● Wind farm layout optimization;<br>● Detailed aerodynamic and structural analysis;<br>● Environmental impact assessment. | Licensed https://plm.sw.siemens.com/en-US/simcenter/fluids-thermal-simulation/star-ccm/ | Linux and Windows |

(TUB) developed a fully open wind power calculator, Qblade, which covers the entire spectrum of aero-servo-hydro-elastic simulations of WTs, enabling efficient multi-fidelity aerodynamic, structural and fluid dynamics solutions (Marten et al., 2013; Marten, 2020). NREL is a leading software developer in the field of wind power and has created several open-source computational models. SOWFA is a solver developed by NREL based on OpenFOAM for high-precision wind farm modeling and simulation. It mainly provides basic components for users to do hydrodynamic calculations and simulations of wind farms, and integrates wind resource simulation algorithms, open-source hydrodynamic calculation software and NREL's own WT modeling software (Churchfield et al., 2012). In order to better adapt to the development of modern wind technology, NREL launched OpenFAST in 2017 (initially an extension of NREL's Fatigue, Aerodynamics, Structures, and Turbulence (FAST) tool), which provides comprehensive WT dynamics simulation and wind farm modeling capabilities (Branlard et al., 2022; Cioffi et al., 2020). FAST.Farm is a component of OpenFAST that adds wind farm-level simulation capabilities to FAST stand-alone calculations, including field-level controllers, wake effects, and so on. It was used to simulate wind farm-scale wakes and interactions, and to simulate the dynamic response of WTs and wind farms using a simplified physical model to achieve the prediction of WT power generation and loads at a lower cost, but the reduction of wake details was not ideal (Jonkman et al., 2017). Subsequently, FLORIS, an open-source software tool for wind farm control and optimization, was jointly developed by NREL and DTU. FLORIS is capable of wake modeling, wind farm control optimization, wind farm layout optimization, and sensitivity analysis, etc., with the main goal of adjusting the control strategy of WTs to maximize energy production and minimize wake losses in wind farms (Ramírez Castillo, 2018). In addition, WindSE developed by NREL is a tool for modeling atmospheric fluid flow in wind farms to optimize the location or operational settings of WTs (WindSE, 2017). For commercial software, Ansys has been providing integrated and comprehensive WT simulation solutions since its inception in 1970 with tools such as Ansys Fluent and Ansys CFX. With automated workflows for 3D computational hydrodynamics wind farm simulation, Ansys is able to determine the overall power of a wind farm, optimize the layout of WTs, and evaluate the behavior of wind farms under specific wind conditions (Calautit et al., 2018). In 1989, DTU developed the WAsP for wind resource assessment and wind farm design. WAsP stands for linear simplified solver, which includes wake models as well as a stabilization model for the average heat flux conditional heat flux, and is capable of modeling the wake of WTs in both flat terrain as well as in moderately complex terrain to assess wind resources and power generation calculations for wind farms (Berge et al.). Subsequently, in 2003, the Norwegian company WindSimAS launched WindSim. WindSim is based on advanced CFD and boundary layer meteorology methods, which can comprehensively simulate and analyze the regional wind resource characteristics, and has become a professional tool for optimizing the design of wind farms (Wallbank, 2008). STAR-CCM+, originally developed by CD-adapco in the 1980s, is a multi-physics CFD software that simulates the complexity and explores the possibilities of WT operation under real conditions (Kovalnogov et al., 2022). These software tools, through continuous technological innovation and functional expansion, offer robust support for the design, optimization, and performance evaluation of wind farms.

## 3. Wakes modeling of wind turbine under complex environmental conditions

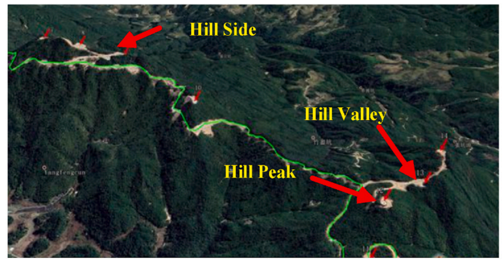
As the wind power industry continues to develop, the availability of flat terrains and nearshore sites suitable for wind farms is becoming increasingly scarce. Consequently, the construction of wind farms is gradually expanding into mountainous regions with higher turbulence, and the dynamic environments of deep-sea locations. These complex climatic and topographic conditions pose a significant challenge to WTs operations. Wakes modeling are no longer only affected by the layout of WT. The traditional wake modeling, which assumes of flat and uniform terrain, is no longer applicable. Therefore, many WTs wake modeling studies on complex terrain have been carried out in recent years. This section reviews the onshore and offshore wind farms under complex environmental conditions.

### *3.1. Wakes modeling of the hill wind turbine*

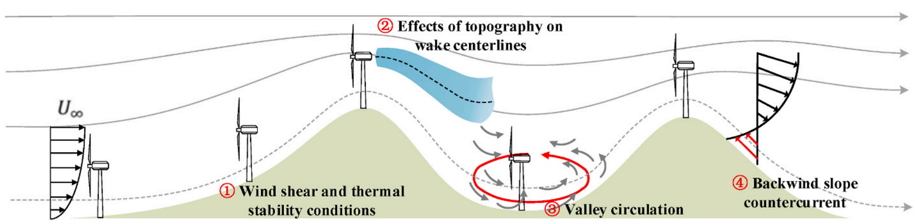
As countries worldwide continue to develop and construct clean energy, WTs installations have increased significantly (Kumar, 2020; Solaun et al., 2020). In recent years, complex mountain wind farms have gradually become the main battlefield of onshore wind farm constructions (Dai et al., 2018; Wang et al., 2021a). However, higher wind resource uncertainty, higher wind shear and turbulence levels in wind farms with complex terrain increase the wake effect of WT, bringing highly unstable air flow to WT (Machefaux et al., 2016; Albornoz et al., 2022). As a result, the WT loads affected by the wake can greatly increase, resulting in reduced performance and a shorter lifespan. To reduce the performance loss caused by terrain changes to WT, the evolution of complex terrain wake has received wide attention.

Reviewing the previous studies on WT wakes in complex terrain, a large number of studies focused on the variation of the wake characteristics of WT under the influence of complex terrain. For wind farms operating in complex terrain, the spatial distribution and velocity distribution of WTs' wake will be changed by the terrain effect. Fig. 7 shows the influences of complex terrain on WT wakes. WTs may be installed in hill peaks, hill sides, and hill valleys in complex mountain wind farms (Liu et al., 2022b). The wake characteristics of mountain WT are affected by wind shear and thermal stability, topographic changes in the wake centerline, valley vortices, and backflow on the leeward slope. As early as 1995, Helmis conducted field measurements on the wake characteristics of a wind farm in the Samos Mountains and found that mountain turbulence had a serious impact on wake recovery at low wind speeds (Helmis et al., 1995). Subsequently, relevant research revealed the influence of hilly terrain on wake characteristics such as average wind speed, turbulence intensity, Reynolds shear stress and velocity fluctuation power spectral density. Vertical wind shear is not a negligible factor when studying mountain wake compared to flat terrain (Barasa et al., 2022; Kozmar et al., 2016; Astolfi et al., 2018). Zhao found that the wake profiles were asymmetrically distributed under the influence of wind shear, the sinking height of the wake centerline was linearly related to the height drop, and the wake recovery rate was proportional to the turbulence intensity (Zhao et al., 2020). In addition, Li revealed that the effect of ground roughness and atmospheric stratification on the wake velocity was mutually beneficial, but the effect on turbulence was offset (Li et al., 2022b). Zhou predicted the turbulent wake flow field over isolated 2D ridges and 3D hills with different slopes and incoming conditions using LES, and clarified the relationship between the wake, topography and incoming conditions (Zhou et al., 2022a). These studies have verified from different perspectives that the influence of complex terrain on the wake characteristics of WTs is not negligible, which provides a theoretical basis for the subsequent development of the wake modeling for WTs in complex terrain.

In the past few years, studies have developed semi-empirical and field models to describe the wake characteristics of WT under different terrain conditions by understanding the ABL and the wake behavior of WT over complex terrain. Fig. 8 shows the timeline for the development of WT wakes modeling over complex terrain. Wakes modeling have developed from traditional CFD modeling to AI modeling. Song considered the wake of a WT as virtual particles generated by the blades and calculated the wake by a particle tracking model, using the concentration of the virtual material to represent the wake intensity. This method reflects the characteristics of the wake flow under complex terrain more accurately than a linear model. After optimizing the layout of the wind farm based on this model, the output power was increased by




(a)




(b)

**Fig. 7.** Schematic diagram of influences of complex terrain on WT wakes. (a) Satellite image of WTs installation in typical hilly wind farms. (b) Influence of terrain on wake characteristics.

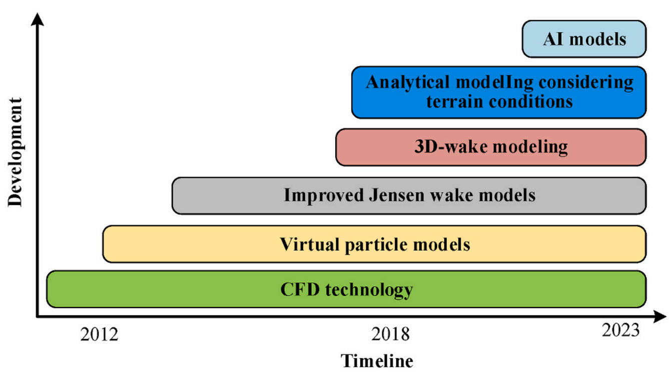



**Fig. 8.** Development roadmap of the WT wakes modeling in complex terrain.

35% (Song et al., 2012). Based on the assumption that the wind direction along the wake centerline changes with the terrain, Feng obtained the inflow conditions of complex terrain by CFD simulation, and developed an adaptive Jensen model to simulate the wake evolution of WT in complex terrain (Feng and Shen, 2014). Kuo proposed a new wake model to solve NS equations on complex terrain by utilizing the idea of a virtual particle model and the turbulent viscosity assumption of the Ainslie wake model. The model accurately describes the wake recovery process and reduces the computational cost by several orders of magnitude (Kuo et al., 2018). Sun proposed a 3D wake model considering the influence of wind shear, and verified that the 3D wake model can only accurately predict the near wake of WT in complex terrain without robustness by actual data from wind farms in complex terrain in China (Sun et al., 2019). Ibrahim proposed a wake model consisting of wake width and wake velocity considering the wind acceleration on 2D hills (Ibrahim et al., 2019). Based on the assumption that the wake centerline follows the background flow field, Brogna proposed a complex terrain wake model superimposed with a Gaussian wake profile in the background flow field, which is capable of predicting the wakes of wind farms in complex terrain with good accuracy in a short time and is suitable for optimization of the layout of wind farms in large-scale complex terrain (Brogna et al., 2020). Aird used the CNN model to identify and describe the wake image of WTs in complex terrain scanned by LiDAR, and the success rate of wake identification reached 95%. After the resolution of the image is reduced by half, the wake recognition success rate is 92% (Aird et al., 2021). This research realized the first use of image processing technology in the wake field, and opened the way for AI technology in WT wakes modeling.

Through a review of previous modeling of WT wakes in complex terrain, wakes modeling in complex terrain often serves the micro-siting of wind farms. There is a lack of complex high-precision models to study the interaction between the evolution of complex terrain WT wakes and the terrain.

1) The extent to which the wake centerline follows the terrain is largely influenced by thermal stability conditions and terrain conditions (El-Askary et al., 2017; Ichenial et al., 2021). However, current wake models for WT in complex terrain all assume that the centerline change is consistent with the terrain change. Therefore, the high-precision wake modeling is needed to fully explore the thermal effects of the wake characteristics of WTs over complex terrain.
2) Hancock and Pasheke conducted research on WT wakes under thermally stable conditions in a large-scale thermally controlled wind tunnel. They found that with changes in thermal stability, simple terrain perturbations, such as 2D and 3D hills, not only altered the mean velocity distribution in the ABL but also changed the intensity of large-scale coherent motions that control the instability of WT performance (Hancock and Pascheke, 2014a, 2014b). Therefore, it is necessary to establish an ABL model suitable for complex terrain to analyze the changes in turbulent boundaries under different boundary layer conditions and explore how the ABL affects the characteristics of WT wakes and the kinematics of the rotor under complex terrain.
3) Considering that CFD modeling is computationally intensive and time-consuming, and that the high-fidelity data required for data-driven modeling is difficult to obtain. For the wakes modeling of WT in complex terrain, the engineering wake models are usually improved according to the terrain features. However, terrain features such as mountains, canyons, and buildings cause different variations in wind farm flow fields, leading to a lack of generality in wakes modeling for wind farms in complex terrain. Therefore, it is necessary to measure and simulate WT wakes under different terrain

conditions, and to further develop highly adaptive models to better simulate these complex terrain effects.

### 3.2. Wakes modeling of the floating wind turbine

Global offshore wind power installed capacity has significantly increased in recent years due to abundant wind energy resources, high offshore wind speeds and low surface roughness (Rodrigues et al., 2015). However, the layout of offshore WT is limited by factors such as cable layout, sea area and intensive use of sea, so that accurate assessment of the wake effect of offshore wind farms is essential for the scientific selection of WT, the optimization of the layout plans, the guarantee of operation safety, and the promotion of overall power generation (Hou et al., 2019; Micallef and Rezaeiha, 2021; Chen et al., 2024; Yang et al., 2022b). Early construction of offshore wind farms lacked advanced experience in location arrangement, and unscientific unit arrangement increased the wake effect. In recent years, the large-scale development of offshore WT has been accompanied by the generation of large blades, and the influence of large WTs wakes on downstream WTs has become more significant (Wang et al., 2019). It is pointed out that the existing engineering wake models can well describe the wake evolution process of stationary offshore WT due to the larger offshore wind speeds, small wind shear, and small turbulence intensity (Hassoine et al., 2022). However, for floating WTs, the complexity of the offshore wind conditions, the variability of the wake field structure, and the type of WTs increase the complexity of the wake aerodynamics of floating WT. The factors affecting the wake of floating WTs are shown in Fig. 9, and the deep-sea environment and the WT structures pose a great challenge to the accurate assessment of the wake of offshore floating wind farms.

As early as 2014, Rockel pointed out through wind tunnel experiments that the complex marine environment and floating structure increased the degree of freedom of WT, making the existing wake models unable to describe the complex wake characteristics of floating WT (Rockel et al., 2014a). The research on the wake modeling of offshore WT can be carried out from three aspects: the deep-sea environment, the structure of the WT and the wake characteristics. Fig. 10 shows the influences of the marine environment and WT structures on floating WT wakes. Firstly, Studies have studied the marine environment in terms of wakes modeling impacts on floating WT. Matha pointed out that under floating conditions and wave impacts, the wake expansion of floating WT is stronger and vortices shedding on the blades leads to a wave boundary layer in the upper part of the wake (Matha et al., 2011). Johlas analyzed the influence of different wind speeds, wave heights, wave linearity and yaw angles on the wake of floating WT through LES technology. The results showed that although these influences bring little difference to wake variations of floating WT, the capacity and load influences should not be ignored (Johlas et al., 2019). In addition, the operation of floating WT is affected by both wind and waves. During operation, the wake of floating WT exhibits complex meandering, turning, and bending due to the non-uniformity of the incoming wind and waves. Therefore, studying the evolution of the wake of floating WT requires an understanding of the coupled wind-wave-wake interactions (Huanqiang et al., 2024). Xiao investigated the effects of wind speed and swell on offshore WT using a hybrid numerical model combining LES and coupled higher-order spectral wave simulation (Xiao and Yang, 2019). Fercak identified and quantified the phase-dependent modulation of the wake by wind and swell using a combination of a wave tank, a wind tunnel, and a scaled fixed-bottom WT model, and found that there is a significant correlation between the wake profile and the position and phase of the wave (Fercak et al., 2022). Yang used the LES technique to study the effects of swell on the marine ABL flow characteristics and the operation of WT. It is found that the WT wake is affected by both the swell-changed wind velocity and turbulence intensity, and the recovery characteristics and meandering degree of the wake are very weak under downwind swell (Yang et al., 2022c). Zhang studied the effects of wind-wave coupling on wake evolution by adjusting the wind shear index, turbulence intensity, WT position, wind rotor deflection angle, and wave surge motion. These studies highlight the complex interactions between wind, waves, and wakes in the operation of floating WT, providing valuable insights for the design and optimization of floating offshore wind farms.

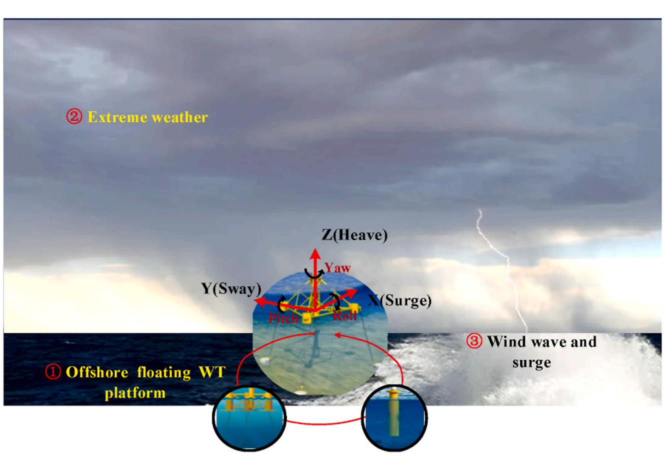



Fig. 9. Influences of the deep-sea environment and WTs structures on floating WT wakes.

Then, the effect of floating platforms on WT wake was investigated from the perspective of WT structure. The pitch and sway motions of the floating platform led to fluctuations in the horizontal and vertical directions of the WTs' wake, inducing meandering phenomena in the wake (Larsen, 2021). The work used the free vortex method and the non-stationary RANS method to observe the distortions produced by the transverse sway and pitch motions of the platform on the wake structure. The effect of platform motion on wake evolution was analyzed through wind tunnel experiments, e.g., Rockel found that the motion of the floating platform significantly affects the mean wind speed and the turbulence level, pointing out that vertical flows and the displacements caused by pitch motion need to be considered when the floating WT wakes modeling (Rockel et al., 2014b). Subsequently, Fu found that the pitch and roll motions of the floating WT increased the turbulence level in the upper part of the wake region and had a significant effect on the wake characteristics in the near-wake (Fu et al., 2019). New research also shows that lateral motions of floating WT can also induce meandering in the wake. Wise found that lateral meandering is insensitive to the type of structure of the floating WT, whereas vertical meandering is largely influenced by the structure of the floating platform (Wise and Bachynski, 2020). Kopperstad also found differential effects of different types of floating platforms on wake recovery (Kopperstad et al., 2020). In addition, Arabgolarch showed that the motion of floating platforms, especially the pitch motion of WT, has a greater effect on blade deformation, vibration and fatigue than the sway motion, resulting in a more unstable wake (Arabgolarcheh et al., 2022). Wise confirmed that the lateral wake meandering increases the yaw motion of the downstream floating WTs, but the surge and pitch motions of the downstream WTs are not affected by the wake meandering (Wise and Bachynski, 2020). Ribeiro also found that the surge and yaw motions are rather insensitive to the wake motion (Ribeiro et al., 2023). Recently, the effect on the wake characteristics of floating WT under pitch and yaw motions is beginning to receive attention (Hu et al., 2023). Tran conducted a numerical study of the non-constant aerodynamic characteristics of rotating blades under pitch and yaw motions of the platform and found that the maximum variation effect of the pitch and roll motions on the non-constant aerodynamic forces and power coefficients is about 12~16 times higher than that of the yaw motions (Tran and Kim, 2015). Ribeiro found that the effect of the yaw motions on the floating WT wake structure and blade tip velocity vortices is low enough that the velocity recovery of the WT wake is slow under yaw motion (Ribeiro

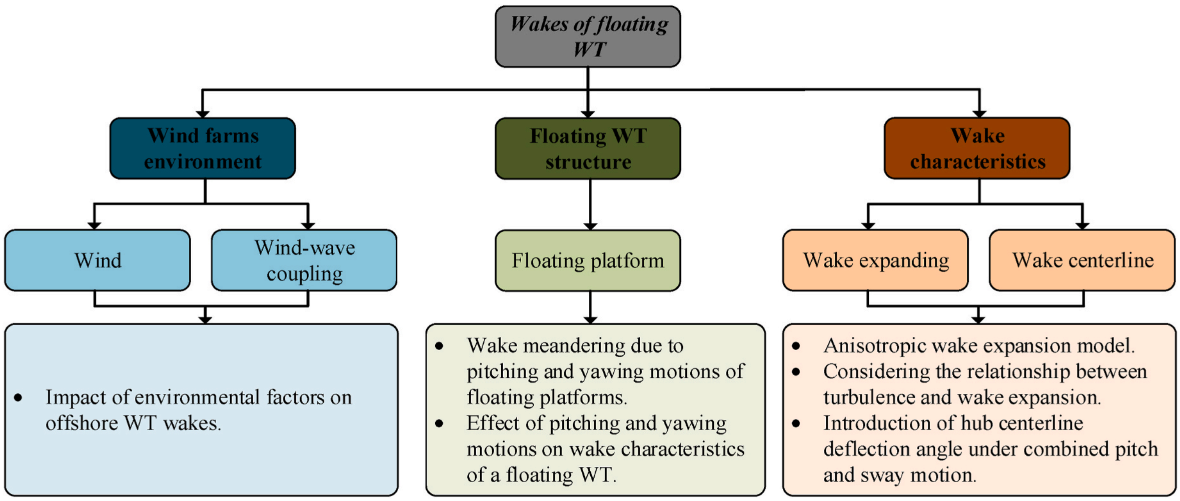



**Fig. 10.** Research framework of floating WT wake models.

et al., 2023).

In addition, WT wake models that conform to the wake evolution law were proposed based on the wake characteristics of offshore WT. Naderi proposed an ADM considering floating WT operation and wake geometry characteristics based on BEM and mass conservation theory, which can describe the wake interaction among WTs with low computational cost (Naderi et al., 2018). Wang proposed a 3D wake model for floating WT considering environmental and structural disturbances by combining wake expansion with incoming wind velocity for the first time, revealing the intrinsic mechanism affecting floating WT wakes, which provides guidance for the aerodynamic characterization and design of offshore floating WT (Wang et al., 2021b). Liu established a wake model for offshore WT with a linear relationship between wake growth rate and environmental turbulence (Liu et al., 2022c). Huang analyzed the drift of the wake centerline of floating WT based on the auxiliary effect of ABL, and derived the wake model under the influence of floating platform motions (Huang et al.).

The wake effect of floating WT is more significant than that of onshore WT due to the flexibility of their location and the complexity of the marine environment. The study of wakes modeling can more accurately predict the interactions between WTs and optimize the turbine layout, thus maximizing the energy output of the wind farm. Although studies have been conducted to describe the wake characteristics of floating WT from different perspectives, and the prediction accuracy of the proposed wake models has been significantly improved. There is still a long way to go in floating WT wakes research in order to promote the sustainable development of the entire offshore wind industry, to realize the goal of global energy transition, and to improve the competitiveness of offshore wind power.

1) More efforts are needed to develop wake models that consider the effects of ocean waves. For offshore wind farms, the current research only confirms that the waves have an impact on the floating WT wake (Ferčá et al., 2022; Zhang et al., 2022). However, it is not clear the mechanism by which waves affect the wake deficit profile of WTs, and the pattern of different wave effects on wake recovery.
2) The complex interaction between blades and annular vortices of offshore WT is studied. Currently, studies have shown that local vortex-ring or surge motion occurs during the operation of floating WT, leading to blade-vortex interaction (Arabgolarcheh et al., 2022; Dong et al., 2022). Studying the dynamic response of the vortex with the blades can help to understand how the vortex affects the vibration, stability and fatigue life of WT. To better understand the wake effect and improve the design, control strategy and performance evaluation of floating WT.
3) As the size of the WT increases, the range of the blades affected by the wind speed also expands, and different types of waves can lead to changes in the actual speed acting on the WT. Under different wind-wave coupling conditions, the output power of the WT at different downstream locations can be significantly different. In addition, the turbulence intensity and wind speed distribution in the wake are dynamically changing on a spatial scale. There is an urgent need to analyze the wind-wave coupling effect in detail using advanced numerical simulation techniques, and to comprehensively study the impact of wind-wave coupling on the performance of WTs by combining the analysis methods at different time and spatial scales.

## 4. Applications of wind turbine wake models

The wake effect is a significant factor that contributes to energy loss in wind farms, and minimizing its impact on WT performance has been a focus of great interest. In general, by considering the impact of WT wakes during the micro-siting stage before construction, controlling wind farms during mid-term operation, and resource assessment, the overall economic benefit of wind farms can be significantly improved. This section will review these three typical applications.

### *4.1. Wind farm layout optimization considering wake effect*

In the early stage of wind farm construction, the layout of wind farms plays a decisive role in the operation and economic benefits of wind farms (Zergane et al., 2018). The layout optimization of wind farms is to arrange WTs reasonably to improve the power generation efficiency and economic benefits of wind farms, considering the distribution of wind resources, the terrain of wind farms, the land utilization ratio in the field and the restriction of power grid connection. Studies have shown that the wake effect is a non-negligible part of wind farm layout optimization, which integrates many factors (Eroğ et al., 2013; Yang et al., 2015).

Table 9 presents a compilation of wind farm layout optimization studies conducted in the last decade that consider the wake effect. These studies are divided into three categories: based on the Jensen model, new wake modeling and comparative studies. As early as 2014, Shakoor reviewed the wind farm layout optimization under the influence of wake, and criticized the shortage of the Jensen model in describing the wake characteristics of complex terrain and the single optimization objective (Shakoor et al., 2016b). In the recent years, relevant researches explored the solutions to these problems. A large number of the improved Jensen models apply wind farm layout optimization to improve the accuracy of wake description, such as the improved Jenson model (Kuo et al., 2015), the Jensen-Gaussian model (Gao et al., 2016)

**Table 9**
Last publications in wind farm layout optimization considering wake effect.

| Aspect | Reference | Wake model | superposition model | Optimization objective | Optimization algorithm |
|---|---|---|---|---|---|
| Relevant research on the Jensen model | Gao et al. (2016) | Jensen-Gaussian model | / | Minimizing COE | Multi-population GA |
| | Kuo et al. (2015) | Jensen model | Improved sum of square | Minimizing loss of kinetic energy | Mathematical programming method |
| | Thomas et al. (2022) | Jensen-cosin/Bastankhah model | Sum of square/linear combination method | Maximizing AEP | Gradient-based sparse nonlinear optimization and gradient-free enhanced lagrange PSO |
| | Ulku and Alabas-Uslu (2019) | Improved Jensen model | Sum of square | Maximizing AEP and minimizing CPE | Mathematical programming method |
| | Yang et al. (2019) | Jensen model | Sum of square | Maximizing AEP and minimizing uniform wake loss | Annealing algorithm |
| | Wang et al. (2017) | Jensen model | Sum of square | Minimizing COE | GA |
| | Song et al. (2017) | Jensen model | Sum of square | Maximizing NPV | GA |
| | Turner et al. (2014) | Jensen model | Sum of energy deficits | Minimizing loss of kinetic energy | Mixed integer linear and quadratic integer programming |
| | Hou et al. (2017) | Jensen model | Sum of energy deficits | Minimizing LPC | Hybrid integer PSO |
| | MirHassani and Yarahmadi (2017) | Jensen model | Sum of energy deficits | Maximizing AEP | Mixed integer quadratic |
| | Kiamehr and Hannani (2014) | Jensen model | Sum of square | Maximizing productivity | Imperialist competition algorithms |
| New wake modeling | Kirchner-Bossi et al. (2018) | Gaussian model | Sum of square | Maximizing the total power | Cross-elite GA and baseline layout EA |
| | Yang et al. (2021) | Bastankhah + GaussBPA model | Sum of square results in an optimal | Minimizing LCOE | GA and PSO |
| | Parada et al. (2017) | Gaussian model | Sum of square | Minimizing COE | GA |
| | DuPont et al. (2016) | 3D extrapolation of the PARK wake model | Sum of square | Maximizing wind farm profit | EPS-MAS |
| | Zhen et al. (2021) | 3D gaussian wake model | Sum of square | Minimum power output cost | Discrete PSO + BPNN ( surrogate model ) |
| | Song et al. (2016) | 3D wake model | / | Maximizing AEP | Intensity pareto EA |
| | Tao et al. (2020) | 3D gaussian model | Sum of square | Maximizing the total power | Mixed discrete PSO |
| | Kuo et al. (2016) | CFD model | / | Maximizing AEP and minimizing LCOE | Mixed integer programming |
| Comparative study | Brogna et al. (2020) | Gaussian model | Sum of square | Maximizing the sum of normalized wind speeds | GS/MS/PS/GA/PSO/SA/LS/RS |
| | Chen et al. (2016) | Linear and particle wake model | Sum of square | Maximizing wind farm profit | 3D GA |
| | Yang and Najafi (2021) | Jensen/Multi-zone/Gaussian/GCH Model | Sum of square | Maximizing AEP | SLSQP |
| | Gao et al. (2020b) | Jensen/Frandsen/Jensen-K/Jensen-Gaussian model | / | Minimum LCOE | Multi-population GA |

and the Jensen-cosine model (Thomas et al., 2022). Optimizing the layout of wind farms is a complex and multidimensional challenge that necessitates extensive research under various environmental and operational conditions. Brogna conducted studies on the impact of complex terrains and multiple optimization algorithms on wind farm layout (Brogna et al., 2020); Ulku explored the effects of multiple wake interactions on wind farm layout (Ulku and Alabas-Uslu, 2019); Yang addressed the issue of uneven wind speed distributions, examining layout optimization to achieve uniform wake effects (Yang et al., 2019); Wang investigated the influence of terrain changes on wind farm layouts (Wang et al., 2017); Song assessed the impacts of construction at different stages and locations on layout strategies (Song et al., 2017). These studies collectively advance the understanding of strategic wind farm design to enhance overall efficiency and performance. The dominant situation of GA has been broken such as mathematical programming, gradient optimization and hybrid optimization in wind farm layout optimization (Turner et al., 2014; Hou et al., 2017; MirHassani and Yarahmadi, 2017). In addition, new engineering wake models have been used, the Gaussian wake model (Kirchner-Bossi et al., 2018; Yang et al., 2021; Parada et al., 2017) and 3D wake model (DuPont et al., 2016; Zhen et al., 2021; Song et al., 2016), which are widely used in wind farm layout optimization. Parada proposed a wind farm layout optimization scheme based on the Gaussian wake model, and compared the uncertainty of the Gaussian wake model under three wind conditions to verify its applicability (Parada et al., 2017). Subsequently, Kirchner-Bossi compared the performance of Jensen and Gaussian wake models in wind farm layout optimization and found that the accuracy of the wake models has a great influence on the power performance improvement of the layout (Kirchner-Bossi et al., 2018). The 3D wake model is applied to the wind farm layout study to further reduce the generation losses of wind farms. Tao proposed a 3D Gaussian wake model to solve the problem of layout optimization in non-uniform wind farms (Tao et al., 2020). Considering the spatial distribution of WTs, Song applied a 3D wake model to the wind farm layout to obtain the best combination of WTs location and tower height (Song et al., 2016).

It is worth noting that for the layout optimization of complex local wind farms, the accuracy of the wake models and the calculation cost need to be considered. Zhen was the first to simplify the integral calculation using a proxy model, which resolved the issue of requiring significant computational resources for power estimation during layout optimization in complex terrain (Zhen et al., 2021). Kuo combined a CFD model with a mathematical programming method to optimize the location layout of wind farms in complex terrain, resulting in an effective layout even when initial wake approximation is poor (Kuo et al., 2016).

In addition, several works have compared layout optimization while considering wake effect from different perspectives. Chen used the linear and particle wake models to study the layout optimization of wind farms with complex terrain, in which the power output of wind farms is significantly improved (Chen et al., 2016). Yang compared the effects of the Jensen/Multi-zone/Gaussian/GCH model on wind farm layout optimization. When optimizing the WT layout without yaw control, the trade-off between accuracy and time cost should be considered (Yang and Najafi, 2021). Gao analyzed the effects of the linear wake model and the 2D wake model on the layout optimization of wind farms, and confirmed that the linear wake model will fail when dealing with complex wind farms (Gao et al., 2020b). Brogna compared the performance of eight optimization algorithms in wind farm layout problems, and experimented to confirm the applicability of RS/LS in WT optimization problems (Brogna et al., 2020).Where, COE: Cost of energy, LCOE: Levelized cost of energy, AEP: Annual energy production, NPV: Net present value, LPC: Levelized production cost, CPE: Cost per power, PSO: Particle swarm optimization, GS: Global search, MS: Multi Start, PS: Pattern search, SA: Simulated annealing, LS: Local search, RS: Random search, EPS-MAS: Extended pattern search-Multi agent system, EA: Evolutionary Algorithm, GCH: Gauss-Curl hybrid, SQP: Sequential quadratic programming, SLSQP: Sequential Least SQP.

From the point of view of wake superposition models, the sum of squares method and the sum of energy deficits method have been widely used in wind farm wake flow modeling. Despite the high accuracy of the sum of squares method and the solid physical foundation of the sum of energy deficits method, the existing wake superposition methods all lead to the problem of the nonlinear objective function in wind farm layout optimization problems if the objective function is to maximize power or energy production capacity. Therefore, the use of existing wake superposition models in a deterministic optimization process remains a major challenge for wind farm layout optimization.

In general, the optimal layout of wind farms is still a key topic in the current wake research field. However, there are still several problems in the existing studies:

1) Although 3D wake models have been applied to wind farm layout optimization, the wake modeling considering additional turbulence effects has not been used yet.
2) Although the sum of squares model is widely used in wind farm layout optimization, it assumes that the velocity losses of each turbine wake are independent, ignoring the nonlinear characteristics of wake interactions. There is a need to develop new wake superposition models that better reflect the energy distribution and transfer between wakes and provide highly accurate computational results.
3) The optimization strategy is single, and comprehensive research on comprehensive optimization strategy is lacking.

### 4.2. *Wind turbine control considering wake effect*

Due to the lack of reasonable layout of wind farms established in the early stage, the downstream WTs have been noticeably affected by the upstream WTs wakes, which greatly reduces the total power generation of the wind farms. Although micro-siting selection is performed at the beginning of modern wind farm construction, the wake effect still exists under the constraints of the exploitation site. In order to reduce the loss of power generation due to the wake effect in wind farms, numerous studies in recent years have focused on mitigating the adverse effects of

**Table 10**
Last publications about WT control considering wake effect.

| Aspect | Ref. | Dataset | Control strategy | Control method | Wake model | Aim/Objective/Focus of Study |
|---|---|---|---|---|---|---|
| Active Wake Control | Rak and Santos Pereira (2022) | NREL 5MW/1 × 8 | Yaw control | Gradient-based SLSQP | Jensen/GCH/GaussBPA model | The linear model is not suitable for yaw control research, while the Gaussian model achieves good results for yaw control of WT. |
| | Wang et al. (2019) | NREL 5MW/2 × 3 | Yaw and tilt control | Pressure implicit split operator method | ALM | Both the yaw and tilt control strategies have an optimum angle of 30° from the initial position. |
| | Fleming et al. (2015) | NREL 5MW/1 × 2 | Yaw, pitch and tilt control | / | LES | To investigate the effect of wake redirection techniques on two WTs systems aligned in the flow. |
| | Qian et al. (2022) | Choshi-2.4 MW | Torque, pitch and yaw control | PI control | ALM | Developing a simulation program of WT for wake control |
| | Nakhchi et al. (2022) | NREL 5MW/2 × 1 | Yaw control | Hybrid control strategy | LES and ALM | Evaluate the performance of WT affected by yaw and tilt angles on the wake. |
| | Ma et al. (2021) | – | Yaw control | GA/Collaborative Control | Shapiro model | Two generalized and effective algebra formulas to determine the WT yaw angles are proposed. |
| | Shu et al. (2022a) | An offshore wind farm of 150 MW with 30 NREL-5MW | Yaw control and pitch control | SQP | Gaussian wake model | A decentralized optimization strategy based on graph theory is proposed to realize real-time control of large wind farms. |
| | Shu et al. (2022b) | DTU-10MW/6 × 6 | Yaw control | SQP and ADMM | GaussBPA model | "Individual + Connection Topology + Communication Rules" multi-agent system technology is established. |
| | Korb et al. (2023) | NREL 5MW/1 × 3 | Independent pitch control： helix approach | Reinforcement learning | LES | A set of analytical tools for examining helical wake is provided. |
| | Frederik et al. (2020) | DTU 10 MW | Independent pitch control | Dynamic induction control | LES | A new method for dynamic control of WT in wind farms is proposed. |
| | Li et al. (2022c) | Zhuanghe wind farm | Yaw control, inductive control and yaw-inductive control | GA/Collaborative control | GaussBPA model | The combined control only slightly outperforms the single yaw control in realistic wind farms. |
| Others | Lyu et al. (2020) | NREL 5MW/3 × 4 | Active power regulation | Adaptive method | Jensen model | To achieve online adjustable control gain and reduce power generation losses caused by the wake effect. |
| | Lyu et al. (2021) | 5MW/2 × 4 | Adaptive Frequency Responsive Control | Droop control | Jensen model | Increase efficiency of the wind farm and alleviate frequent pitching action of WT. |
| | Vali et al. (2022) | NREL 5MW/3 × 4 | Active power control | MPC | LES | A strategy of wind farm wake AMPC is proposed. |
| | Shen et al. (2022) | Horns Rev wind farm | Active power coordination control | Intelligent control | Jensen model | The output power of the wind farm increases by about 10%. |
| | Chen et al. (2021b) | NREL 5MW/3 × 3 | Automatic generation control | Deep learning assisted MPC | DNN | A new MPC framework is proposed to coordinate different WTs. |

wake by adjusting the operation of upstream WTs. Nash reviewed the active wake control strategies of WT and summarized the advantages and disadvantages of each wake control technology (Nash et al., 2021). The widely used active wake control strategies mainly include yaw control, pitch control, torque control and tilt control. Yaw control and tilt control affect the direction of the wake while pitch control and torque control affect the strength and recovery speed of the wake. Table 10 lists the latest studies on wake control over the past two years and summarizes the research by datasets, control strategies, control methods, wake models and research objectives.

From the point of view of control strategies, WTs' yaw control considering wake effect remains important research. Using full wake scenarios for two WTs, Fleming investigated wake redirection strategies such as yaw, pitch and tilt, and analyzed the effect of wake on WTs power and load (Fleming et al., 2015). Qian first implemented torque, pitch and yaw control in LES using the ALM and developed a control-oriented WT simulation program (Qian et al., 2022). Subsequently, ALM has been widely used. Wang studied the effect of different control strategies on the wake under 24 operating conditions and found that the yaw control strategy can achieve more total output power of offshore wind farms than the tilt control strategy (Wang et al., 2019). Based on accurate aerodynamic load forecasting and ALM, Nakhchi investigated the effects of yaw and tilt angles on wake and unit power, and presented a hybrid wake control strategy to optimize the power generation of wind farms (Nakhchi et al., 2022). Although the ALM can accurately describe the wake characteristics of WTs, its potential for yaw control and optimization of WTs cannot be fully explored due to the complexity of the calculation. Rak investigated the potential of each engineering wake model for wind farm control strategies under different atmospheric conditions and wind farm layouts (Rak and Santos Pereira, 2022). Ma constructed two algebraic formulas for fast yaw calculation of WTs considering thrust factor, turbulence intensity and WTs spacing, which greatly reduced the wake deficits of wind farms with aligned WTs (Ma et al., 2021). For large wind farms, Tong used the sparse wake orientation maps and the wake intensity weighting matrices to divide the wind farms into several uncoupled cluster sets for control respectively. Through multi-agent collaboration, the wake losses were reduced and the wind farm productivity was improved (Shu et al., 2022a, 2022b). A compelling independent pitch control method has been proposed where the helix approach is used to mitigate the wake effect of WT. The helical approach helps to induce wake steering earlier and also deflects the center of the rotating wake, thus reducing the wake effect on downstream WTs (Korb et al., 2023). Since changes in induction factor and yaw angle signals can lead to significant changes in rotor thrust, which in turn affects the power output and causes complex fluctuations, the new study combines the concepts of independent pitch control for wake orientation with dynamic wind farm control to achieve enhanced wake mixing with minimal power and thrust variations (Frederik et al., 2020).

In addition, with the increasing proportion of wind energy in modern power systems, research pay more attention to the power regulation of wind farms. Considering the inherent wake effect of wind farms, power regulation control of wind farms is challenged. Li analyzed the power changes of wind farms under different control modes, which guided wake control of wind farms with regular and irregular layouts (Li et al., 2022c). Lyu proposed an adaptive method to assign the tasks of active power regulation to WT, considering the complex wake models of wind farms, the time-varying characteristics of wind speed and load demand (Lyu et al., 2020). Subsequently, it was proposed to consider the WTs wake effect in the frequency control, and both the total power generation and the frequency regulation capability were overestimated under the influence of the wake (Lyu et al., 2021). Vali proposed a wind farm adaptive model predictive control (AMPC) based on the wake effect, which is used to track the wind farm power benchmark and optimize and coordinate the structural load of WTs (Vali et al., 2022; Vali et al.). Shen investigated the cooperative control strategy of active power for wind farms under the influence of wake (Shen et al., 2022). Chen proposed a deep learning-assisted model predictive control (MPC) algorithm for optimal control of wind farms based on the DNN wake model. The method can improve the tracking power range by 50% compared to ProD control (Chen et al., 2021b).

In general, active wake control is the primary means of reducing the wake effect in wind farms. Fig. 11 shows the impact of active wake control on the wind farm output. According to the research report on the total power generation in wind farms, wake deflection can effectively improve the power output of wind farms, the power generation of each wind farm is increased by more than 7%, and the average power generation is increased by 11.00%. The average power generation increased by 8.1% compared with the statistics in the work (Ali et al., 2021a), which indicates that the active wake control strategy has great potential to improve the performance of WTs. It is also found that hybrid control improves the overall performance of WTs better than single yaw control and tilt control. The hybrid active wake control is more effective for improving the performance of complex terrain and large wind farms, and this method will become the main research direction for reducing the wake effect. Secondly, dynamic active wake control has high potential because it can better adapt to changing wind field conditions and improve energy capture efficiency (Meyers et al., 2022). However, in dynamic active wake control, dynamic wake modeling is highly complex and computationally intensive. The problem of how to balance low computational complexity and high fidelity of dynamic wake modeling in wind farms needs to be solved urgently. AI technology can help reduce the computational complexity, and how intelligent control methods can achieve real-time data and model updates for intelligent decision making, so as to better cope with dynamic wind field conditions. Finally, the theory of establishing an effective double-layer control framework when combining hybrid dynamic control with yaw control and induced control is not well developed.

Additionally, the implementation of active yaw control strategies for WTs can lead to additional stress on the blades and towers of upstream WTs, increasing fatigue loads. Frequent yaw adjustments may lead to increased wear and tear of mechanical components, consequently shortening the lifespan of the WT. The FAST software provides extensive aeroelastic numerical simulations under various wake inflow and yaw misalignment conditions, enabling the assessment of damage equivalent loads on key components of WT. Shaler analyzed the effect of wake on the structural response of the WT by combining the FAST and FVW model, and found that the power of the WT and the out-of-plane root bending moments increased non-cointantaneous under the influence of wake (Shaler et al., 2019). Subsequently, Shaler analyzed the sensitivity of 28 wind inflow and wake parameters, and found that the ambient turbulence and shear in the main wind direction are the most sensitive parameters affecting the fatigue and ultimate loads of WTs (Shaler et al., 2023). Similarly, Sun has conducted a comparative analysis using OpenFAST on the impact of fatigue loads of key components of WT under various yaw and wake interaction conditions, finding that environmental wind speed and atmospheric turbulence have a decisive impact on the fatigue loads of blades and towers (Sun et al., 2022). This effect was subsequently quantified by Thedin, where LES of different steady states from neutral to unsteady revealed substantial changes in turbulent inflow-induced WT loads, with turbulence affecting rotor and tower loads was 10 times greater than that of the mean shear surface (Stanislawski et al., 2023). Frederik analyzed the loads of WT with different active wake mixing strategies using both OpenFAST and SOWFA simulations, discovering that all active wake control strategies increased the damage equivalent loads of the WT blades and towers (Frederik and van Wingerden, 2022). He noted that enhancing the total power output of a wind farm through wake steering often comes at the cost of increased structural loads (He et al., 2024). Subsequently, Tao verified through Floris and OpenFAST that considering wake effects, yaw optimization control can significantly increase the annual electricity output of wind farms, but at the cost of reducing the fatigue life of

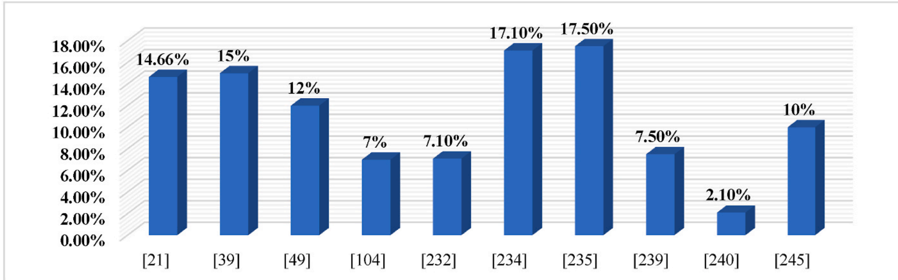



**Fig. 11.** Influence of the latest published active wake control methods on wind farm power.

tower bolts by 3~9 years (Tao et al., 2024). Overall, to achieve the goals of maximizing power output and reducing loads, further research into reasonable control strategies and WTs arrangements is necessary.Where, PI: Proportional integral, ADMM: Alternating direction method of multipliers.

### *4.3. Resource assessment of wind farm considering wake effect*

Resource assessment under the influence of WT wakes is aimed at determining the actual wind resource for individual WT in a wind farm, considering the wind speed and direction after the wake effect. Advanced numerical simulation tools and models are utilized to simulate the propagation and effects of the wake to accurately predict the power generation of the WT and the power generation capacity of the entire wind farm. The studies in Sections 4.1 and 4.2 have proved that optimizing the layout of WT and changing the active yaw control strategies of the wake track can reduce the influence of the wake effect on the wind farm and improve the efficiency of the wind farm generation. Research have explored power prediction models considering wake effects. These models are categorized into machine algorithm-based and weather research and forecasting model (WRF)-based power prediction model. Fig. 12(a) shows the basic framework of a power prediction model based on machine learning algorithms, which uses the wake characteristics as inputs or changes the network structure to analyze the influence mechanism of wake on power. Sun developed an ANN model for estimating the capacity of wind farms using wake models and terrain information, and combined this model with GA to achieve a downstream WTs power ratio of more than 0.96 (Sun et al., 2020b). Nakhchi used the XGBoost algorithm to predict the power of WTs under the influence of wake and found that the XGBoost method is superior to the ANN method in terms of computation time and prediction accuracy at different yaw angles (Nakhchi et al., 2023). By combining machine learning techniques with physical models, the accuracy of prediction and the physical consistency of the models are improved. Zhou proposed an ANN power prediction model with wake mechanism and data-driven parallel, which realized the resistance of the model to singular data (Zhou et al., 2022b). In addition, Guo proposed a short-term power prediction model using a wake physical model to stimulate the neural network, which improved

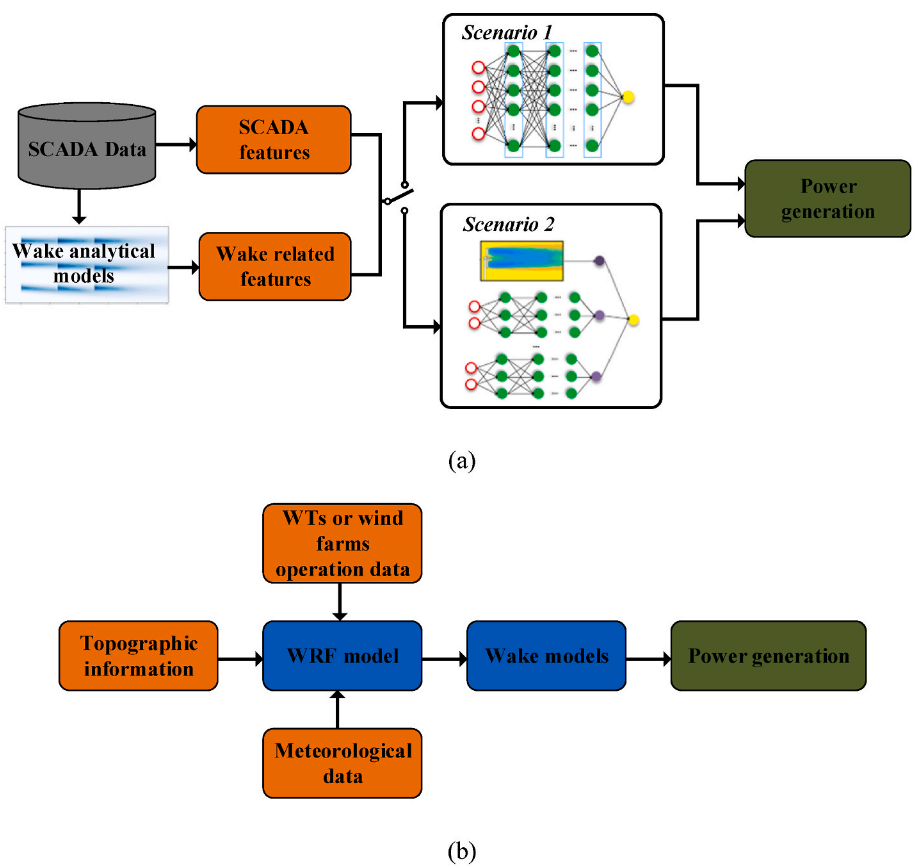



**Fig. 12.** Modeling framework for power prediction considering wake effect. (a) Based on machine learning algorithms. (b) Based on the WRF model.

the prediction accuracy by more than 20% compared with the traditional neural network model (Guo et al., 2022b).

The WRF model solves the complex meteorological processes using topographic information and particle flow coordinates based on Euler specifications. Due to its excellent estimation of wake irregularities and high computational efficiency for complex terrain, it is widely used for power forecasting of WT. Fig. 12(b) shows the structure of the WRF-based power prediction model. Cuevas analyzed the effect of the wake on the output of wind farms through the WRF model. It was found that the wake below the rated wind speed would reduce the output of downstream WTs by 20% and the annual output of wind farms by 13~17% (Cuevas-Figueroa et al., 2022). Prósper investigated the loss of wind resources due to wake effects using a WRF model with a high resolution, and found a power loss of 0.5% even for WT 17.5 km away (Pró et al., 2019). Feroz studied the wake effect between wind farms based on the WRF model, which confirmed that it is necessary to consider the wake effect of neighboring wind farms in power forecasting (Feroz et al., 2020).

It is worth noting that the quality of the power prediction model based on the machine learning algorithm largely depends on the quality of the data. However, there are errors in calculating wind speed characteristics with the wake models. How to improve the accuracy and efficiency of power under the conditions of inaccurate incoming wind speed is a challenging problem. In addition, a more comprehensive multi-physics modeling approach is developed to improve the accuracy of power prediction by considering factors such as meteorological conditions, topography, and WT characteristics, and by combining the wake models and WT performance models. Finally, the uncertainty of wake effects, including meteorological condition uncertainty and model parameter uncertainty, is investigated to develop more robust power prediction models.

## 5. Discussion and future trends

Reviewing the studies on WT wakes modeling, it can be concluded that significant progress has been made in improving the accuracy of wake models and reducing their complexity and computational cost. These advancements are detailed in Section 2. Section 3 analyzes the wakes modeling of WT in complex terrain, pointing out the need to better understand the interaction of complex terrain and deep-sea conditions with WT wakes and to develop more accurate and efficient modeling methods. Combining these analyses, this review highlights current trends in wakes modeling and important areas for future research, focusing on deep learning-driven fluid dynamics, establishment of WT wake databases, the study of wake superposition mechanism models, multi-scale wakes modeling, and field group wake. By focusing on these rapidly developing and important areas, future research will be able to further advance the development of WT wakes modeling.

1) Adaptability problem of AI wake models: considering the problem that the existing data-driven wake modeling based on data is more individual and difficult to generalize, it can be improved in two aspects: firstly, the introduction of transfer learning technology into the modeling of WT wakes can help to improve the performance of the AI model in the new scenarios. Secondly, open datasets, as CFD and field measurements take a lot of time, resulting in a single structure of the dataset for training AI models. Forming an open wake dataset to increase the diversity of model training data can help models generalize better to various scenarios and tasks.
2) Wakes modeling combining AI technology with physical process: The latest research by ArcVera Renewables shows that the current analytical wakes modeling seriously underestimates the energy loss caused by the far wake (Stoelinga et al., 2022). In addition, the latest studies have confirmed the superiority of AI technology in describing the evolution of WT wakes (Ti et al., 2020; Nai-Zhi et al., 2022). A physically enhanced deep learning model is constructed based on the powerful data processing capability of AI and its adaptability to nonlinear problems. Physical rules such as the control equations and boundary conditions of fluid dynamics are embedded in the model, and deep learning algorithms are used to process the partial differential equations, which enhances the generalization and prediction ability of the model, and improves the accuracy and physical consistency of the model.
3) Develop a wake superposition model with a physical basis: In modern wind farms, the inflow wind speed of downstream WTs affected by the wake of multiple WTs is analyzed using superposition models. However, currently used wake superposition models are empirical and lack a clear physical meaning, making it difficult to improve them through numerical simulation or experiments. Although AI has been used to simulate wake superposition models, and its accuracy has been greatly improved compared to traditional methods, it is still unable to analyze the flow field movement around the downstream WTs wakes from a mechanistic perspective. Therefore, constructing a wake superposition model based on physical principles can provide new ideas, and enable fatigue analysis of downstream WTs by combining wake and turbulence in the future. Meanwhile, traditional localized superposition models can also be improved to enhance the computational accuracy of the flow field distribution in wind farms based on the phenomenon that high turbulence intensity in wake superposition region leads to faster velocity recovery.
4) Cross-scale modeling of wake models: Use of micro-scale wake models to simulate the wake behavior of a single WT. A macro-scale wake model is used to simulate the interaction between multiple WTs in the wind farm. The microscale and macroscale models are then coupled together to establish the relationship between the wake behavior of individual WT and the performance of the wind farm. Through cross-scale modeling, the interactions between WTs within a wind farm can be better understood to optimize the layout of the wind farm and improve the wind farm control strategy to increase the energy capture efficiency and reduce the effect of wake on efficiency.
5) Research on wake control of field group: In recent years, the research on wake effect mainly focuses on the interaction and control of WT in wind farms, while the wake effect between wind farms is often ignored (Mayol et al.; Fischereit et al., 2022). In most cases, WT's wake refers to the local effects of a wind farm. However, related studies have found that under stable atmospheric conditions, the influence range of the wake of onshore WT is more than 40 km (Platis et al., 2021). Since the atmosphere in the ocean is more stable than on land, the wakes of large WT can extend beyond 100 km (Maas and Raasch, 2022). In addition, with more investment in the wind power industry from all over the world, wind farms are being built more intensively due to the constraints of land and available sea area resources. Therefore, it is urgent to solve the control method research of WT under the wake interference of the farm group to reduce the loss caused by the unreasonable layout. At the same time, the law of wake disturbance between wind farms needs to be explored to provide new engineering guidance for the location and control of wind farms.

In section 4, by reviewing the application of WT wake models in wind farm layout optimization, wind farm control and resource assessment, the shortcomings of these studies are pointed out and the research trends of future studies are analyzed. Additionally, to better apply the WT wake models, this review also focuses on the development of WT wakes in the fields of wake assessment, structural load assessment, WT design and grid connection from the perspective of the impact of wake on WT performance, as detailed below:

1) Develop wind resource assessment modeling tools for each scenario: Currently, the wake models used in wake evaluation software, such as the Jensen model and the improved Jensen models, have

limitations in modeling under complex terrain and unstable atmospheric boundary layer conditions. Furthermore, with the increasing development of offshore wind power, there is a growing need for wind resource assessment tools that do not rely on field observation data such as wind towers. Existing engineering wake models and CFD models have limited applicability in such scenarios, and the use of these models may face greater challenges in wind farms with complex environments. Therefore, it is important to develop wind resource assessment software that is suitable for mountainous and marine environments. At the same time, complex modeling frameworks such as multi-scale nesting and atmospheric coupling will become increasingly important in the development of wake assessment tools for complex environments.

2) Study of the relationship between inflow conditions and wake evolution: The measurement, simulation and modeling of realistic and complex wind conditions in the field must be emphasized to obtain accurate and reliable turbine operation and design conditions. Studying the relationship between inflow conditions and wake evolution can provide valuable insights into the complex physical characteristics of WTs wake under complex terrain, and further improve the accuracy of wake modeling to build engineering models that are more in line with the actual wind farm operating environment.
3) Structural load modeling of WT under the influence of wake : the influence of wake effects on the fatigue loads of critical components of WT is poorly understood, and wake suppression mechanisms within wind farms remain unclear. Therefore, it is necessary to develop integrated multi-physics field models including fluid dynamics, structural mechanics and aeroelasticity to accurately predict the complex interactions and load distributions of WT. In addition, detailed turbulence modeling and wake interactions should be incorporated to assess their effects on structural loads, especially on WT operating in closely spaced arrays.
4) Improved WT design: Improving the design of WT to better withstand wake interactions and perform under unsteady, multi-scale effects and thermo-dynamic coupling is essential to maximize the efficiency and lifespan of wind farms. Design WT blade and rotor configurations to minimize turbulence-induced velocity deficits and increased turbulence intensity. Developing materials and structural designs capable of withstanding the periodic loads and stresses induced by vortices can help reduce fatigue and extend the lifespan of WT. Advanced control systems should be implemented to adjust turbine operations in real-time based on wake interactions between WTs and momentum mixing with the atmosphere, optimizing performance and reducing structural loads.
5) Grid integration of WT considering the wake effect: The high proportion of new energy power generation equipment connected to the grid has a great impact on the stable operation of the power grid as the investment in new energy power generation continues to increase in various countries (Schmietendorf et al., 2017; Kesavan et al., 2024). New energy grid integration will introduce grid fluctuations at different time scales, which increases the difficulty of power balancing more, and puts higher requirements on the grid's peaking capacity (Martí et al., 2023). It is found that the intermittency of wind power directly translates into frequency and voltage fluctuations, which seriously breaks the stability of the grid (Wang et al., 2023). The complex dynamic inflow seriously affects the output of WTs. If the traditional wind farm output model is used for estimation and calculation, its deviation will have a significant impact on the wind power penetration power limit, resulting in the power system not being able to utilize the wind power efficiently and rationally. Therefore, there is an urgent need to establish a stochastic optimal tidal current model that considers the influence of the wake effect to break through the bottleneck of large-scale wind power grid integration.

## 6. Conclusions

The wake is one of the main factors affecting the fatigue loading of WT and the capacity of wind farms. An accurate assessment of WT wake effect is required for minimizing or even eliminating the effects of wake effects in wind farms. The assessment of WT wakes is a multidisciplinary research field involving many aspects such as fluid dynamics, meteorology, mechanical engineering and electrical engineering. Accurate wake assessment can help optimize wind farm design, minimize wake impacts through rational turbine layout and control strategies, and improve the overall efficiency and generating capacity of the wind farm. This review provides a comprehensive review of WT wakes modeling and applications, which can provide theoretical basis and technical guidance for WT wake-related researchers.

However, since the research on floating WT wakes modeling is in its infancy, and this review is not comprehensive enough to review them. Onshore WT wakes research provides a theoretical foundation and technical approach to the study of floating WT wakes, particularly in terms of wake modeling, impact assessment, and wake control methods. While the basic wake theory is designed for fixed-base wind farms, the core principles of these models are equally applicable to understanding the wake characteristics of floating WT. To accommodate the dynamic ocean environment of floating WT, these models need to be adapted and improved to more accurately simulate the complex dynamic response of floating platforms and the corresponding wake effects. Meanwhile, wake control techniques developed in onshore wind farms, including dynamic yaw control and variable pitch regulation, provide a practical framework for wake management in floating WT. The application of these technologies in floating WT can effectively reduce the dynamic loads and power losses caused by wake currents, thus improving the overall operational efficiency of wind farms and extending equipment life. In addition, the experience of onshore WT wakes research in wind farm layout optimization and multi-scale modeling provides valuable insights for designing floating wind farms with efficient wake management under complex ocean conditions. The application of these methods and strategies can optimize the energy capture efficiency and reduce the environmental impact of floating wind farms, supporting the development and sustainable implementation of floating offshore wind technology. Therefore, reducing the wake effect will be a driving force in achieving zero-carbon emissions from wind power.

## CRediT authorship contribution statement

**Li Wang:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mi Dong:** Writing – review & editing, Funding acquisition, Data curation, Conceptualization. **Jian Yang:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Lei Wang:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Sifan Chen:** Writing – review & editing, Data curation. **Neven Duić:** Writing – review & editing, Formal analysis. **Young Hoon Joo:** Writing – review & editing, Funding acquisition. **Dongran Song:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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