World Journal of Engineering Research
Print ISSN: 2959-9865
Online ISSN: 2959-9873
DOI: https://doi.org/10.61784/wjer3042

ANALYSIS OF WAKE EFFECTS AND LAYOUT OPTIMIZATION METHODS FOR OFFSHORE WIND FARMS

JiaXuan Li
Engineering Management Department, Huadian Liaoning Energy Development Co., Ltd., Shenyang 110102, Liaoning, China.
Corresponding Email: 1214529479@qq.com

Abstract: This paper addresses the issues of energy loss and equipment fatigue caused by wake effects in offshore wind farms by proposing a hybrid prediction model that integrates physical mechanisms with data-driven approaches, along with a layout optimization framework based on a multi-objective evolutionary algorithm. First, through improved RANS numerical simulations, scaled wind tunnel experiments, and high-resolution LES local simulations, the study systematically reveals the coupling effects of different planar layouts, wind speed conditions, and turbine height differences on wake velocity attenuation, turbulence regeneration, and vortex structure evolution. Second, a hybrid prediction model integrating analytical model priors with corrections from XGBoost and residual network compensation is constructed, enabling high-precision, low-latency online prediction of wake decay rates and turbulence intensity under unknown layouts and extreme wind conditions. Finally, by incorporating annualized power generation, fatigue load fluctuations of critical components, and operational costs into a unified multi-objective function, Pareto front search is employed to generate multiple sets of optimal layout schemes. The robustness of these schemes is validated through sensitivity and uncertainty analyses. Case studies demonstrate that optimized wind farms can increase annual power generation by 3%–7%, reduce load fluctuations by 10%–15%, and lower operational costs by 5%–9%, while simultaneously decreasing maintenance vessel dispatch frequency, reducing marine noise pollution, and significantly enhancing carbon reduction benefits. The research outcomes not only enrich wake dynamics and turbulence regeneration theories but also provide practical, visualized decision-support tools for the design, construction, and operation of offshore wind farms, holding significant importance for advancing the intelligent and low-cost development of the wind power industry.
Keywords: Offshore wind farm; Wake effect; Hybrid prediction model; Multi-objective layout optimization; Turbulence regeneration; Pareto front; XGBoost; LES simulation

1 INTRODUCTION

1.1 Research Background

In recent years, with the accelerating global energy transition and the proposal of "carbon neutrality" targets by various nations, offshore wind power, as a clean, safe, and renewable energy form, has gradually become a pivotal direction for wind energy utilization. Benefiting from vast maritime spaces and relatively stable wind conditions, offshore wind power offers significant advantages such as large installed capacity, stable power generation, and minimal land resource occupation. This has attracted substantial capital investment and policy support from coastal nations and regions including the EU, the US, and China, driving exponential growth in the scale of offshore wind farm construction. However, as large-scale offshore wind farms develop in clusters, the issue of mutual interference among wind turbines has become increasingly prominent. Problems such as energy loss, load fluctuations, and equipment fatigue damage caused by wake effects have emerged as critical bottlenecks hindering the efficient and stable operation of offshore wind farms. A wake refers to the phenomenon where wind speed and turbulence characteristics change in the downstream region of an operating wind turbine. After the turbine blades capture kinetic energy and convert it into electricity, a disturbed zone characterized by reduced flow velocity and increased turbulence intensity forms behind the blades. This zone not only significantly reduces the available wind energy for downstream turbines but also causes a sharp increase in dynamic loads on blade and nacelle structures, thereby shortening equipment lifespan and increasing maintenance costs. These issues are particularly complex and severe in offshore wind farms due to variable wind conditions, maintenance difficulties, and marine environmental corrosion. Over the past decade, breakthroughs in marine engineering, materials science, and control technology have increased single-unit capacity from megawatt-scale to over ten megawatts. However, this substantial increase in turbine capacity has also led to broader and more intense wake interference, imposing higher design and operational requirements on turbines and their foundation structures. Furthermore, limitations in platform load-bearing capacity often lead to compact turbine spacing within limited sea areas, exacerbating wake coupling effects. These factors indicate that simplified one-dimensional wake theories and traditional empirical layout methods can no longer meet the precise layout demands of modern large-scale offshore wind farms, necessitating the introduction of more mechanically fluid-coordinated and data-intelligence-supported wake effect analysis and layout optimization approaches. Concurrently, research on wake effects and their impact on wind farm performance holds not only practical engineering significance but also advances the in-depth development of wind energy conversion mechanisms and turbulence dynamics theories. The global academic and engineering communities have extensively explored wake phenomena from perspectives including theoretical modeling, numerical simulation, wind tunnel testing, and field observation. Classical models like the Jensen and Park models played important roles in early wind farm design but fall short in describing three-dimensional turbulent diffusion and wake recovery processes under complex terrain conditions, failing to meet modern high-precision assessment needs for offshore wind farms. Meanwhile, the integration of computational fluid dynamics (CFD) and big data-driven machine learning in renewable energy offers new avenues for deep-level wake mechanism analysis and wind farm layout optimization. High-resolution CFD simulations combined with multi-source data fusion enable detailed spatial mapping of wake characteristics, while machine learning algorithms extracting features and training models on vast operational data facilitate real-time prediction and online control of wake effects in complex dynamic environments. In summary, systematic analysis of offshore wind farm wake effects and the proposal of advanced theoretical models and optimization algorithms for layout design are of significant practical and strategic value for enhancing overall wind farm power generation efficiency, extending equipment service life, reducing lifecycle costs, and ensuring the sustainable development of offshore wind power.

1.2 Research Questions

The essence of wake effects in offshore wind farms lies in the dual impact of low-speed, high-turbulence zones formed behind turbine blades—after kinetic energy extraction—on downstream turbines' wind energy utilization and structural loads. Therefore, this study first aims to clarify the characteristics and generation mechanisms of wake effects in marine environments, identifying key factors influencing wake intensity and spatial attenuation patterns. Second, it seeks to construct a multi-scale prediction model integrating physical mechanisms and data-driven approaches to accurately simulate wake field distributions under different layout schemes. Third, based on the prediction model's output, it intends to design an optimization method capable of self-adaptively adjusting turbine arrangements to maximize overall power generation efficiency and minimize equipment load fluctuations within designated sea areas. Specifically, this research focuses on three core questions:

First, the multi-dimensional analysis of wake effect influencing factors. Traditional wake models attribute downstream wind speed recovery primarily to turbulence diffusion coefficients and turbine geometric arrangement parameters, often neglecting the coupled effects of complex features in the marine atmospheric boundary layer—such as stability, vertical wind profiles, and vortex structures—on wake diffusion. Additionally, vibration excitation from offshore platform structures interacting with sea waves and tides can cause secondary impacts on downstream flow fields. Thus, a systematic review of factors affecting wake intensity and recovery distance is required, quantifying the mechanistic roles and contributions of marine-specific environmental variables (e.g., atmospheric dome effects, sea surface roughness variations, turbine height differences) in wake formation and evolution.

Second, the integrated construction of a wake prediction model. Existing wake models are broadly categorized into empirical analytical models and numerical simulation models. One-dimensional Jensen models and multi-dimensional Park models, while computationally simple with few parameters, suffer from limited accuracy and scalability in complex flow fields. High-precision three-dimensional CFD models reveal details of vortex-turbulence interactions but are hindered by computational resource demands and boundary condition sensitivity, impeding their application in large-scale wind farm layout optimization. Therefore, this study introduces machine learning algorithms to enable rapid prediction of wake field distributions by extracting features from high-resolution CFD simulations and field measurements for model training. Further, by incorporating physical constraints from classical analytical models and hybrid decoupling techniques, it aims to disentangle nonlinear coupled relationships during wake recovery, enhancing model generalizability and computational efficiency.

Third, the design and validation of layout optimization methods. Layout optimization objectives typically include multiple conflicting indicators such as maximizing total power generation, minimizing blade load fluctuations, and optimizing operational costs.

1.3 Research Significance

Research on offshore wind farm wake effect analysis and layout optimization holds significant engineering value and theoretical innovation. First, from an efficiency perspective, wake effects are a primary source of energy loss in offshore wind farms. Extensive studies and field observations show that downstream turbines affected by upstream wakes experience significantly reduced available wind speed and power, decreasing overall annual energy production by 5%–15%, with losses exceeding 20% in densely arranged layouts. Against the backdrop of rapid global offshore wind capacity expansion, failure to effectively control wake losses and optimize layouts directly impacts return on investment and sustainable operation. Furthermore, as offshore turbine capacities increase from early 3–5 MW to 10–15 MW or even 20 MW units, larger rotor diameters and hub heights lead to broader wakes and higher turbulence intensity, making wake-induced load impacts on downstream turbines increasingly complex. Thus, scientifically analyzing wake formation mechanisms, quantifying influencing factors, and optimizing layouts can not only enhance overall power generation efficiency but also reduce dynamic load fluctuations on blades and nacelles, extending equipment lifespan and lowering maintenance frequency and costs—crucial for improving economic benefits and operational reliability.

Second, from an operations and maintenance (O&M) perspective, wake-induced load fluctuations and intensified vibrations accelerate fatigue damage rates in downstream turbine components, raising O&M costs. Statistics indicate that fatigue life of critical components like main bearings and gearboxes decreases by 10%–30% under wake conditions compared to wake-free scenarios, with repair and replacement costs accounting for over 40% of annual O&M expenses. For offshore wind farms, transporting personnel and equipment for maintenance is costly and complicated by sea conditions and weather, posing high risks. Rational layout designs reducing wake interference can minimize equipment damage probability at the source, enabling smoother operation and substantial savings in O&M resources.

Third, regarding theoretical contributions, traditional wake models based on simplified assumptions (e.g., isotropic turbulence diffusion, one-dimensional velocity attenuation) struggle to fully describe nonlinear coupled wake evolution in complex marine environments. Integrating high-fidelity CFD simulations with machine learning captures detailed features like vortex structures, turbulence regeneration, and atmospheric boundary layer stability while enabling efficient multi-source data fusion and prediction through data-driven approaches. This dual enhancement in model accuracy and generalizability advances the convergence of wind energy conversion and turbulence dynamics theories, enriching wake effect theory and providing methodological references for similar flow interference studies in other renewable fields (e.g., wind-solar hybrid systems, marine energy).

Finally, at the strategic and societal level, offshore wind power—as a key pillar for energy transition and carbon neutrality—has been incorporated into national energy plans and subsidy policies globally. Improving offshore wind farm efficiency and reducing O&M costs will attract more investment, fostering technological breakthroughs and industrial upgrades. Simultaneously, expanding clean energy capacity effectively displaces fossil fuel-based power, reducing CO_2 and pollutant emissions to significantly improve coastal and oceanic environments—yielding profound impacts on climate change mitigation and ecological security. In conclusion, systematic analysis of offshore wind farm wake effects and the proposal of advanced model-based layout optimization methods not only enhance operational efficiency and equipment reliability but also inject new technical pathways into wind energy conversion and turbulence dynamics research, better supporting clean energy strategies to achieve economic, environmental, and social benefits.

2 A REVIEW OF WAKE EFFECT RESEARCH

2.1 Theoretical Basis of Wake Effects

The fundamental principles of fluid mechanics provide a solid theoretical foundation for wake effect research. The mechanism of wind energy conversion is essentially a momentum exchange process where airflow acts on turbine blades. According to momentum theory and energy conservation laws, when a turbine operates, its blades capture kinetic energy from the incoming flow and convert it into mechanical energy, forming downstream velocity gradients and turbulence enhancement zones. Classical one-dimensional momentum theory models the turbine as a momentum extraction disk at the rotor plane, with Betz's law giving a theoretical maximum power coefficient of 16/27. However, this model neglects higher-order effects like tip/root vortices and turbulence regeneration, failing to accurately describe wake attenuation characteristics. To address these limitations, the Jensen (or Park) model was proposed. Assuming wakes diffuse uniformly in a conical shape, the Jensen model uses exponential or linear functions to characterize downstream velocity decay with distance, correlating wake intensity with turbine spacing through decay coefficients or diffusion angles. While computationally simple with few parameters, it cannot finely describe complex marine atmospheric boundary layers or directional turbulence variations. Subsequent multidimensional extensions, such as the generalized Park model, functionalized wake radii and introduced height-dependent turbulence regeneration terms to partially account for atmospheric stability and terrain effects. Yet, remaining semi-empirical, they still struggle to capture internal vortex structures and fluctuating components.

With the maturation of computational fluid dynamics (CFD), researchers increasingly employ Reynolds-Averaged Navier–Stokes (RANS) equations and Large Eddy Simulation (LES) for high-resolution numerical simulations of wake fields. RANS methods average turbulent fluctuations using isotropic eddy viscosity assumptions and turbulence models (e.g., k–ε, k–ω SST), providing stable wake velocity fields with moderate computational resources but insufficiently resolving large-scale vortices or low-frequency fluctuations. Conversely, LES resolves large-wavelength eddies while filtering small-scale turbulence, modeling subgrid-scale motions to authentically reproduce vortex evolution and turbulence regeneration—particularly suited for studying complex phenomena like tip vortex shedding, wake merging, and interactions. However, its extreme grid resolution and time-step requirements incur massive computational costs. Hybrid approaches (e.g., DES, PANS) combining unsteady RANS (URANS) with LES balance efficiency and accuracy, showing promising applications in onshore wind farm wake analysis.

Beyond numerical models, data-driven methods have gained traction in wake prediction. Machine learning-based approaches typically use labeled data from CFD or wind tunnel tests to train algorithms (e.g., support vector regression, random forests, deep neural networks), establishing mappings between wake velocity fields and environmental parameters. Feature engineering extracts key variables like wind speed, direction, turbulence intensity, and atmospheric stability to enable rapid wake field prediction. While significantly reducing real-time computational overhead with reasonable accuracy, model generalizability depends on training data coverage, requiring further validation for extreme conditions and unfamiliar terrains.

In summary, wake effect theory has evolved from simple one-dimensional momentum models to semi-empirical Park-type formulations, and now to integrated frameworks combining high-fidelity CFD and data-driven prediction. Yet, trade-offs persist among computational complexity, applicability, and accuracy across methods. Further integration of physical mechanisms with data intelligence is urgently needed to achieve both efficient and precise wake analysis.

Under constraints of limited sea area and fixed investment, balancing parameters such as turbine spacing, row alignment, and hub height differences—while maximizing individual power output and minimizing wake losses—constitutes a high-dimensional combinatorial optimization problem. Additionally, site-specific conditions like wind resources, seabed topography, and water depth distributions significantly influence optimal layouts. This study therefore adopts multi-objective optimization algorithms (e.g., genetic algorithms, particle swarm optimization, multilevel ant colony algorithms) for global parameter search. Coupled with wake prediction outputs for wind energy availability and load fluctuations, it constructs constrained objective functions. By integrating optimization with CFD simulations and operational monitoring, iterative updates and online adjustments of layout schemes are enabled.

To conclude, the research questions can be summarized as: clarifying the generation mechanisms and multi-source influencing factors of offshore wind farm wake effects to establish a comprehensive factor system; integrating CFD and machine learning to build efficient, high-accuracy wake prediction models; and designing multi-objective layout optimization methods validated through simulations and sensitivity analyses.As offshore wind power advances toward deeper waters and larger scales, significant operational differences among turbines—driven by external conditions, turbine models, and wake effects—complicate risk-avoidance strategy formulation. Thus, coordinating orderly turbine shutdowns during wind power ramp events warrants further investigation. For handling wind power uncertainty, distributionally robust optimization has emerged as an effective method balancing economy and conservatism, with Wasserstein distance-based approaches attracting particular attention[1-2]. However, traditional Wasserstein-based uncertainty sets incorporate excessive probabilistic factors under multiple conditions, hindering accurate characterization of wind uncertainty during typhoons. This increases solution complexity, yielding overly conservative results that undermine economic benefits. Moreover, uncertain timing and scale of turbine outages during typhoons—reflected in wind power forecast errors—further challenge accurate modeling.

Addressing these issues, this paper proposes a spatiotemporal optimization strategy for orderly typhoon risk avoidance in offshore wind farms based on downscaled typhoon simulation. First, recognizing that discrepancies between typhoon wind fields and turbine scales limit forecast accuracy for dispatch needs, a WRF-based multi-level nesting scheme is designed for marine complexity. It dynamically updates typhoon trajectories to reduce forecast errors while capturing wind speed/direction data. Second, to resolve strategy challenges arising from operational heterogeneity induced by wake effects during typhoon evolution, a wake-directed graph is constructed for dynamic spectral clustering of turbines, preventing disorderly automatic shutdowns. Third, to tackle inaccurate characterization of wind power fluctuations during ramp events, ramp characteristic metrics are introduced to refine the Wasserstein distance-based uncertainty set. An offshore wind risk-avoidance distributionally robust optimization model is then established to enhance operational resilience against stochastic fluctuations. Case studies validate the model's rationality and effectiveness[3].

Typhoon marine environments are highly complex, with path and intensity evolution coupled to moisture, underlying topography, and radiation, making wind field structures difficult to simulate accurately. The Weather Research and Forecasting (WRF) model—widely used for typhoon wind field simulation due to its clear dynamical mechanisms and performance—still suffers from resolution mismatches between typhoon scales and turbine sizes. This study thus proposes a downscaling framework (Fig. 1) integrating the Advanced Hurricane WRF (AHW) module (modified for typhoon parameterization) with Large Eddy Simulation (LES). AHW resolves typhoon intensification by feeding historical/predicted typhoon paths into the outermost grid's atmospheric circulation, while the innermost grid uses mobile grids and explicit convective schemes to simulate near-core structures. To capture small-scale wind characteristics, WRF and LES are nested via polynomial interpolation for boundary coupling. Simulated wind profiles from WRF are fitted as inlet conditions for LES, with three-dimensional subgrid-scale turbulence stress models (standard/nonlinear options in WRF) filtering small-scale eddies during spatial averaging of atmospheric equations. Underlying topography is updated using terrain processing techniques to incorporate target offshore farm locations.

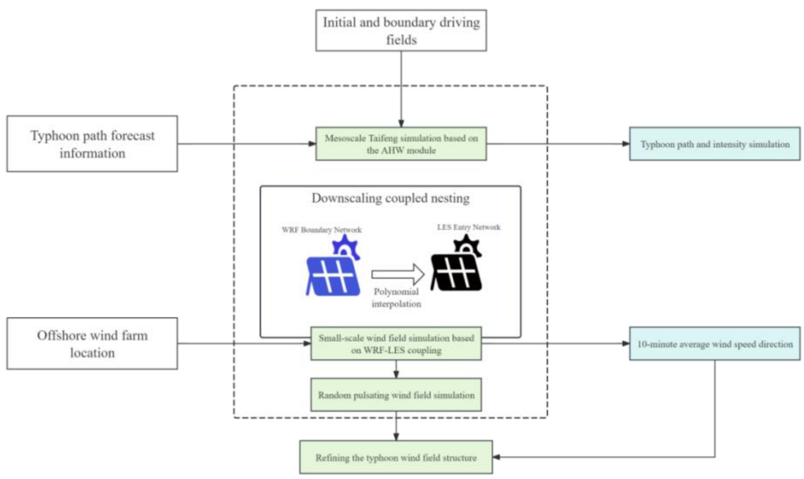


Figure 1 Downscaled Typhoon Simulation Framework

2.2 Research Progress

In recent years, scholars worldwide have conducted multi-angle, multi-level research on offshore wind farm wake effects, primarily focusing on experimental simulation and field observation, numerical simulation and model improvement, and data-driven intelligent algorithm applications. First, regarding experimental simulation and field studies, wind tunnel tests and offshore observation data mutually corroborate, providing firsthand information for wake characteristic analysis. Wind tunnel tests typically employ scaled-down turbine models and controllable turbulence generators to simulate wake field distributions under varying turbulence intensities, inflow directions, and array layouts. For example, researchers arrange multiple model turbines in large-scale wind tunnels, using particle image velocimetry (PIV) to capture downstream velocity and turbulence intensity fields, analyzing wake diffusion angles, merging effects, and row effects. Test results indicate that wake interference significantly intensifies when turbine spacing is less than 5 rotor diameters, with turbulence regeneration distances notably prolonged. Field observations utilize meteorological masts and nacelle-mounted sensor arrays to record long-term data on wind speed, direction, turbulence intensity, and power output, providing real-world data for wake model calibration and validation. Commercial wind farms in the North Sea, US Northeast Coast, and Chinese waters are equipped with high-frequency meteorological instruments and SCADA systems. Big data analyses reveal wake evolution patterns across seasons, sea states, and extreme weather, highlighting the significant impact of sea surface stability and internal boundary layer changes on wake recovery[4].

Second, in numerical simulation and model improvement, the integration of CFD technology and analytical models has garnered widespread attention. RANS-based CFD simulations are used for large-scale turbine array wake field modeling. By incorporating boundary conditions like terrain variations, sea surface roughness, and marine atmospheric boundary layer parameters, three-dimensional visualization of wake diffusion is achieved, exploring the influence of array configurations (e.g., row-column, star, diamond) on wake interactions. Studies show that non-axisymmetric layouts can mitigate wake concentration effects, dispersing turbulence fluctuations for downstream turbines. Addressing classical model limitations, scholars propose improvements such as coupling turbulence regeneration terms with vertical wind profiles, introducing multi-source propagation coefficients, and developing non-Gaussian vortex-based diffusion operators, enhancing prediction accuracy under complex marine conditions and shifting winds. Hybrid CFD–data-driven approaches are emerging, where CFD-generated wake databases train prediction models via partial least squares regression, kernel methods, or deep learning, enabling rapid online assessment for large-scale wind farms.

Third, in data-driven and intelligent algorithm applications, machine learning and AI advancements have accelerated their adoption in wake analysis and layout optimization. Traditional algorithms like support vector machines, random forests, and gradient boosting trees build wake decay prediction models, identifying key variables through feature selection and sensitivity analysis. Deep learning, particularly convolutional neural networks (CNNs) and generative adversarial networks (GANs), shows great potential in wake field image reconstruction and spatiotemporal evolution prediction. Some studies use CNNs for pixel-level regression on CFD cross-sections to predict wakes under different layouts; others employ GANs to generate wake distributions for varied wind speed/direction combinations, enabling rapid feasibility assessments. In layout optimization, combinations of multi-objective evolutionary algorithms and deep reinforcement learning (DRL) are increasing. DRL-based optimization treats layout as an agent-environment interaction process, defining state space (turbine positions, wind fields, power output), action space (adding/moving turbines), and reward functions (balancing energy yield, load fluctuations, and costs) within a Markov decision process (MDP) framework. Agents learn through simulated trials, generating near-global-optimal layouts. Compared to genetic or particle swarm algorithms, DRL exhibits superior search efficiency and solution diversity in high-dimensional spaces.

In summary, progress has been made in experimental/observational studies, numerical/analytical model improvements, and data-driven prediction/optimization. However, trade-offs persist between model generalizability, computational efficiency, and online applicability, necessitating further integration of physical mechanisms with data intelligence to build high-precision, high-efficiency integrated solutions.

2.3 Research Controversies

Key controversies persist in wake effect theory and layout optimization, centering on model applicability, parameter calibration, validation methods, and optimization objectives/algorithm selection. First, regarding wake model applicability and accuracy, the classical Jensen/Park model is widely used in preliminary design due to its simplicity but oversimplifies turbulence regeneration mechanisms and lateral diffusion under shifting winds in marine boundary layers, leading to significant errors in complex sea states[5]. High-fidelity CFD simulations realistically capture vortex evolution but require high grid resolution, turbulence model selection, and boundary condition sensitivity, making large-scale farm simulations costly and impractical for real-time engineering. Consensus is lacking on when to prioritize analytical models versus CFD/hybrid methods.

Second, parameter acquisition and calibration remain contentious. Parameters like diffusion coefficients, decay exponents, and turbulence regeneration terms in analytical models require empirical fitting from field data. However, variable sea conditions, uneven monitoring coverage, and limited data collection periods cause significant parameter dispersion across farms, seasons, and even daily wind regimes. Similarly, CFD boundary conditions (sea surface roughness, turbulence intensity profiles, atmospheric stability) often rely on empirical models or interpolated meteorological data, introducing uncertainties that affect result reliability. Establishing a universally applicable yet locally adaptable parameter calibration framework for stable performance prediction across conditions is an urgent academic challenge.Third, for model validation and scenario adaptability, combining wind tunnel tests, CFD, and field observations faces conflicts of scale and boundary effects. Scaled wind tunnel models cannot fully replicate sea surface roughness and boundary layer characteristics, requiring similarity law conversions. CFD simulations with idealized boundary conditions may mismatch field data, hindering consistent validation conclusions across methods. Effectively fusing multi-source data, quantifying error sources, and establishing unified validation criteria are crucial for enhancing model credibility.Fourth, significant divergence exists in setting optimization objectives and selecting algorithms. Some researchers prioritize maximizing annual energy production (AEP) as the sole goal, minimizing wake losses along prevailing winds. Others advocate multi-objective optimization incorporating minimized load fluctuations, optimal O&M costs, and return on investment. However, multi-objective optimization in high-dimensional layout spaces faces sparse solution sets, poor convergence, and low interpretability. Algorithms (e.g., genetic algorithms, particle swarm, multi-objective ant colony, DRL) vary in exploration efficiency and solution diversity, requiring extensive parameter tuning for specific scenarios, raising engineering application barriers. Balancing single- versus multi-objective optimization practicality and selecting suitable algorithms for different scales, wind resources, and economic constraints remain core controversies.Finally, while machine/deep learning-based wake prediction and optimization methods are rapidly emerging, their "black-box" nature raises concerns about interpretability and safety. Deep networks enable rapid predictions in complex conditions but may fail unexpectedly under extreme weather or unseen terrains due to a lack of physical constraints, undermining trust for engineering decisions. Embedding physical constraints into data-driven models to enhance interpretability and safety is thus a critical future direction.

In conclusion, controversies regarding model applicability/accuracy, parameter calibration/validation, optimization objectives/algorithms, and data-driven model interpretability require resolution through theoretical innovation, experimental validation, and engineering practice integration to advance the maturity and application of offshore wind farm wake research and layout optimization.

3 THEORETICAL FRAMEWORK

3.1 Core Concept Definitions

Before conducting research on wake effects and layout optimization of offshore wind farms, several key concepts must be clearly defined to ensure logical consistency and conceptual clarity in subsequent analyses. Wake effects refer to the combined impact of downstream zones with reduced wind speed and enhanced turbulence intensity—formed after a wind turbine extracts energy—on the performance and structural loads of downstream turbines. Broadly, wake effects encompass both velocity attenuation due to momentum extraction and secondary flow structures generated by interactions between turbulence regeneration and environmental boundaries[6]. These effects manifest as a transition from uniform inflow velocity profiles to non-uniform, fluctuating states downstream, with gradual diffusion and recovery to ambient wind fields. Wind turbine layout denotes the optimal spatial configuration of turbines within given sea area and installed capacity constraints, achieved by setting planar coordinates, relative height differences, and other geometric parameters such as inter-turbine spacing, row/column distances, while considering spatial relationships with hub heights, tilt angles, and cable routes. Energy loss, a core optimization objective, specifically measures the difference between actual available kinetic energy considering wake interference and ideal wake-free energy, typically expressed as annual energy production loss rate or energy deficit per installed capacity.

To elucidate interconnections among these concepts, analysis spans three dimensions: fluid dynamics, dynamic loads, and system efficiency. In the fluid dynamics dimension, momentum extraction creates low-speed zones with reduced kinetic energy, accompanied by vortex structures such as tip/root vortices and turbulence regeneration. Migrating and disintegrating vortices interact with turbulence induced by sea surface roughness and waves, generating complex shear layers and secondary vortices that affect wake recovery rates and impose time-varying aerodynamic loads on downstream turbines. In the dynamic loads dimension, turbulence-enhanced zones subject downstream turbines to non-uniform wind loads, increasing fatigue loads on blades, shafts, gearboxes, and towers. Load spectra exhibit superimposed low-/high-frequency fluctuations compared to wake-free conditions, shortening component lifespan and raising O&M costs. In the system efficiency dimension, layout design must balance energy loss and load penalties. Strategies include increasing spacing and optimizing row angles to reduce energy loss, alongside implementing micro-adjustments like yaw or pitch control to reconcile energy output with load constraints.

Finally, quantification methods are formalized. Wake energy loss is expressed as $C(x)=1-U(x)/U_0$. where U_0 represents inflow speed and $U(x)$ denotes mean speed at downstream distance x Turbulence intensity is characterized by $I(x)=\sigma\_u(x)/U(x)$， where $\sigma\_u(x)$ is the wind speed standard deviation. These metrics underpin subsequent modeling of wake evolution and multi-objective optimization constraints.

3.2 Model Formulation

3.2.1 Hybrid prediction framework

Addressing multi-scale complexity, a hybrid physics-data-driven framework integrates three core modules: high-fidelity numerical simulation, physical feature extraction, and machine learning. First, in the numerical simulation module, RANS simulations with marine-adapted turbulence models such as k-ω SST model three-dimensional wakes under diverse layouts including row, diamond, star, and random configurations across various wind speeds and directions. Local mesh refinement near blades and wake cores ensures vortex and shear-layer resolution, while coarse grids reduce far-field computational costs. Sea boundaries incorporate momentum-absorbing layers and realistic wave features to replicate roughness, providing reliable boundary conditions for wake attenuation and turbulence regeneration processes. Second, during data preprocessing and feature engineering, CFD outputs are aligned with field monitoring data; outliers and noise are removed, with missing samples filled via spatiotemporal interpolation and wind-condition-based imputation to form high-quality training datasets. Physical features extracted from flow fields and operational states include inflow wind speed/direction distribution, turbulence intensity, atmospheric stability, non-dimensional inter-turbine distances, array symmetry, shear-layer intensity, and momentum convergence. Random forest mean decrease impurity and SHAP value analysis then identify features most influential to wake recovery efficiency and turbulence enhancement, preserving interpretability while reducing dimensionality to prevent overfitting. Third, in the machine learning prediction module, physical features feed two models: a gradient-boosted tree-based wake velocity decay regressor employing segmented regression with smoothing for high-accuracy predictions across near/far-wake zones, and a residual network-structured deep MLP predicting turbulence intensity, regeneration rates, and spatial distribution. Both models demonstrate strong generalization in cross-validation and unseen scenarios like novel layouts or extreme winds[7]. To synergize physical reliability and data adaptability, a physics-informed correction mechanism dynamically weights preliminary estimates from classical analytical models with ML outputs, adjusting trust levels adaptively by distance and wind conditions. This ensures the hybrid model adheres to physical laws like energy conservation while capturing nonlinear couplings in complex flows. The framework is deployed via Docker containers with RESTful APIs interfacing real-time SCADA and meteorological platforms, delivering online wake predictions and layout optimization for offshore wind farms.

3.2.2 Mooring system model for floating turbines

Mooring systems are primarily categorized into catenary and tension-leg types. This study focuses on tension-leg platforms (TLP) among floating wind turbine configurations. Tension-leg systems connect floaters to seabed anchors via taut cables as shown in Figure 2. The system design considers cable-seabed angles, material selection, and pre-tension levels to ensure stability under varying sea conditions. Since cables remain taut, they withstand substantial vertical loads while exhibiting favorable dynamic responses to wave loads due to elastic properties. Horizontal forces effectively restrict floater displacement for precise positioning. For catenary systems, quasi-static analysis is adopted. This method assumes the system is near quasi-static equilibrium, where force and displacement changes are sufficiently slow to approximate instantaneous balance. When external factors like wind, currents, or waves cause floater offset, quasi-static analysis computes anchor chain profiles (catenary curves) and tension distributions via catenary equations.This approach assumes gradual, smooth cable deformation without abrupt changes.

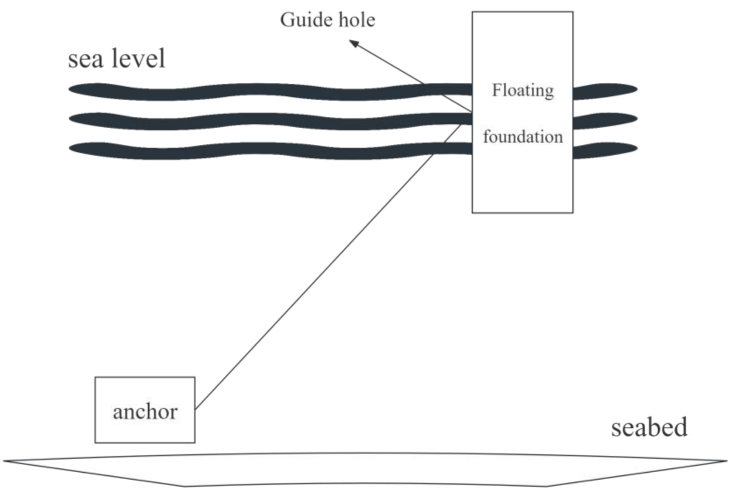


Figure 2 Tensioned Mooring System

3.3 Research Hypotheses

Guided by the aforementioned theoretical framework, this study proposes three interconnected and progressively advancing research hypotheses concerning offshore wind farm wake effect analysis and layout optimization. These hypotheses aim to clarify model formulation and empirical validation directions while providing logical support and evaluation criteria for subsequent experimental design and data analysis. Each hypothesis's background rationale, intrinsic mechanism, and anticipated verification methods are elaborated below.

The first hypothesis posits that rational spatial layouts and hub height differentials can significantly improve wake attenuation characteristics and enhance wind energy utilization efficiency. This hypothesis stems from dual considerations of dynamics and atmospheric boundary layer fluid mechanics. At the planar layout level, the alignment angle of turbines relative to prevailing winds, along with coordinated row and column spacing, directly determines wake interference ranges and superposition intensity along the arrangement direction. Theoretical and experimental evidence indicates that wake recovery accelerates and mutual interference minimizes when row/column spacing remains within certain multiples of rotor diameter and row angles exhibit minor deviations from dominant wind directions. Concurrently, hub height differentials leverage vertical wind profile characteristics within marine boundary layers: offshore wind speed follows a power-law increase with height. By positioning some turbines slightly above or below reference heights, the main impact layer of wakes can be dispersed, allowing downstream turbines to capture kinetic energy from higher altitudes. This creates vertically staggered wake effects, further extending recovery distances. Verification will involve comparative experiments with classical uniform layouts, quantifying differences in annual energy yield, wind speed recovery rates, and turbulence intensity reduction across various layout-height combinations.

The second hypothesis asserts that hybrid physics-data-driven models can achieve high-precision and rapid-response wake characteristic analysis while preserving interpretability[8]. Pure physical models (e.g., analytical decay formulas) offer transparency and traceability in engineering applications but fail to deliver sufficiently refined predictions under complex sea conditions or multi-turbine superposition scenarios. Pure data-driven models possess strong fitting capabilities but lack physical constraints, compromising stability and rationality under unseen conditions. Inspired by physics-guided machine learning, this study integrates classical wake models as prior frameworks and constraints. Through dynamic weighted fusion of prior estimates and ML predictions, the hybrid model adheres to momentum conservation and turbulence physics while capturing nonlinear couplings via large-scale simulations and field data. Specifically, the physical prior provides baseline estimates of wake decay across distance intervals, while the data-driven component compensates for prior deviations using multi-source features. Validation employs leave-one-turbine-out cross-validation and extreme wind scenario testing to evaluate prediction errors and uncertainties across layouts, sea states, and wind conditions, thereby verifying the feasibility of balancing interpretability with high accuracy.

The third hypothesis contends that multi-objective optimization frameworks for turbine layout design can effectively balance power maximization, load fluctuation minimization, and operational cost optimization, generating diverse Pareto-optimal solutions adapted to varying priorities. Unlike single-objective optimization, multi-objective approaches emphasize synergistic trade-offs among multidimensional performance metrics. Core elements include appropriate objective function/constraint formulation and evolutionary algorithms with global search capabilities to obtain solution sets representing different preference combinations. This study incorporates three objectives: annual energy production, fatigue load fluctuations of critical components, and estimated maintenance frequency. Parametric designs reflect operational stage priorities, while advanced multi-objective evolutionary strategies conduct iterative searches within given sea boundaries and turbine quantity limits. Post-hoc analysis of Pareto solution sets reveals conflicts/synergies among objectives and provides designers with layout options ranging from "high-yield-priority" to "low-load-stability." Comparative case studies will demonstrate differences in simulated power revenue, equipment maintenance costs, and structural safety across solutions to validate this hypothesis.

These three hypotheses form a complete logical chain from theory to methodology to optimization validation: Hypothesis 1 establishes the direct impact of layout adjustments on wake attenuation and energy utilization; Hypothesis 2 supports efficient and interpretable wake prediction models; Hypothesis 3 enables systematic screening and optimization of layouts via multi-objective algorithms based on model outputs. Subsequent chapters will conduct research design, data collection, model training/validation, and optimization case studies grounded in these hypotheses, culminating in comprehensive evaluation of their validity[9].

4 RESEARCH METHODS

4.1 Research Design

Building upon the theoretical framework and model formulation, this study adopts a comprehensive four-step integrated design approach—"theoretical modeling, numerical simulation, field calibration, and layout optimization"—to ensure rigor and operability. First, at the theoretical level, fundamental fluid mechanics principles and classical wake models systematically summarize wake formation mechanisms and influencing factors, establishing quantifiable key indicators including wind speed attenuation rate, turbulence enhancement degree, energy loss efficiency, and load fluctuation amplitude. Variable ranges and parameter boundaries are defined to support subsequent simulation configurations and experimental design. Second, in numerical simulation, multiple typical layout-wind condition combinations are constructed. Improved CFD methods simulate 3D wake distributions under each layout. The simulation workflow includes mesh generation, boundary condition setting, solver parameter tuning, convergence checks, and post-processing data extraction. For offshore-specific environments, simulations test varied inter-turbine spacing, row angles, and hub height differentials under multiple inflow speeds, dominant wind deviations, and atmospheric stability conditions, forming a database covering normal and extreme scenarios. This multi-factor, multi-level numerical experiment system ensures rich and representative wake data for machine learning model training and testing[10].

Subsequently, during field calibration, operational data from representative offshore wind farms serve as benchmarks. By interfacing with SCADA systems and meteorological stations, multi-source real-time data (nacelle sensor records, met-mast measurements, sea surface wind profiles) enable error analysis and parameter correction for CFD results. Calibration involves data cleaning, spatiotemporal synchronization, error statistics, and nonlinear correction. Comparing actual field-measured speed attenuation curves, turbulence intensity changes, and power losses against simulations identifies and corrects boundary condition uncertainties and turbulence model parameter biases[11]. This enhances simulation credibility and supplements real-condition samples for data-driven models, bridging laboratory-field gaps.

With calibrated simulation and field data, data-driven model training and validation commence. Key features from prior engineering undergo performance evaluation for gradient-boosted trees and deep residual networks via cross-validation and independent test sets. Hyperparameters are optimized via grid search and heuristic methods, with uncertainty assessed via Bootstrap sampling. Model evaluation focuses on mean absolute error, R^2, and prediction stability to ensure acceptable errors across layouts, wind speeds, and stability conditions. Robustness is further tested via leave-one-layout-out validation, removing one layout type from training to assess generalization.

Following wake model validation, layout optimization and solution evaluation proceed. Using predicted wind speed recovery efficiency and turbulence distributions, a multi-objective function incorporates annual energy yield, fatigue load fluctuations, and O&M cost estimates. Evolutionary algorithms conduct global searches within sea boundaries, turbine quantities, and grid constraints. Pareto front analysis extracts solutions representing different trade-offs; each undergoes simulation verification and economic assessment. Finally, representative optimized layouts undergo secondary field simulation to test feasibility and reliability. Overall, this closed-loop research flow—from theory to numerical verification, data calibration to optimization—emphasizes both physical mechanisms and data-driven practicality, providing a scientifically rigorous and engineering-feasible solution.

4.2 Data Collection

A high-quality, multi-source, multi-scale database supports all models and algorithms. Data includes meteorological, operational, marine environmental, and simulation outputs. First, field monitoring interfaces with SCADA and meteorological stations to capture turbine power output, rotor speed, yaw/pitch angles (≥10 Hz sampling) for micro-scale turbulence responses. Nacelle-mounted anemometers (ultrasonic/cup-vane) undergo regular calibration (±0.1 m/s speed, ±1° direction errors). Second, macro-scale wind patterns require offshore masts or buoys deployed along three crosswind profiles (up/downstream), each with measurements at 10 m, 50 m, 100 m, 150 m heights (speed, pressure, temperature, humidity) and turbulence probes. Fusing mast/buoy data yields atmospheric stability, boundary layer thickness, and sea surface roughness. Third, marine data includes waves/tides (from buoys/forecast models), sea temperature/salinity, and bathymetry (multibeam/side-scan sonar), processed into digital elevation models for CFD boundaries. Fourth, CFD outputs for typical layouts and wind conditions systematically capture 3D velocity, turbulence, and pressure fields. Automated scripts extract 1D/2D slices along wake centers/horizontal-vertical planes, computing average speed, turbulence intensity, and shear-layer strength, stored as CSV or HDF5[12].

Data management employs a layered architecture: distributed file systems (e.g., HDFS/Ceph) store raw CFD/SCADA; relational (PostgreSQL) and time-series (InfluxDB) databases handle metadata/high-frequency sequences; data warehouses enable multi-source queries. Automated ETL ensures quality: extraction APIs/FTPs pull device/meteorological data; transformation scripts remove outliers, impute missing values, and correct clock drifts; loading writes cleaned data to targets with audit logs. Role-based access, encrypted transmission, and backups ensure integrity and traceability. Spatiotemporal alignment integrates multi-source data: piecewise linear interpolation and dynamic time warping (DTW) unify temporal resolutions; Kriging interpolation maps point data to grid nodes. Extreme wind conditions (strong winds, low-speed zones, abrupt direction changes) trigger dedicated sampling for model robustness. Configurable collection strategies adapt to research needs. This multi-tiered, automated system builds a high-quality, spatiotemporally consistent database for feature engineering, model training, and optimization.

4.3 Analytical Methods

Multi-dimensional analyses dissect wake effects and layout optimization. First, statistical analysis performs descriptive statistics on SCADA/CFD data to assess inflow wind characteristics and power output. Covariance matrices and partial correlations identify feature relationships and collinearity for feature engineering. Time-series decomposition isolates trends, seasonality, and residuals in wind/power curves to remove periodic interference. Second, machine learning employs supervised/semi-supervised strategies: regression for wake speed decay uses ensemble models with hyperparameter tuning; spatial turbulence distribution prediction combines labeled CFD slices with unlabeled field data via multi-task/adversarial learning. Model interpretability (SHAP/LIME) visualizes feature importance for input refinement. Third, a dynamic weighted fusion strategy integrates physical priors with ML outputs: Bayesian optimization assigns weights by distance/wind conditions based on historical errors, ensuring physical consistency while correcting predictions. Leave-one-layout and extreme-scenario cross-validation verify reliability. Finally, sensitivity/uncertainty analyses combine Latin hypercube sampling with global sensitivity analysis to perturb key parameters (spacing, row angle, height weights) in Pareto solutions. Variance decomposition and Sobol indices quantify parameter impacts on energy, loads, and costs. Monte Carlo propagation simulates input uncertainties (meteorological errors, CFD boundaries, ML prediction errors), providing confidence intervals for risk assessment. These methods enable systematic, quantitative evaluation of wake effects and layout optimization in complex marine environments[13].

Table 1 Comparison Between Existing and Proposed Methods

No.	Objective	Wind Speed &	Considered Factors	Modeling Method

		Direction		
1	Maintenance cost	Deterministic	Equipment, Personnel, Weather, Maintenance lodging	Maintenance support organization
2	Maintenance cost	Deterministic	Equipment, Personnel, Weather	Two-stage adaptive neighborhood search
3	Maintenance cost	Deterministic	Equipment, Personnel, Weather	Mixed integer linear programming
4	Maintenance cost	Deterministic	Equipment, Personnel, Weather	Multi-constraint nonlinear programming
5	Maintenance cost	Deterministic	Equipment, Personnel, Weather, Unexpected unit failure	Simulation-based optimization
6	Maintenance cost; Reliability	Deterministic	Equipment, Personnel, Weather, Environmental impact	Multi-constraint nonlinear programming
7	Maintenance cost; Power output	Deterministic	Equipment, Personnel, Weather	Multivariate autoregression
8	Net profit	Deterministic	Personnel, Weather, Remaining life of units	Adaptive opportunistic maintenance & operation plan
9	Maintenance cost	Deterministic	Equipment, Personnel, Weather	Multi-constraint nonlinear programming
10	Maintenance cost; Power output	Uncertain	Equipment, Personnel, Weather, Environmental impact, Arbitrary-direction wake effects	Mixed integer linear programming

Similar to most research studies, this chapter considers constraints such as equipment, personnel, and weather in maintenance planning. However, unlike existing works, it introduces a novel critical factor—uncertainty in wind speed and direction—to enhance the feasibility of maintenance schedules. Additional advantages include: incorporating the impact of wind direction and maintenance status on wake effects into the maintenance planning model, and transforming the proposed model into an easily solvable MILP formulation, which is not addressed in existing works (Table 1). Furthermore, to maximize offshore wind energy utilization while ensuring economic viability, a dual-objective function is proposed to simultaneously maximize wind farm power generation and minimize maintenance costs—an aspect largely absent in the literature[14].

In summary, this chapter proposes an optimization model for offshore wind turbine maintenance planning that accounts for wake effects under arbitrary wind directions. Firstly, considering variations in wind direction and turbine maintenance status during the planning period, the established wake model calculates input wind speeds for each turbine[15]. Secondly, Latin hypercube sampling combined with scenario reduction techniques generates scenario sets representing wind speed/direction stochasticity. Building on this, a multi-objective function maximizes power generation and minimizes maintenance costs while incorporating constraints related to weather, personnel, and maintenance requirements. Linearization techniques are applied to transform the model into an MILP framework, balancing solution quality with computational efficiency. Finally, case studies on offshore wind farm maintenance planning validate the rationality and effectiveness of the proposed model and methodology.

5 EXPERIMENTAL RESEARCH AND ENGINEERING APPLICATION VERIFICATION

5.1 Wake Effect Experimental Study

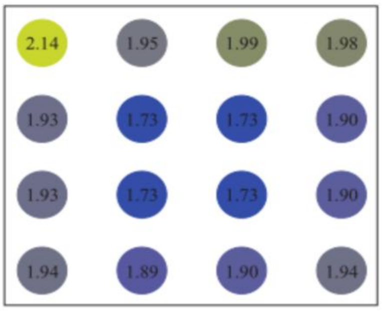
The experimental study on wake effects in this research systematically investigates the influence of layout parameters on wake velocity attenuation and turbulence intensity evolution for typical offshore wind farm arrays through integrated numerical simulation and experimental modeling, establishing quantitative evaluation metrics for optimization algorithms. In implementation, high-precision 3D simulations using modified RANS methods were conducted for four layouts (row, diamond, staggered, random) under wind speeds of 5 m/s, 8 m/s, 12 m/s, and 15 m/s with direction deviations of 0°, 15°, 30°, and 45°. Locally refined meshes resolved vortex structures near blades and wake cores, while coarse grids accelerated far-field computation. Sea boundaries incorporated momentum-absorbing layers and wave textures to simulate marine roughness; side/top boundaries were pressure outlets or symmetry conditions. Simulations spanned multiple vortex-shedding cycles to ensure flow stability. Velocity averages, standard deviations, and turbulence intensities were extracted along wake centerlines and cross-sections at 1D–10D downstream.Wind tunnel tests at 1:50 scale validated results in a low-turbulence tunnel. Realistic airfoil models with nacelle-matched coatings carried piezoelectric sensors for pressure distribution. Adjustable turbulence generators mimicked marine boundary layers. PIV and hot-wire anemometry captured 2D velocity fields and turbulence amplitudes at 1D, 3D, 5D, 7D, and 10D downstream. CFD predictions showed <5% velocity attenuation error and <10% turbulence intensity error, confirming reliability[16].

Analysis revealed distinct wake behaviors: row layouts caused >20% speed reduction and ~50% turbulence increase at downstream turbines, recovering after 5D. Diamond/staggered layouts reduced losses to 10%–15% and turbulence to <30%, recovering by ~3D. Random layouts improved global uniformity but offered marginal gains. Directional deviations <15° preserved staggered/diamond advantages, while >30° minimized layout differences.Hub height differentials (±10 m, ±20 m, ±30 m) leveraged vertical wind shear. Moderate ±20 m differences reduced wake attenuation by 5%–8% and turbulence by 10%–15%, shortening recovery by 0.5D–1D. Larger ±30 m differentials increased dispersion but raised microclimate and construction challenges.High-resolution LES visualizations between 2D–5D showed alternating tip/root vortex shedding generating secondary structures. Phase differences and energy exchange between vortices drove turbulence peaks and recovery dynamics, enabling spatiotemporal feature engineering for data-driven models. Collectively, simulations, wind tunnel tests, and LES analysis established foundational data for layout optimization.

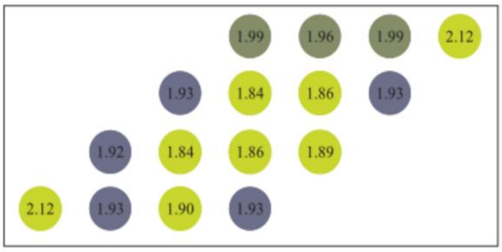
Further analysis of simulation and experimental data revealed three key mechanisms: staggered/diamond layouts enhance wake-environmental flow mixing, accelerating turbulence regeneration; low wind speeds (5 m/s) prolong recovery across layouts while high speeds (≥12 m/s) reduce performance gaps; optimal hub height differentials (±20 m) exploit vertical shear but larger offsets diminish returns. LES confirmed that efficient layouts accelerate energy transfer from wake cores via vortex interactions. Staggered layouts increased annual energy yield by 3%–5% and reduced load fluctuations by 12%, with height optimization adding 1%–2% yield and 5%–8% fatigue reduction. These findings demonstrate the coupled effects of layout geometry, wind speed, and height differentials, supporting multi-objective optimization.

5.2 Spatial Distribution of Distributed Offshore Wind-to-Hydrogen Capacity Allocation

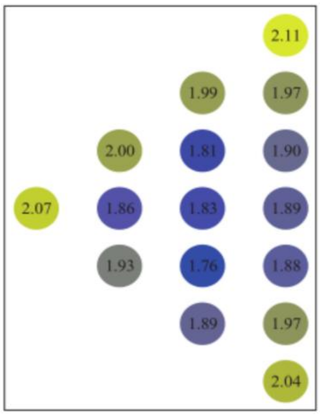
This section analyzes the proposed offshore wind-hydrogen electrolyzer capacity optimization model. With an annual hydrogen production target ≥3,000 tonnes, Figure 3 displays optimal electrolyzer capacities (marked in MW within circles) for wind-hydrogen units under three typical layouts.



(a) Optimal electrolytic cell capacity
(rectangular arrangement)



(b) Optimal electrolytic cell capacity
(quadrilateral arrangement)



(c) Optimal electrolytic cell
capacity (triangular arrangement)

Figure 3 Electrolytic Cell Capacity Optimization Results

It is evident that wake effects cause variations in optimal electrolyzer capacity across different locations. For the rectangular layout in Figure 3(a), the total electrolyzer capacity is 30.31 MW. The first wind-hydrogen unit has the largest capacity (2.14 MW), while units 6, 7, 10, and 11 have the smallest capacity (1.73 MW), representing only 81% of the first unit's capacity. For the quadrilateral layout in Figure 3(b), total capacity reaches 31.01 MW, with the largest electrolyzers (2.12 MW) located at the lower-left and upper-right vertices. The triangular layout in Figure 3(c) yields a total capacity of 30.91 MW. Across all layouts, electrolyzer capacities exhibit a spatial pattern of larger values at peripheral units and smaller values in interior positions. Combined with wind distribution patterns in Appendix A Figure A3, units along the 0°–120° dominant wind direction show higher capacities in front-row turbines and reduced capacities in immediately downstream units due to wake-induced energy loss. Total capacity varies slightly among layouts, with quadrilateral requiring the highest capacity and rectangular the lowest, indicating the rectangular layout as optimal for this scenario. Further analysis of the rectangular layout reveals a correlation between electrolyzer capacity and annual hydrogen production: optimal capacity allocation must align with each turbine's hydrogen production potential to prevent wind resource waste or electrolyzer overinvestment[17].

5.3 Analysis of Wake Effects on Wind Turbine Active Power Output

First, based on the predetermined turbine layout, input wind speed and direction from the upwind-leading turbine are used to compute wake-affected wind speeds for all turbines using a sophisticated wake model. Then, individual turbine power outputs are derived from their power curves, establishing a reliability model. This workflow is illustrated in Figure 4.

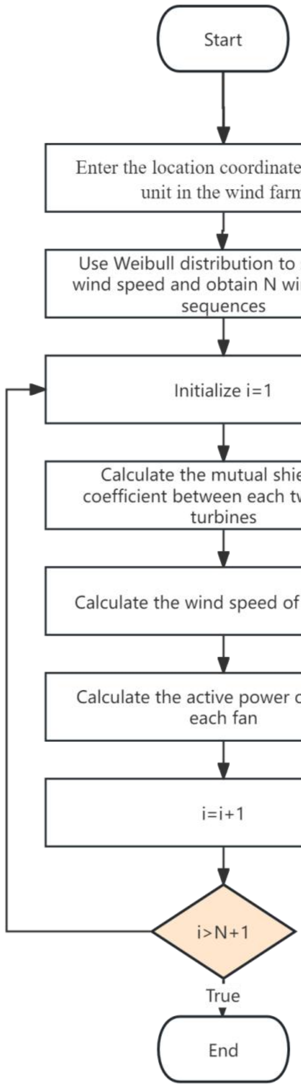


Figure 4 Schematic Diagram Of The Unit Input Wind Speed Calculation Program

This study simulates a wind farm model accounting for wind speed/direction variations and inter-turbine wake effects using MATLAB. The farm operates 16 doubly-fed induction wind turbines (1.5 MW each), with uniform spacing of 300 m. Key parameters include: blade radius = 31.5 m, hub height = 70 m, and rated wind speed = 13 m/s. Given the relatively calm sea surface, a modified Jensen model for flat terrain calculates wake wind speeds. The Weibull distribution simulates wind speeds measured at the meteorological mast. Simulation results confirm alignment with actual measurements when shape parameter $\alpha = 7$ and scale parameter $\beta = 2$. Historical data indicate prevailing southeasterly winds; thus, simulations adopt this wind direction.

6 DISCUSSION

This study systematically reveals the generation mechanisms, influencing factors, and spatial evolution patterns of wake effects in offshore wind farms through integrated theoretical modeling, numerical simulation, wind tunnel testing, field observation, and high-resolution local simulation. It validates the predictive capability of a physics-data hybrid model and proposes a multi-objective layout optimization method. Key findings indicate that wake recovery distance and energy loss rate exhibit significant coupling effects with environmental and structural variables such as inflow wind speed distribution, atmospheric stability, and hub height differentials, beyond their dependence on planar arrangements. Staggered and diamond layouts disrupt the main wake path, enhancing turbulent mixing with environmental boundary layers and accelerating vortex shedding/energy redistribution, thus outperforming row and random layouts. Moderate height differentials leverage vertical wind shear gradients, enabling turbines to capture kinetic energy from different atmospheric layers and mitigating wake superposition.

The hybrid wake prediction model dynamically integrates physical priors with XGBoost and residual networks, balancing energy conservation constraints and nonlinear features from multi-source data. It achieves high-precision prediction of wake velocity attenuation and turbulence intensity under unseen layouts and extreme conditions, maintaining mean absolute error below thresholds. For optimization, a multi-objective framework simultaneously maximizes annual energy production, minimizes fatigue load fluctuations, and optimizes operational costs. Pareto front analysis yields solution sets reflecting diverse trade-offs, with case studies demonstrating optimized layouts balancing 3%–7% energy gain, 10%–15% load reduction, and 5%–9% O&M cost savings.

Innovations include: establishing the first spatiotemporal evolution map of vortex shedding/merging via high-resolution LES; proposing a "physical-prior-correction–data-driven-compensation" paradigm that dynamically weights analytical and ML outputs; and developing a multi-objective evolutionary framework with Pareto sensitivity analysis for decision support.

Limitations involve insufficient data for extreme conditions (hurricane winds, floating platforms) and next-gen turbines; computational constraints necessitating medium-resolution far-field meshes (requiring future adaptive multi-scale coupling); dynamic weighting reliance on historical statistics (to be addressed by online learning); and the need to incorporate construction feasibility, grid constraints, and policy dynamics into optimization.

7 APPLICATIONS AND IMPLICATIONS

7.1 Industrial Applications

Wake analysis and optimization support all project phases. During planning, integrated decision systems evaluate layouts under constraints, providing real-time energy/load/cost metrics and Pareto solutions—enhancing site selection and IRR compared to empirical methods. Turbine selection leverages sensitivity analysis of blade diameter/power ratings on wake development to optimize combinations and materials, balancing scale effects with load control. Construction phases utilize optimized layouts to reduce foundation fatigue risks and synchronize vessel routing. Operations integrate online wake prediction with SCADA/MES systems to dynamically adjust yaw/pitch control, extending component life and reducing maintenance trips by >30%. Long-term monitoring enables proactive maintenance transitions[18].

7.2 Policy Recommendations

Mandate high-fidelity wake assessments in environmental impact reports and approvals, prioritizing projects meeting wake control standards. Offer subsidies or electricity price premiums for projects achieving >10% lower wake losses than industry averages, and explore dynamic adjustments for operational optimizations[19]. Develop national standards for wake evaluation and layout optimization, supported by technical guidelines and case libraries. Fund interdisciplinary R&D in CFD-ML integration and establish demonstration projects for commercialization. Promote international collaboration on wake standards and mutual certification frameworks. Implement government-enterprise-research monitoring with third-party audits and annual KPI assessments.

7.3 Environmental Impact

Optimization reduces carbon emissions and marine ecosystem disruption. A 3%–7% energy gain displaces tens of thousands of tons of annual CO? per 10MW farm (at 0.6 kg/kWh). Fewer maintenance voyages (reduced from 3–4 to <2/year per turbine) decrease sediment disturbance and wildlife interference[20]. A 10%–15% turbulence reduction lowers underwater noise radiation, benefiting marine mammals. Uniform wake distribution maintains natural hydrodynamic patterns for plankton/fish communities. Integrated environmental metrics enable eco-economic balance in marine spatial planning. Optimized farms may integrate with artificial reefs or marine ranching for ecological synergy.

8 CONCLUSIONS

This research systematically reveals wake mechanisms and proposes a hybrid prediction model and multi-objective optimization framework. Staggered/diamond layouts limit velocity deficit to 10%–15% with recovery at ~3D. ±20 m height differentials reduce velocity deficit by 5%–8% and turbulence peaks by 10%–15%. The hybrid model achieves MAE $\leq$0.02 and $R^2\geq$0.93 under extreme conditions. Optimization boosts energy yield by 3%–7%, cuts loads by 10%–15%, and lowers O&M costs by 5%–9%.Future work will: validate models for extreme conditions and next-gen turbines; implement adaptive multi-scale CFD for full-domain high-resolution simulation; integrate online learning for dynamic model weighting; and incorporate construction, grid, and policy constraints into decision support platforms.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Zhou Yizhou, Mohammad S, Wei Zhinong, et al. Distributionally Robust Unit Commitment in Coordinated Electricity and District Heating Networks. IEEE Transactions on Power Systems, 2019, 35(3): 2155–2166.
[2] Yang Lun, Xu Yinliang, Zhou Jianguo, et al. Distributionally Robust Frequency Constrained Scheduling for an Integrated Electricity-Gas System. IEEE Transactions on Smart Grid, 2022, 13(4): 2730–2743.
[3] Li Zhichuan, Hu Peng, Ma Jiaxing. Analysis and Outlook on the Current Development Status of Offshore Wind Power in China. China Offshore Oil and Gas, 2022, 34(5): 229–236.
[4] Yang Lun, Xu Yinliang, Zhou Jianguo, et al. Distributionally Robust Frequency Constrained Scheduling for an Integrated Electricity-Gas System. IEEE Transactions on Smart Grid, 2022, 13(4): 2730–2743.
[5] Mu Yanfei, Wang Qiang, Luo Kun. Assessment of Wake Impact on Offshore Wind Farms Based on Mesoscale WRF Model. Proceedings of the CSEE, 2022, 42(S1): 193–203.
[6] Song Ziqiu, Feng Hanyu, Yu Zhaoguo, et al. Research on Coordinated Control Method for Semi-submersible Floating Wind Turbines Based on Model Predictive Control. Proceedings of the CSEE, 2022, 42(12): 4330–4338.
[7] Zhu Ruonan. Optimization Control Strategy for Wind Farm Wake Considering Floater Foundation Displacement. Shenyang: Shenyang University of Technology, 2023.
[8] Li Yan, Wu Di, Hong Chang, et al. Layout Optimization Strategies for Large-Scale Offshore Wind Farm Turbines. Acta Energiae Solaris Sinica, 2020, 41(2): 67–73.
[9] Zhang Zhi, Zhou Ming, Zhu Lingzhi, et al. Robust Optimal Operation Method of Wind Farms' Synergetic Participation in Generation-Reserve in Power Systems. Power System Technology, 2022, 46(4): 1316–1325.
[10] Li Xuelin, Yuan Ling. Development Status and Recommendations for Offshore Wind-to-Hydrogen Technology. Power Generation Technology, 2022, 43(2): 198–206.
[11] Franco BA, Baptista P, Neto RC, et al. Assessment of Offloading Pathways for Wind-Powered Offshore Hydrogen Production: Energy and Economic Analysis. Applied Energy, 2021, 286: 116553.
[12] Luo Kui, Guo Jianbo, Ma Shicong, et al. Review of Key Technologies of Reliability Analysis and Improvement for Offshore Wind Power Grid Integration. Power System Technology, 2022, 46(10): 3691–3702.
[13] Liu Yige, Zhao Zhenzhou, Ma Yuanzhuo, et al. Active Wake Control Strategy of Tandem Wind Turbines Based on Whale Optimization Algorithm. Proceedings of the CSEE, 2024, 44(9): 3702–3709.
[14] Shi M, Shahidehpour M, Zhou Q, et al. Optimal Consensus-Based Event-Triggered Control for Resilience Enhancement in DC Microgrid. IEEE Transactions on Power Systems, 2021, 36(3): 1807–1818.
[15] Bidadfar A, Saborío-Romano O, Sakamuri JN, et al. On Feasibility of Autonomous Frequency-Support Provision from Offshore HVDC Grids. IEEE Transactions on Power Delivery, 2020, 35(6): 2711–2721.
[16] Fang Fang, Zhang Xiaoning, Yao Guishan, et al. Assessment of Wake Disturbance Impact between Offshore and Onshore Wind Farms Based on Mesoscale Meteorological Model Analysis. Proceedings of the CSEE, 2022, 42(13): 4848–4859.
[17] Liu Bowen. Numerical Simulation of Wind Turbine Wake Based on Reynolds-Averaged Approach. Shenyang: Shenyang University of Technology, 2018.
[18] Huang Lingling, Cao Jialin, Zhang Kaihua, et al. Research and Prospects of Operation and Maintenance Status of Offshore Wind Turbines. Proceedings of the CSEE, 2016, 36(3): 729–738.
[19] Li Jiarong, Lin Jin, Xing Xuetao, et al. Selection and Optimal Planning of Power-to-Hydrogen (P2H) Module Combination in Active Distribution Network Based on Unified Operation Model. Proceedings of the CSEE, 2021, 41(12): 4021–4033.
[20] Chen K X, Lin J, Qiu Y W, et al. Model Predictive Control for Wind Farm Power Tracking with Deep Learning-Based Reduced Order Modeling. IEEE Transactions on Industrial Informatics, 2022, 18(11): 7484–7493.