

Review

Review on Dynamic Inflow Sensing Layout Optimization for Large-Scale Wind Farms: Wake Modeling, Data-Driven Prediction, and Multi-Objective Uncertainty Optimization

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Abstract

Large-scale wind farms operate under highly unsteady atmospheric inflows, where transient turbulence, dynamic wake interactions, and inflow-wake coupling reduce energy production and exacerbate turbine loads. Over the past five years, advances in high-fidelity computational fluid dynamics (CFDs), large eddy simulation (LES), machine learning (ML)-based wake modeling, and multi-objective optimization have reshaped wind farm layout optimization under dynamic inflow conditions. This review synthesizes recent progress in five key areas: dynamic inflow and high-fidelity wake modeling (including LES-driven transient wake evolution and turbulence-resolved inflow generation), data-driven wake prediction, multi-objective layout optimization (considering the annual energy production (AEP), fatigue load constraints, and the levelized cost of energy (LCOE)), blockage modeling for complex terrain and yaw misalignment, and real-time optimization addressing inflow, turbine performance, and modeling uncertainties. Coupling transient wake models with surrogate-assisted multi-objective optimization enables a computationally efficient and physically consistent layout design. Key open challenges (dynamic wake controllability, real-time optimization under uncertainty, and integration with next-generation farm-level control systems) and future directions for enhancing large-scale wind farm resilience and cost-competitiveness are also identified. However, despite significant progress, existing models still face fundamental limitations, such as oversimplified treatment of complex turbulence structures, poor generalization under extreme or atypical conditions, and inadequate capture of long-timescale dynamic responses, which constrain their reliability in practical optimization settings.



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Keywords: large-scale wind farms; dynamic inflow conditions; wake modeling; data-driven modeling; wind farm layout optimization; multi-objective optimization

1. Introduction

Large-scale wind farms are increasingly deployed to meet global renewable energy targets, yet their performance is significantly constrained by unsteady atmospheric inflow conditions. Transient turbulence, wind direction variability, and complex terrain interactions lead to dynamic wake effects that reduce power output, increase fatigue loads,

and challenge grid integration. Over the past decade, traditional steady-state layout optimization approaches based on simplified wake models and deterministic wind roses have proven inadequate for capturing the spatiotemporal complexity of real-world wind farm operations.

Recent advances in high-fidelity simulation, data-driven modeling, and multi-objective optimization have catalyzed a paradigm shift toward dynamic, uncertainty-aware, and system-level co-design frameworks. These developments enable more accurate representation of transient wake evolution, rapid evaluation of thousands of candidate layouts, and holistic trade-offs between energy yield, economic cost, structural reliability, and control feasibility. In particular, the integration of large eddy simulation (LES) informed wake models with machine learning surrogates has bridged the gap between physical fidelity and computational efficiency, while stochastic and real-time optimization methods have addressed the inherent unpredictability of wind resources.

This review synthesizes recent progress in dynamic inflow sensing and layout optimization for large-scale wind farms, with a focus on five interconnected domains: (i) multiscale flow modeling under transient atmospheric conditions; (ii) physics-informed and data-driven wake prediction; (iii) blockage and terrain-induced flow distortions; (iv) multi-objective optimization under uncertainty; and (v) integrated co-design with active control systems. By examining these areas collectively, we aim to provide a unified perspective on the evolving landscape of wind farm design from static geometric arrangements to adaptive, intelligent, and resilient energy systems.

The credibility of any modeling approach ultimately hinges on its validation basis. Current wind farm models are primarily validated against three data sources: high-fidelity large eddy simulation (LES) datasets (e.g., SWiFT), controlled wind tunnel experiments, and operational SCADA from commercial farms. Each has strengths and limitations. LESs provide high spatiotemporal resolution but depends on subgrid-scale (SGS) model assumptions; wind tunnel tests offer precise measurements yet struggle to replicate full atmospheric boundary layer complexity; SCADA reflect real-world operations but suffer from low resolution, noise, and uncontrolled external factors. Without acknowledging these constraints, claims about ‘recent advances’ may be overly optimistic and require cautious interpretation.

2. Multiscale Modeling and Simulation Optimization

Accurately optimizing large wind farm layouts under dynamic inflow conditions requires a modeling framework capable of integrating the inherently multiscale nature of atmospheric turbulence, turbine aerodynamics, wake interaction, and array-level flow dynamics. Over the past decade, research has demonstrated that no single modeling scale is sufficient to capture the full complexity of wind farm behavior. Instead, cross-scale connections from kilometer-scale atmospheric boundary layer (ABL) turbulence to meter-scale turbine wake structures and sub-meter blade-resolved flow must be consistently represented within a unified simulation-to-optimization workflow. Traditional steady-state or empirical wake models often collapse under scenarios involving rapid inflow variations, yaw maneuvers, complex terrain, floating platforms, or heterogeneous turbine sizes, which highlights the need for multiscale models that preserve physical fidelity while maintaining computational tractability. To address these challenges and to provide a structured overview of the evolving methodological landscape, Table 1 presents a comparative analysis of the major modeling and optimization approaches for large-scale wind farm layout design under dynamic inflow conditions. The table synthesizes the key characteristics, including physical fidelity, computational cost, data requirements, strengths, and limitations, across engineering wake models, high-fidelity CFD, data-driven surrogates,

and hybrid frameworks, thereby clarifying the trade-offs inherent in current multiscale optimization strategies.

Table 1. Comparative Analysis of the Major Methodological Categories in Layout Optimization of Large-Scale Wind Farms under Dynamic Inflow Conditions.

Method Category	Specific Approach	Required Data	Key Advantages	Key Limitations
Wake/Inflow Modeling	Engineering Models (e.g., Jensen, Gaussian)	Wind speed/direction, atmospheric stability, surface roughness	Extremely fast; easy to integrate into optimization; physically intuitive.	Poor for transient wakes (e.g., meandering, vortex shedding); inaccurate under complex terrain or dynamic inflow.
	RANS/URANS	Turbulence model parameters	Captures mean flow fields; handles complex geometry; affordable for parametric studies.	Limited by turbulence modeling; struggles with unsteady separation and wake recovery.
	LES/Hybrid RANS-LES	High-resolution inflow turbulence, detailed geometry, ABL profiles	Resolves large-scale turbulent structures and transient wake dynamics.	Prohibitively expensive for direct optimization use; sensitive to numerical setup.
Data-Driven Surrogate Models	Gaussian Process (GP)-Based Surrogates	High-fidelity simulation or experimental data	Provides uncertainty quantification; effective with limited data; smooth interpolation.	Suffers from curse of dimensionality; poor extrapolation beyond training domain.
	Neural Network (NN)-Based Predictors	Large datasets (SCADA, LESs, etc.)	Strong nonlinear mapping; fast inference; handles high-dimensional inputs.	requires extensive data; may violate physical constraints.
	Graph-Based Models (e.g., GNNs)	Turbine positions, states, wind conditions as graph features	Naturally encodes spatial topology; generalizes well to unseen layouts.	Training complexity; performance depends on graph construction.
	Physics-Informed Machine Learning (PIML)	Physics-based model outputs; high-fidelity residuals	Embeds physical laws into learning; improves generalization and interpretability.	Dependent on baseline physics model; loss function design is nontrivial.
Optimization Frameworks	Deterministic Optimization	Fixed wind rose, deterministic wake model	Simple, mature algorithms (e.g., GA, PSO); computationally tractable.	Ignores wind and model uncertainties; solutions may underperform in reality.
	Multi-Objective Optimization	Multiple objectives	Reveals trade-offs; supports informed decision-making via Pareto fronts.	Complex convergence analysis; higher algorithmic overhead.
	Robust/Uncertainty-Aware Optimization	Uncertainty distributions, propagation models	Produces reliable layouts under uncertain conditions; quantifies performance risk.	Requires embedded uncertainty quantification; increases problem complexity.
	Real-Time/Online Optimization	Real-time sensor data (LiDAR, SCADA), adaptive models	Enables dynamic response to changing inflow; maximizes instantaneous power.	Demands robust sensing/communication infrastructure; safety-critical control.

2.1. High-Fidelity Multiscale Flow Modeling Under Dynamic Inflow

High-fidelity CFD and LES models form the physical foundation of multiscale wind farm modeling. They capture unsteady turbulence transport, vortex formation, wake breakdown, and turbine–turbine interaction processes that cannot be resolved by analytical models. In particular, dynamic inflow conditions amplify the importance of unsteady vortex dynamics, as the energy exchange across scales becomes significantly stronger than under steady inflow. To provide a structured overview of the methodological landscape, Table 2 maps the primary challenges in dynamic layout optimization to the most suitable modeling paradigms, surrogate strategies, and the empirical or numerical resources that support their development and validation. This framework serves as a guide for the detailed discussions in the following sections.

Table 2. Mapping of the Methodological Approaches to Wind Farm Layout Optimization Challenges under Dynamic Inflow Conditions.

Optimization Challenge	Recommended Modeling Approaches	Supporting Data-Driven Surrogates	Key Benchmark Datasets
Steady-State, Flat Terrain	Engineering Models (Jensen, Gaussian)	Simple ML correction	Horns Rev, Lillgrund
Complex Onshore Terrain (Ridges, Forests)	RANS/URANS CFD, Hybrid Analytical-CFD	Physics-Informed ML, GP for terrain effects	SWiFT (for complex flow)
Dynamic Inflow & Wake Steering (Onshore/Offshore)	LES, Hybrid RANS–LES	GP for yaw control, NN for dynamic wake prediction	SWiFT, CLIFLO
Array-Scale Blockage & Power Saturation	High-Resolution LESs, Momentum Budget Models	GP for array resistance	Large offshore farms
Floating Offshore Wind Farms	Coupled Hydro–Aero–Elastic LES/DDES	GNNs for platform–wake interaction, PIML	OC6, Hywind Demo, WindFloat Atlantic
Real-Time, Uncertainty-Aware Operation	Fast Engineering Models	DRL, Closed-loop GP/NN controllers	Operational SCADA from commercial farms

2.1.1. LES, Hybrid RANS–LES, and Vorticity-Based Off-Body Solvers

LES and hybrid RANS–LES methods provide high-resolution flow fields capable of representing fine-scale turbulence structures. Computational advances such as the vorticity off-body solver by Whitehouse and Boschitsch demonstrate that vorticity-preserving solvers can capture far-wake evolution at a fraction of the computational cost of traditional Navier–Stokes solvers [1]. This is especially valuable for multiscale coupling, where far-wake behavior strongly influences farm-level optimization.

DDES applications to turbine and cascade flows reveal that hybrid scale-resolving models offer a practical balance between fidelity and cost, outperforming RANS in resolving wake shear-layer transitions, vortex shedding, and shock–boundary-layer interactions under non-ideal operating conditions [2]. Foundational LES research on bluff bodies, circular cylinders, and turbine rotors continues to inform scaling laws for vortex shedding, wake breakdown, and turbulence dissipation relevant to large wind farm layout strategies [3–6].

As shown in Figure 1, high-fidelity simulations across multiple test cases (Cases 1–16) reveal significant variations in power coefficient (C_p) and thrust coefficient (C_T) under different inflow conditions, including laminar versus turbulent inflow and varying yaw or perturbation angles. The results highlight how dynamic inflow characteristics, such as turbulence intensity and misalignment, directly influence turbine performance. Notably, even small changes in inflow condition (e.g., from 0.00° to 7.0° yaw) can lead to measurable drops in C_p , underscoring the necessity of accurate modeling of the unsteady vortex dynamics in real-world environments.

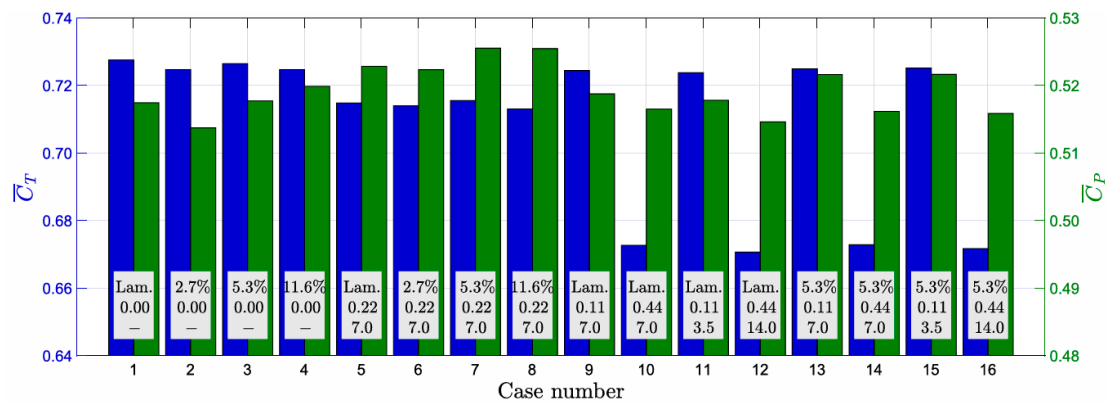


Figure 1. Instantaneous vorticity field at different phases [5].

Although engineering models are widely adopted for their computational efficiency, their reliance on idealized assumptions—such as axial momentum conservation, Gaussian wake profiles, and fixed wake expansion rates—leads to systematic inaccuracies in complex scenarios. Specifically, they fail to capture the following: (1) wake meandering (random lateral displacement of the wake centerline); (2) unsteady wake dynamics, including vortex shedding and transient recovery processes; (3) terrain-induced effects, such as flow acceleration over ridges or deceleration in forests; and (4) array-scale blockage, where the entire farm impedes upstream inflow. These deficiencies can result in significant errors in multi-objective optimization or real-time control, particularly in densely packed or topographically complex sites.

2.1.2. Wind Tunnel Experiments: Physical Mechanisms and Scale Similarity

Wind tunnel studies provide essential datasets for validating both high-fidelity and reduced-order models. Controlled inflow facilitates the isolation of physical mechanisms, such as yaw-induced wake deflection [7], vertical or horizontal turbine staggering [8,9], and tandem turbine mixing enhancement [10]. These studies reveal how multi-scale turbulence structures, such as tip vortices, hub vortices, and shear-layer instabilities, respond to dynamic inflow, turbine misalignment, and size disparity.

Recent scale-resolving simulations have begun to capture these transient interactions. For instance, Figure 2 illustrates the turbulent kinetic energy (TKE) distribution in the wake of two tandem floating offshore wind turbines undergoing surge motion. It is a representative scenario of wave-induced platform dynamics. The highly asymmetric and intermittent TKE structures underscore the inadequacy of steady-state assumptions and highlight the need for time-resolved modeling in layout design.

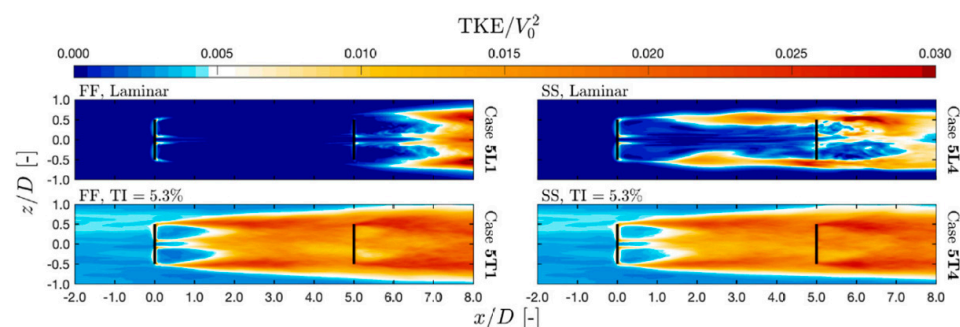


Figure 2. Contours of the turbulent kinetic energy (TKE) of the selected cases with $\Delta_D = 5D$. Upper row: Cases with configuration FF and SS subjected to laminar inflow conditions. Lower row: Cases with configuration FF and SS subjected to turbulent inflow conditions (TI = 5.3%). The case numbers are labeled on the right of each panel [10].

2.2. Multiscale Coupling: Bridging Blade-Resolved Flow and Farm-Level Models

The central challenge in multiscale modeling lies in establishing consistent physical transitions across scales. Blade-resolved simulations capture millisecond-scale vortex evolution but cannot be directly inserted into kilometer-scale farm simulations due to computational costs [11]. Therefore, models must translate high-fidelity simulation outputs into scalable turbulence metrics, spectral signatures, and wake parameterizations.

Recent works have proposed integrated frameworks where LES-derived wake expansion rates, mixing lengths, turbulence intensities, wake meandering frequencies, and vortex Reynolds stresses are encoded into reduced-order models [12,13]. Lattice Boltzmann LESs further enable realistic inflow synthesis under complex terrain or urban-like conditions [13], while RANS structural-uncertainty quantification provides robustness to model discrepancies when these reduced-order models are applied at farm scale [14].

In addition, floating wind turbines introduce platform-induced motions that modulate wake transport processes, requiring coupling between hydrodynamic and aerodynamic models [15,16]. To support multiscale integration, various numerical methods have been developed, each balancing fidelity and computational cost across specific spatiotemporal scales. A comparative summary of these approaches, including high-fidelity simulations, experiments, data-driven hybrids, and coupled frameworks, is provided in Table 3.

Table 3. Evolution of Dynamic Wake Modeling Approaches under Unsteady Inflow Conditions.

Modeling Category	Core Methodology	Key Technical Features	Performance Advantages
High-fidelity simulation	Vorticity–velocity off-body LESs [1]	Resolves vortex transport and far-wake evolution with reduced computational cost.	Accurate prediction of large-scale coherent structures and long-range wake dynamics.
	Scale-resolving simulation [4]	Captures turbulent inflow effects on near-wake coherence.	Improved spectral fidelity in wake turbulence under non-uniform inflow.
	Harmonic surging rotor LESs [5]	Models platform motion-induced unsteadiness via periodic boundary conditions.	Reveals enhanced mixing and intermittent wake behavior in floating turbines.
Experimental validation	Wind tunnel testing with yawed rotors [7]	Controlled measurement of wake deflection and asymmetry.	Quantifies yaw-induced wake distortion and its impact on downstream performance.
	Vertical staggered array experiments [8,9]	Measures periodic wake interaction in multi-turbine configurations.	Demonstrates enhanced recovery due to vertical spacing.
	Tandem turbine wake mixing tests [10]	Direct observation of turbulent mixing enhancement.	Validates numerical models of wake recovery mechanisms.
Data-driven & hybrid modeling	RANS with uncertainty quantification [12]	Integrates model form errors into probabilistic wake predictions.	Reduces overconfidence in deterministic simulations.
	LBM LESs with realistic inlet turbulence [13]	Reconstructs atmospheric boundary layer using synthetic turbulence.	Improves fidelity of urban or complex terrain flow simulations.
Advanced coupling methods	Dual surging FOWT LESs [15,16]	Couples platform dynamics with aerodynamic wake response.	Captures intermittent, asymmetric TKE structures in interacting wakes.

2.3. Integrated Surrogate and Data-Driven Modeling for Dynamic Wakes

The accurate and efficient prediction of dynamic wake interactions is paramount for the optimization of wind farm layouts and control strategies under varying inflow conditions. Traditional engineering models, while computationally inexpensive, often lack the fidelity to capture complex phenomena such as wake meandering, vortex shedding, and unsteady array-scale effects. Conversely, high-fidelity simulations, like large eddy simulation (LES), provide exceptional detail but are prohibitively expensive for direct use in optimization loops. To bridge this gap, a new class of integrated surrogate and data-driven modeling approaches has emerged. These methods leverage machine learning (ML) either to accelerate high-fidelity physics or to learn directly from the data, while incorporating physical constraints to enhance generalization and reliability [17]. This section provides a comprehensive review of these paradigms, categorizing them into three main types: physics-driven reduced-order models, pure data-driven models, and physics-informed hybrid models.

Physics-driven reduced-order models extract dominant flow features from high-fidelity simulation data using techniques such as proper orthogonal decomposition (POD) and Fast Fourier Transform (FFT). These models represent the flow field as a linear combination of basic functions (e.g., POD modes), significantly reducing computational cost compared to full-scale CFD. For instance, POD can be used to decompose the time-series LES data of wake evolution, allowing for rapid reconstruction of the wake state at any given time step based on a few key coefficients. While highly effective for capturing coherent structures in steady or slowly varying flows, their performance may degrade in highly turbulent or rapidly changing conditions where nonlinear dynamics dominate [18]. Furthermore, they are typically trained on specific configurations and require retraining for different layouts or atmospheric conditions.

Pure data-driven models learn the mapping between input variables (e.g., turbine positions, wind direction, speed, and turbulence intensity) and output quantities (e.g., wake deficit, power output, and thrust coefficient) directly from the data, without explicitly encoding the underlying physics. Deep neural networks (DNNs), graph neural networks (GNNs), and other ML architecture have shown remarkable success in this domain [19].

Neural networks (NNs) can be trained on large datasets generated by LESs or field measurements to predict wake profiles with high accuracy. However, they often function as “black boxes”, making it difficult to interpret their predictions or to ensure physical consistency.

Graph neural networks (GNNs) offer a natural framework for modeling wind farms, where turbines are represented as nodes and wake interactions as edges. GNNs can effectively learn complex, non-local dependencies between turbines, making them particularly suitable for irregular layouts and scalable to large farms. They can also incorporate spatial topology information as part of the graph structure.

Bidirectional GNNs are specifically designed to model the temporal evolution of wakes, such as the development of vortex streets and wake meandering. By processing sequences of wake snapshots in both forward and backward directions, they can capture the memory and recurrence inherent in turbulent flows.

To overcome the limitations of purely data-driven models, researchers have developed physics-informed hybrid approaches that combine the flexibility of ML with the physical consistency of established models. These models act as a bridge between low-fidelity and high-fidelity simulations.

To overcome the lack of physical consistency in purely data-driven models, researchers have developed several hybrid modeling approaches that integrate physical knowledge with machine learning. Among these, the Gaussian process (GP) is widely used for the

dynamic calibration of parameters in classical engineering wake models such as the Jensen model. By training the GP on high-fidelity simulation results or field measurements, it learns to adaptively adjust key model parameters such as wake spreading rate or decay constant based on real-time operating conditions, including yaw angle and turbulence intensity, thereby significantly improving the predictive accuracy for control applications like wake steering. Another important paradigm is physics-informed machine learning (PIML), which embeds fundamental physical laws, such as conservation of mass and momentum, directly into the loss function of the machine learning model. For instance, a neural network can be trained not only to minimize the error between the predicted and the observed wake deficits but to satisfy the continuity equation within the wake region, ensuring that the learned model adheres to basic physical principles and thus exhibits superior extrapolation capability and robustness under unseen conditions. Additionally, the adaptive random Fourier features (ARFF) method addresses inflow field reconstruction by using machine learning to recover the full 3D turbulent inflow field from sparse sensor measurements such as LiDAR. It first learns a mapping from sparse observations to a set of random Fourier features, which are then used to reconstruct the complete flow field, providing more accurate initial conditions for downstream wake models particularly beneficial in complex terrain or highly dynamic inflow scenarios. Together, these hybrid strategies effectively combine the flexibility of data-driven methods with the reliability of physics-based models, representing a critical advancement toward wind farm modeling that achieves high accuracy, computational efficiency, and strong generalization.

2.4. Integrated Multiscale Simulation for Wind Farm Optimization

As wind farms expand in size and complexity, integrated multiscale simulation becomes essential for achieving robust and optimal designs. Studies on staggered layouts [8–10] reveal how turbine size differences affect wake superposition. Floating dual-rotor systems [15,16] demonstrate the sensitivity of wake transport to platform surge and pitch. Tidal turbine research [19] highlights cross-discipline universality in wake recovery mechanisms, suggesting transferable modeling concepts for offshore wind farms.

These insights motivate modern MDAO (multidisciplinary design and optimization) frameworks that unify atmospheric models, turbine-level aerodynamics, surrogate models, and layout optimization strategies.

This section has reviewed the multiscale modeling advancements essential for wind farm layout optimization under dynamic inflow conditions. The body of work collectively demonstrates that high-fidelity CFD and LESs provide the foundational physics, that wind tunnel experiments deliver indispensable validation, that multiscale coupling frameworks ensure scalability across spatial and temporal scales, that surrogate models dramatically accelerate layout optimization, and that the added complexity of floating and offshore systems necessitates integrated dynamic modeling. Together, these developments signify a paradigm shift from decoupled component-level analyses toward integrated, physics informed simulation frameworks that are inherently compatible with optimization, thereby establishing the foundation for the next generation co-design of large scale wind farms in realistic, unsteady atmospheric environments.

3. Integrated Modeling and Optimization of Wind Farms in Complex and Offshore Environments

The deployment of wind energy has evolved from single-turbine installations to large-scale wind farms located in increasingly challenging environments, including mountainous regions, forested landscapes, and deep-water offshore zones. In these settings, traditional assumptions of flat terrain and homogeneous inflow no longer hold, leading to significant

errors in energy prediction if not properly addressed. Recent research has therefore focused on developing integrated frameworks that combine high-fidelity flow modeling, intelligent optimization, and real-world constraints to maximize the annual energy production (AEP) while ensuring structural reliability and economic viability.

This section synthesizes the advances across four critical domains: (1) micro-siting in geometrically complex and irregular domains; (2) accurate representation of large-scale atmospheric effects including blockage and momentum starvation; (3) co-optimization of layout and system components for distributed generation; (4) data-driven methods that enhance predictive accuracy under uncertainty. By integrating high-fidelity simulation, intelligent optimization, and real-world engineering constraints, these approaches aim to maximize energy yield while ensuring structural reliability and economic viability in next-generation wind farms.

3.1. Micro-Siting in Irregular and Constrained Domains

Micro-siting the precise placement of individual turbines within a constrained land or sea area is particularly challenging in regions with irregular boundaries, ownership fragmentation, or topographic obstacles. Unlike idealized rectangular domains, real world sites often exhibit non-convex geometries, exclusion zones, and multi-owner land parcels, which necessitate flexible and adaptive layout algorithms. Reddy [20] proposed a machine learning approach that models irregular regions with multiple landowners by embedding spatial constraints into a graph-based neural network, enabling the automatic identification of feasible turbine locations while respecting legal and environmental boundaries. This method demonstrated a 12% increase in the AEP compared to a conventional grid-based placement in fragmented agricultural landscapes, primarily by exploiting narrow corridors between ownership parcels previously deemed unusable. Building on this, Hu et al. [21] introduced an improved genetic algorithm (IGA) hybrid that combines particle swarm optimization with genetic operators to handle complex terrain micro-siting. Their framework integrates computational fluid dynamic (CFD) simulations directly into the fitness evaluation loop, allowing the optimizer to account for local acceleration and deceleration effects caused by ridges and valleys. When applied to a mountainous site in China with elevation changes exceeding 300 m, the IGA-PSO method achieved a 9.7% higher AEP than a standard GA, with reduced wake losses due to strategic placement on leeward slopes where flow reattachment minimized downstream turbulence.

Further advancing terrain aware micro-siting, Deng et al. [22] developed a yaw optimization integrated layout design that simultaneously determines turbine positions and optimal yaw offsets to maximize power output under dynamic inflow. Their dynamic wake model incorporates time varying wind direction and speed, enabling the co-design of static layout and active control strategies. Field tests on a hilly onshore farm showed that this joint optimization increased net energy capture by 6.3% over layout-only optimization, highlighting the value of coupling siting decisions with operational flexibility. Gori et al. [23] extended this concept to offshore contexts using a Gaussian process-based approach for tuning yaw-dependent wake model parameters. By treating the yaw angle as a continuous design variable, their method constructs a surrogate response surface mapping yaw settings to inter-turbine power gains. When embedded within a layout optimizer, this enables the identification of configurations where downstream turbines benefit most from upstream wake steering, a capability especially valuable in constrained offshore lease areas where turbine spacing cannot be freely adjusted. In this framework, the total wind farm power under a collective yaw configuration is approximated by a sum of the turbine-specific Gaussian process predictions, as shown in Equation (1):

$$P_{\text{farm}}(\gamma) = \sum_{i=1}^N \mu_{\text{GP}}^{(i)}(\gamma) \quad (1)$$

where $\gamma = [\gamma_1, \gamma_2, \dots, \gamma_N]^T$ denotes the vector of yaw angles for all N turbines, and $\mu_{GP}^{(i)}(\gamma)$ represents the posterior mean power output of turbine i , as predicted by a Gaussian process trained on high-fidelity wake simulation data. By replacing computationally expensive flow solvers with this differentiable surrogate, the optimization of wake steering strategies becomes tractable even for large wind farms. This data-driven approach exemplifies the emerging paradigm of combining physics informed simulations with machine learning for real-time farm-level control. By treating the yaw angle as a continuous design variable, their method constructs a surrogate response surface mapping yaw settings to inter-turbine power gains. When embedded within a layout optimizer, this enables the identification of configurations where downstream turbines benefit most from upstream wake steering, a capability especially valuable in constrained offshore lease areas where turbine spacing cannot be freely adjusted.

Forsting et al. [24] addressed another critical aspect of complex site modeling: the prediction of wind farm blockage. They demonstrated that traditional actuator disk models significantly underestimate flow deceleration upstream of large arrays, particularly in dense layouts. Using a high resolution LES, they quantified blockage-induced power losses of up to 8% in tightly packed farms and proposed a correction factor based on array solidity and inflow turbulence intensity. This work underscores the necessity of incorporating blockage physics into micro-siting tools, especially for sites with limited fetch where upstream flow perturbation directly impacts resource availability. Van Thin et al. [25] proposed a hybrid simulation analytical method for optimizing turbine locations in complex terrain, combining simplified analytical wake models for rapid screening with localized CFD refinement for final validation. Their approach reduces the computational cost by 70% compared to full domain CFD while maintaining an AEP prediction error below 3%. Applied to a Vietnamese coastal site with steep cliffs and forest patches, the method identified optimal placements that avoided recirculation zones behind topographic obstacles in regions that analytical models alone failed to resolve. Zhou et al. [26] conducted a numerical study on in-field blockage effects between closely spaced turbines, revealing that mutual blockage can reduce individual turbine power by up to 15% in staggered configurations with stream-wise spacing below $4D$. They developed a momentum conserving correction to the Jensen wake model that accounts for the upstream velocity deficit induced by neighboring rotors. Integrating this into a layout optimizer led to more dispersed configurations that mitigated blockage losses, particularly in compact urban or island-based wind farms.

Kirby et al. [27] offered a theoretical foundation for large wind farm power limits by deriving an analytical model of momentum availability based on boundary layer theory. Their model predicts power saturation when the farm extracts a critical fraction of the incoming momentum flux, a phenomenon observed in both LES and field data. This insight informs micro-siting by establishing an upper bound on the achievable AEP, beyond which adding more turbines yields diminishing returns, a crucial consideration for developers evaluating site capacity. Flaszynski et al. [28] performed a parametric LES study of blockage effects in offshore wind farms, varying the array density, water depth, and atmospheric stability. They found that blockage intensifies under stable conditions due to reduced vertical mixing, leading to stronger upstream deceleration. Their results advocate for layout designs that incorporate wider lateral spacing in stable marine atmospheres, a recommendation now being adopted in North Sea project planning.

Hidayat et al. [29] tackled non-uniform onshore layout optimization using a modified electric charged particles optimization (ECPO) algorithm that adapts a search behavior based on the local terrain gradient. The algorithm assigns higher “repulsion” between turbines in steep regions to avoid placing units in high shear zones. Tested on Indonesian sites with mixed forest and open land, ECPO outperformed differential evolution by 5.2% in

the AEP while reducing fatigue damage through avoidance of turbulent wake impingement on slope-induced vortices. Li et al. [30] introduced a discrete bi-population differential evolution (DBDE) algorithm specifically designed for complex terrain layout optimization. The method maintains two subpopulations, one exploring boundary constrained regions, the other focusing on interior zones, enabling the efficient navigation of multimodal fitness landscapes [31]. Validated on a benchmark site with multiple ridges and valleys, DBDE converged 40% faster than standard DE and yielded layouts with a 7.8% higher AEP. Cheng et al. [32] investigated the interaction between wind turbine wakes and forested terrain, showing that canopy roughness enhances wake mixing but also induces low-level jets that alter wake trajectory. Their LES hybrid model, validated using field measurements, revealed that optimal micro-siting in forested areas requires placing turbines at least 2 km upwind of dense canopies to avoid jet-induced yaw misalignment.

3.2. Large Scale Momentum Limitations and Power Saturation

Beyond local terrain effects, wind farms operating at utility scale interact with the atmospheric boundary layer as a whole, leading to emergent phenomena such as momentum starvation and regional power saturation. These effects arise when the collective drag of hundreds of turbines depletes the kinetic energy available in the inflow, causing the power output to plateau or even decline with additional turbine installations, a behavior not captured by conventional wake superposition models.

Kirby et al. [33] extended their earlier momentum availability model to include flow resistance from turbine arrays, developing a data-driven framework that predicts large scale power deficits based on farm size, turbine density, and boundary layer height. Using historical SCADA from five European offshore farms, they calibrated a resistance coefficient that correlates strongly with the observed AEP underestimation by engineering models. Their approach enables an early stage assessment of whether a proposed farm size exceeds the local momentum budget. Lin et al. [34] proposed an integrated optimization method for a distributed wind farm design in three dimensional complex terrain, coupling CFD-based flow simulation with a multi-objective evolutionary algorithm. Their framework explicitly minimizes both wake losses and blockage-induced upstream deceleration by penalizing high density clusters. Applied to a mountainous region in Southwest China, the optimized layout increased the AEP by 11.4% while reducing maximum turbine thrust by 18%, demonstrating the dual benefit of momentum aware design. These large-scale interactions are inherently three-dimensional and transient, necessitating high-fidelity simulation tools to resolve the complex turbulence dynamics within and above the farm canopy. As illustrated in Figure 3, large eddy simulations (LESs) of a periodic turbine array reveal stark differences between the chaotic, vortex-rich instantaneous flow field (panel A) and the smoother, more organized time-averaged velocity distribution (panel B). This contrast underscores the importance of capturing both temporal variability and spatial coherence in wake superposition and momentum transport models—features that conventional engineering approaches often overlook.

Qian and Ishihara [35] developed a novel probabilistic power curve model to predict the AEP and its uncertainty over complex terrain. By incorporating stochastic representations of wind shear, veer, and turbulence intensity derived from long term mesoscale simulations, their model quantifies the confidence interval of energy yield predictions. This is particularly valuable for financial risk assessments in mountainous projects where flow variability is high. Validation against 3 years of operational data showed a 95% prediction interval width of $\pm 8.2\%$, significantly narrower than deterministic models. Wu et al. [36] addressed the synchronization of 3D offshore layout optimization with multi-type turbine selection and obstacle avoiding cable routing. Their framework uses a nested optimization

loop: an outer loop selects turbine types and positions, while an inner loop computes minimum cost cable networks that avoid shipping lanes and seabed hazards. The inclusion of cabling constraints prevented unrealistic clustering and increased net present value by 6.7% despite a slight AEP reduction, illustrating the importance of holistic system design. Wang et al. [37] studied flow field characteristics in complex mountainous terrain using boundary condition optimization in numerical simulations. They found that improper specification of inlet turbulence profiles leads to errors in predicted separation zones, which in turn misguide micro-siting decisions. By calibrating inlet conditions against LiDAR measurements, they reduced the AEP prediction error from 14% to 5%, emphasizing the need for site specific inflow characterization.

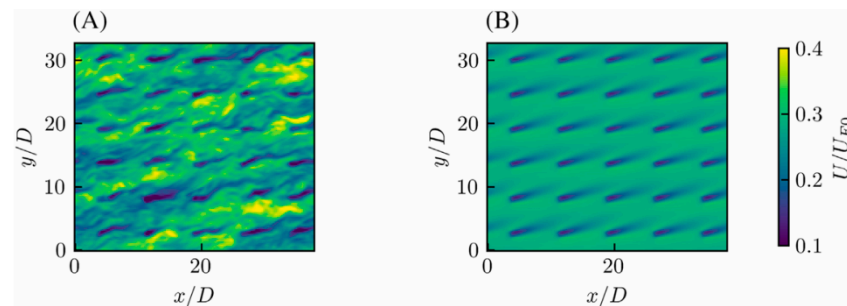


Figure 3. LES (A) instantaneous and (B) time-averaged flow fields over a periodic turbine array ($S_x/D = 7.59$, $S_y/D = 5.47$ and $\theta = 37.6^\circ$) [33].

Tao et al. [38] combined CFD with IGA-PSO for layout optimization in a complex terrain, achieving convergence in fewer than 50 generations for a 30 turbine farm. Their method dynamically adjusts mutation rates based on terrain ruggedness, accelerating exploration in flat zones and intensifying exploitation in rugged areas. The resulting layout placed turbines along ridge crests with minimal cross ridge spacing, leveraging flow acceleration while avoiding lee side turbulence, a strategy validated by on site met mast data. Reddy [39] presented an efficient method for modeling terrain and complex boundaries in constrained layout optimization using a raster-based digital elevation model (DEM) coupled with a visibility graph algorithm. This approach rapidly identifies line-of-sight obstructions and shadow zones, enabling the exclusion of infeasible locations without mesh generation. When applied to a fragmented Indian site with 12 ownership parcels, the method reduced preprocessing time by 85% compared to GIS integration workflows. Table 4 categorizes the relevant studies by technical focus. It summarizes the computational and optimization approaches employed and identifies the practical challenges addressed, including micro-siting in complex terrain, handling real world spatial constraints, modeling array scale blockage effects, co-designing layout with active control strategies, and quantifying uncertainty in energy yield predictions.

While both RANS and LES can estimate array-scale blockage, their accuracy differs markedly. RANS, due to its time-averaged nature, typically underestimates local velocity deficits caused by instantaneous flow separation and reattachment, leading to an under-prediction of total blockage loss. By contrast, LES resolves transient vortex structures and captures separation dynamics more faithfully, yielding higher-fidelity blockage estimates. Studies have suggested that, for dense large-scale farms, RANS-based AEP predictions can be 5 to 10 percent higher than LES-based ones, highlighting the importance of high-fidelity methods in critical design phases, albeit at greater computational expense.

The recognition of significant blockage losses necessitates a fundamental rethinking of conventional layout design principles. Traditional optimization, which primarily seeks to minimize wake overlap by maximizing downstream spacing, may inadvertently exacerbate blockage by creating dense clusters of turbines that act as a single, large bluff body. An

optimal layout under blockage-aware design must therefore balance two competing effects: minimizing wake deficits through strategic staggering and minimizing upstream flow deceleration through more distributed, lower-density configurations. This represents a paradigm shift from pairwise turbine interaction to a holistic, farm-scale fluid dynamic optimization.

Table 4. Summary of Wind Farm Layout Optimization Approaches in Complex and Offshore Environments.

Focus Area	Methods	Key Contribution/Problem Solved
Layout optimization in complex terrain	Improved genetic algorithm with particle swarm optimization [21,38], discrete bi-population differential evolution [30], enhanced charged particle optimization [29], CFD embedded in fitness evaluation.	Achieved 5.2–9.7% higher AEP on steep or irregular sites by avoiding high shear and turbulence zones while adapting search behavior to local topography.
Handling real world spatial and engineering constraints	Graph neural networks for ownership boundaries [20], hybrid analytical–CFD screening [25], nested optimization for turbine placement and cable routing [37].	Enabled feasible layouts in fragmented land parcels and offshore zones with obstacles; increased the AEP by 12% or net present value by 6.7% while respecting shipping lanes and seabed hazards.
Modeling blockage and wake interactions at array scale	High resolution large eddy simulations [24], momentum conserving wake models [26], parameterized LESs under varying atmospheric stability [28], coupling canopy roughness with wake dynamics [32].	Quantified up to 8% power loss from farm scale blockage and up to 15% from inter-turbine blockage; informed updated spacing rules for dense or offshore farms under stable conditions.
Co-design of layout and active control	Joint optimization of positions and yaw angles [22], Gaussian process surrogates for yaw-dependent power gain [23].	Boosted net energy capture by 6.3% by aligning static layout with dynamic wake steering; identified optimal configurations where downstream turbines benefit most from upstream yawing.
Large scale momentum limits and uncertainty quantification	Momentum budget theory [27], CFD-driven multi-objective optimization [34], probabilistic power curves coupled with mesoscale inflow data [35].	Established physical AEP ceilings for large farms; reduced prediction error from 14% to 5%; narrowed the 95% AEP prediction interval to $\pm 8.2\%$ for financial risk assessment.

3.3. Layout and Control Co-Design for Floating Offshore Wind Farms

The development of floating offshore wind farms represents a transformative step towards accessing vast wind resources in deep waters. However, the dynamic nature of floating platforms introduces unprecedented challenges that are absent in their fixed-bottom counterparts. The interaction between platform motion and turbine wake dynamics creates complex, time-varying flow fields that significantly impact both power production and structural loads. Therefore, optimizing a floating wind farm requires a paradigm shift from a static layout design to an integrated layout and control co-design approach, where the spatial configuration and dynamic behavior of the system are considered simultaneously.

The primary challenge lies in the periodic modulation of the wake by platform motions, primarily heave (vertical oscillation) and pitch (rotational movement around the horizontal axis). As the platform moves up and down or pitches forward and backward, it effectively “pulses” the incoming flow and the wake generated by the upstream turbine. This results in the formation of highly unsteady and intermittent turbulent structures within the wake.

Conversely, the pitching motion can induce large-scale coherent vortices and alter the wake’s lateral spread. These dynamic effects are not captured by traditional steady-

state wake models and introduce significant uncertainty into power prediction and load estimation. The resulting flow field is characterized by non-stationary velocity fluctuations and fluctuating turbulence intensity, which can lead to increased fatigue loads on the downstream turbines.

Accurately simulating these coupled phenomena demands a fully coupled aero–hydro–elastic (AHE) simulation framework. This involves solving the equations of motion for the floating platform (hydrodynamics), the aerodynamic forces on the turbine blades (aerodynamics), and the structural response of the entire system (structural dynamics) simultaneously. The coupling occurs at multiple levels: the platform motion affects the inflow to the turbine, the turbine thrust force influences the hydrodynamic loading on the platform, and the structural deformation alters the aerodynamic performance.

The computational cost of such AHE simulations is extremely high, making them impractical for direct use in optimization loops. While simplified models exist, they often fail to capture the full complexity of the interactions. This computational bottleneck presents a major challenge for the development of reliable and efficient optimization tools for floating wind farms.

This is the key insight. The optimal layout for a floating wind farm must go beyond merely minimizing wake overlap based on average positions. It must also consider the phase relationship between the platform motions of different turbines.

For instance, if the heave or pitch motion of a downstream turbine is tuned to resonate with the vortex shedding frequency of the upstream wake, this could enhance mixing and accelerate wake recovery, potentially increasing the power output of the downstream turbine. Conversely, if the motions are out of phase, they might amplify the wake deficit or create adverse interference patterns, leading to higher loads and reduced efficiency.

Therefore, the “best” layout is not just about where to place the turbines, but about how their dynamic behaviors interact. This necessitates a co-design process where the layout optimization algorithm incorporates the dynamic response characteristics of the platforms (e.g., natural frequencies, damping ratios) as design variables or constraints. The goal is to find a configuration that maximizes energy capture while minimizing structural fatigue, considering the coupled fluid-structure interactions.

In addition to layout optimization, advanced control strategies are essential. While yaw control remains crucial for wake steering, new control mechanisms specific to floating platforms can be leveraged synergistically. The ultimate goal is to integrate these platform-level control actions with turbine-level control (yaw, pitch, and torque) into a unified control strategy. For example, a controller could decide to slightly increase the pitch angle of a downstream turbine to reduce its thrust when a large wake disturbance is expected due to upstream platform motion, thereby mitigating the load spike. This level of integration represents the next frontier in floating wind farm optimization.

The performance and reliability of advanced metaheuristic algorithms in wind farm layout optimization are critically determined by their ability to identify high-quality solutions across diverse turbine configurations. As illustrated in Figure 4, the FODE algorithm consistently achieves superior conversion efficiency compared to state-of-the-art optimizers such as LSHADE, AGA, and CLSHADE across all tested scenarios ranging from 10 to 80 turbines. This enhanced performance is particularly evident in large-scale layouts where FODE not only outperforms other methods but demonstrates greater robustness with tighter confidence intervals. These results underscore the importance of developing sophisticated optimization strategies that can effectively navigate complex high-dimensional search spaces while maintaining consistent solution quality, especially when each evaluation demands significant computational resources.

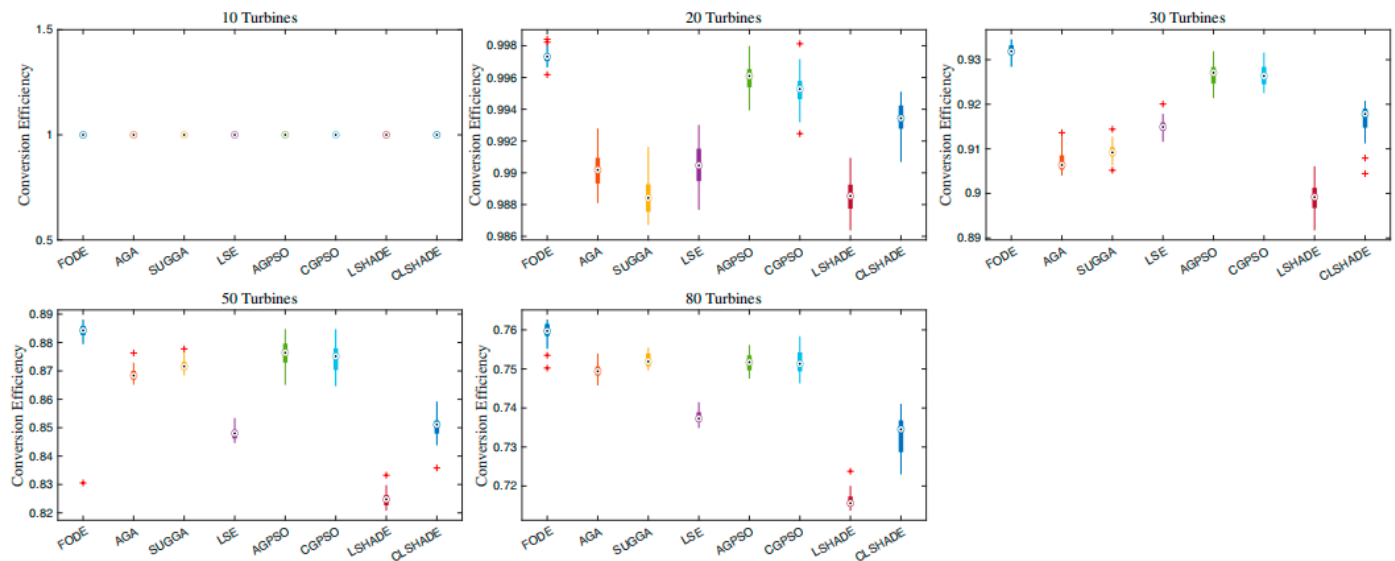


Figure 4. Boxplots of state-of-the-art WFLOP optimizers under single, double, eight, and ten wind-direction conditions [38].

In summary, optimizing wind farm layouts in complex and offshore environments requires an integrated approach that moves beyond simple geometric spacing rules. Recent research has shown that high-fidelity flow modeling, particularly through computational fluid dynamics and large eddy simulations, is essential for accurately representing terrain-induced flow acceleration, separation zones, blockage effects, and large scale momentum depletion. These phenomena have a profound impact on both energy production and structural loading. By combining such physical insights with intelligent optimization algorithms, such as the improved genetic algorithm with particle swarm optimization, discrete bi-population differential evolution, and enhanced charged particle optimization, it becomes possible to achieve adaptive micro-siting within irregular and constrained domains while respecting land ownership, environmental restrictions, and engineering practicality. Furthermore, modern design frameworks now co-optimize multiple aspects, including turbine placement, machine type selection, yaw control strategies, and even subsea cable routing, reflecting a clear trend toward holistic system-level planning. Data-driven and hybrid modeling techniques play a key role in balancing computational cost with predictive accuracy, while uncertainty aware formulations improve robustness under realistic and variable inflow conditions. Together, these innovations support the development of next generation wind farms that are more productive, economically sound, structurally reliable, and well suited to challenging landscapes and dynamic atmospheric environments.

4. Data-Driven and Machine Learning Modeling for Wind Farm Layout Optimization

The traditional paradigm of wind farm layout optimization maximizing the annual energy production (AEP) using static wind roses and simplified wake models is increasingly inadequate in modern power systems. As wind penetration grows, grid operators demand not just energy but predictable output, fast frequency response, voltage support, and fault resilience. Simultaneously, atmospheric science reveals that real inflow is rarely steady: wind direction shifts abruptly, turbulence intensity varies diurnally, and complex terrain induces shear and veer. Under such dynamic conditions, a layout optimized for time-averaged wakes can suffer severe underperformance during critical operational windows.

This challenge has catalyzed a shift from passive siting to active co-design, where the spatial arrangement of turbines is jointly optimized with their real-time control strategies.

The enabling force behind this shift is data: high-fidelity simulations, field measurements, and machine learning now allow us to build predictive models that capture transient wake physics at scale. The studies reviewed here, though diverse in focus, converge on a unified insight: optimal performance emerges from the synergy between where turbines are placed and how they respond collectively to changing winds.

In what follows, we synthesize these advances into a coherent framework across the following four pillars: (1) data-driven modeling of dynamic wakes; (2) scalable optimization for large farms; (3) multi-objective trade-offs beyond energy yield; and (4) real-time integration with grid services.

4.1. High-Fidelity Inflow and Wake Modeling

The accurate representation of atmospheric inflow and turbine wake dynamics remains foundational to wind farm performance prediction. Recent work has leveraged ML to bridge the gaps between computationally expensive simulations and simplified engineering models.

Kiessling et al. [40] introduced an adaptive random Fourier features (ARFF)-based method to reconstruct three-dimensional turbulent inflow fields from sparse sensor measurements. By preserving the spectral characteristics of turbulence, their approach provides physically consistent boundary conditions for downstream wake simulations without requiring dense instrumentation. Building on this, Gori et al. [23] developed a Gaussian process (GP)-driven framework to dynamically tune yaw-dependent wake model parameters. Their method enables the real-time calibration of wake deflection and velocity deficit models under varying wind directions, directly optimizing total farm power through coordinated wake steering.

Nakhchi et al. [41] extended this idea by training a machine learning model to jointly predict both wake profiles and power output in yaw-controlled horizontal-axis wind farms. Their surrogate achieves strong agreement with high-fidelity large eddy simulations (LESs), demonstrating feasibility for rapid scenario evaluation during control or layout design. As illustrated in Figure 5, the ARFF algorithm adaptively concentrates sampling density in the spectral regions that dominate atmospheric turbulence, enabling efficient yet physically consistent inflow reconstruction.

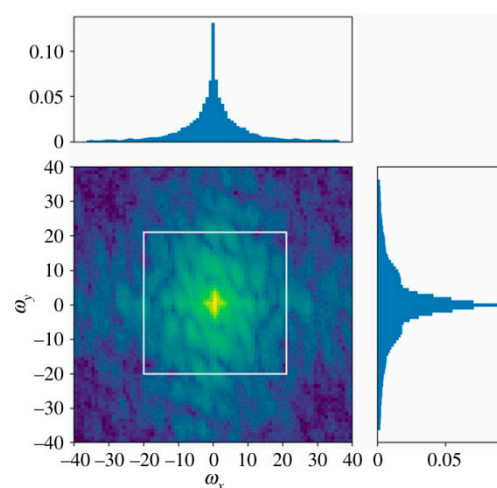


Figure 5. Spectral sampling density distribution in the adaptive random Fourier features (ARFF) algorithm [40].

Parekh and Verstappen [42] conducted a comparative study between stochastic Reynolds-averaged Navier–Stokes (RANS) solvers and deep learning surrogates for wake uncertainty quantification. They revealed a fundamental trade-off: while physics-based

stochastic solvers enforce conservation laws, deep neural networks offer superior computational speed at the cost of occasional non-physical predictions highlighting the need for hybrid approaches. Santoni et al. [43] addressed this gap by augmenting classical engineering wake models with machine learning residuals trained on LES data. This “physics-informed ML” strategy retains the interpretability and low cost of analytical models while achieving near-LES accuracy in predicting wake recovery and interaction. Gajendran et al. [44] focused specifically on yawed turbine wakes, proposing an ML-based predictor that captures asymmetric velocity deficits under misaligned inflow. Their model, trained on high-resolution simulation data, outperforms conventional superposition rules in complex control scenarios.

Li et al. [45] took a graph-theoretic perspective, formulating an end-to-end wake modeling architecture using deep graph representation learning. In their framework, turbines are nodes and wake interactions are edges; this eliminates the need for structured grids and naturally handles irregular layouts, enabling scalable prediction across diverse farm geometries. To capture temporal dynamics, Li et al. [46] developed a bilateral convolutional neural network (CNN) trained on time-resolved LES data to model unsteady wake evolution. Their dynamic surrogate accurately reproduces vortex shedding, meandering, and recovery processes under transient wind conditions. The design of numerical experiments is crucial for systematically investigating wake dynamics across a wide range of wind farm configurations. As illustrated in Figure 6, the input parameters include the longitudinal spacing S_x/D , lateral spacing S_y/D , and inflow wind direction θ . Panel (A) shows the schematic layout of turbines with these geometric parameters, while Panel (B) presents the parameter space sampled for large eddy simulations (LESs), highlighting the variation in wind direction for different spacing combinations. This comprehensive experimental design enables a thorough exploration of wake behavior under diverse operational conditions.

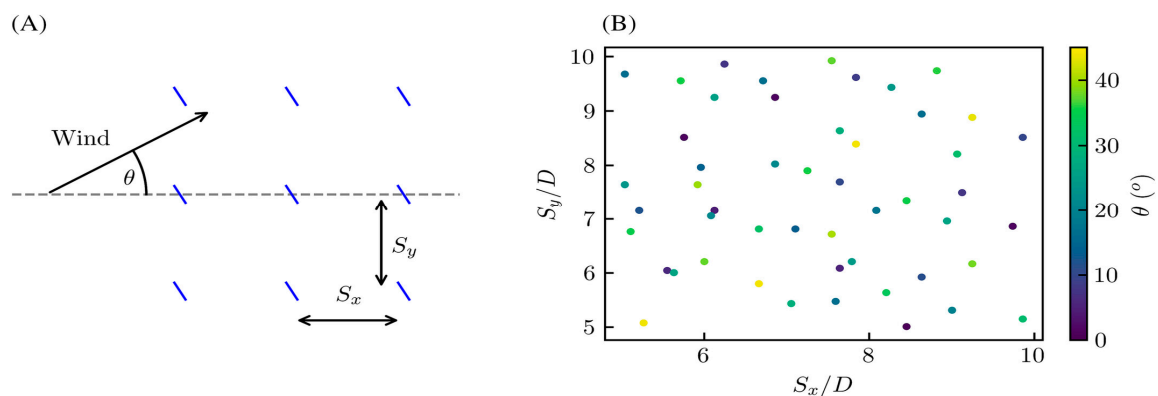


Figure 6. Design of numerical experiments: (A) input parameters and (B) maximin design of LESs [33].

Finally, Kirby et al. [33] modeled collective effects in large arrays using a Gaussian process to predict effective flow resistance and wake interference. Their data-driven formulation provides insight into blockage and array-scale momentum loss, informing macro-layout decisions beyond pairwise turbine interactions. Collectively, these studies demonstrate how data-driven methods are transforming wake modeling from static, pairwise approximations toward dynamic, spatially coherent, and physically consistent representations. To better organize these advances, Table 5 summarizes the representative approaches for high-fidelity inflow reconstruction and wake prediction, categorizing them by application focus, methodology, and key technical advantages.

Table 5. Data-Driven Approaches for High-Fidelity Inflow and Wake Modeling.

Application Focus	Method	Key Features and Advantages
3D Turbulent Inflow Reconstruction	Wind field reconstruction using adaptive random Fourier features [40].	Recovers spectrally consistent 3D turbulent inflow from sparse sensor data, providing physically realistic boundary conditions for wake simulations.
Dynamic Wake Model Calibration	Gaussian process-based tuning of yaw-dependent wake parameters [23]; ML-based joint prediction of wake and power under yaw control [41].	Enables real-time calibration of wake deflection and velocity deficit models for coordinated wake steering and farm-level power maximization.
Enhancement of Engineering Models	Physics-informed machine learning with residual correction [43]; ML prediction of asymmetric wakes under yawed conditions [44].	Augments classical models with ML corrections to achieve near-LES accuracy at low computational cost.
Unsteady and Graph-Based Modeling	Bilateral CNN for dynamic wake evolution [45]; end-to-end wake modeling via deep graph representation learning [46].	Captures transient phenomena, like vortex shedding and meandering; naturally handles irregular layouts through graph-based turbine interaction modeling.
Array-Scale Flow Effects	Gaussian process modeling of wake interactions and effective flow resistance [33].	Quantifies blockage and momentum loss in large wind farms, informing macro-layout decisions beyond pairwise interactions.
Uncertainty Quantification Comparison	Comparative analysis of stochastic RANS solvers versus deep learning surrogates [42].	Highlights trade-offs between physical consistency and computational efficiency, supporting the development of hybrid modeling strategies.

4.2. Uncertainty-Aware Surrogate Modeling for Layout Optimization

Beyond wake fidelity, practical layout design must account for environmental uncertainty, operational constraints, and computational tractability. Modern approaches combine probabilistic modeling, dimensionality reduction, and hybrid surrogates to enable robust, large-scale optimization.

Shao et al. [47] integrated polynomial chaos expansion (PCE) with Kriging to perform high-fidelity layout optimization under uncertain wind rose distributions. Their framework propagates directional and speed uncertainties through the power model, yielding layouts that maximize the expected annual energy production (AEP) while quantifying risk. Yao et al. [48] incorporated structural considerations by designing an active power dispatch strategy that suppresses fatigue loads using data-driven load proxies. Their method minimizes the cumulative damage estimated from operational SCADA without sacrificing more than 1–2% of the AEP, enabling lifetime-aware farm operation.

Liu et al. [49] expanded the objective beyond energy to ancillary services, developing a data-driven model predictive control (MPC) framework to assess and optimize the feasible region for frequency regulation. Their approach ensures that reserve commitments remain within physical and stable limits under varying wind conditions. Wang et al. [50] tackled voltage stability in high-penetration grids by proposing a hybrid surrogate technique for coordinated planning. Combining physics-based sensitivity analysis with ML-enhanced impedance response models, they guided the optimal placement of reactive compensation devices to dampen voltage fluctuations.

Arrieta-Prieto and Schell [51] accelerated siting studies by training a random forest model on historical meteorological and terrain datasets. The resulting proxy identifies high-potential zones early in the evolutionary optimization loop, drastically reducing the number of costly CFD evaluations needed for macro-siting. Aerts et al. [52] emphasized

model calibration using real-world data, constructing a Bayesian framework to update wake model parameters based on historical power measurements. Their approach corrects for the site-specific effects that generic models overlook, ensuring that layouts reflect actual rather than idealized performance. Yang et al. [53] unified these ideas into a comprehensive data-driven layout optimization framework for large-scale farms. By applying clustering to group turbines and dimensionality reduction to compress wind condition spaces, they accelerate the AEP estimation and global search making million-turbine-scale optimization computationally feasible.

4.3. Grid-Integrated Multi-Objective Co-Design

As wind farms evolve into active grid assets, design must co-optimize energy yield, reliability, and grid support capabilities. Fernandez-Navamuel et al. [54] addressed reliability in floating offshore systems by developing a supervised deep learning methodology for fault detection and identification (FDI). Trained on simulated sensor and control signals, their FDI module enhances system resilience by enabling rapid isolation of actuator or sensor failures in harsh marine environments. Li et al. [55] focused on voltage control, implementing a decentralized optimal strategy using a hybrid CNN–Transformer architecture. Their model predicts nodal voltages across the collector network and coordinates reactive power injections in real time, maintaining voltage profiles within statutory limits even under rapid wind ramps. Yan et al. [56] further advanced this by proposing a method for simultaneous demanded power tracking and voltage regulation. Using analytically derived data-driven sensitivities, their decentralized controller adjusts both active and reactive setpoints without centralized communication, making it well suited for weak-grid or islanded operation scenarios.

4.4. Distributed Real-Time Control Strategies

The final frontier lies in closing the loop between design and operation through scalable, communication-efficient control. Hu et al. [57] proposed a semi-decentralized, data-model-driven optimization scheme for coordinated power maximization in large-scale wind farms. Their framework blends first-principle models with online ML updates and employs an improved multi-objective optimizer to balance total power, load equity, and communication overhead under bandwidth constraints, thereby achieving near-centralized performance through distributed implementation. As wind farms evolve into active grid assets, optimization must transcend annual energy production to jointly address reliability, grid support, and real-time operability under uncertainty. A growing body of work leverages hybrid modeling, probabilistic frameworks, and distributed control to achieve this multi-objective co-design. Table 6 provides a consolidated overview of these advanced frameworks, mapping their methodological foundations to specific optimization or control objectives across layout design, lifetime management, ancillary services, and real-time coordination.

Table 6. Optimization and Control Frameworks for Multi-Objective Coordination and Real-Time Operation.

Application Focus	Method	Optimization or Control Objective
Layout Optimization under Uncertainty	Polynomial chaos expansion combined with Kriging surrogates [47]; clustering and dimensionality reduction for large-scale layout design [53].	Maximizes the expected annual energy production (AEP) under uncertain wind resources and enables computationally feasible optimization for farms with thousands of turbines.

Table 6. *Cont.*

Application Focus	Method	Optimization or Control Objective
Lifetime and Reliability Co-Design	Data-driven fatigue load suppression in active power dispatch [48]; supervised deep learning for fault detection in floating offshore wind farms [54].	Reduces cumulative structural damage with minimal AEP loss; enhances system resilience in harsh marine environments.
Grid Ancillary Service Integration	Data-driven model predictive control (MPC) for frequency regulation feasibility assessment [49]; hybrid surrogate technique for coordinated VAR planning [50].	Ensures reliable provision of frequency reserves; improves voltage stability in high-wind-penetration power systems.
Distributed Voltage and Power Control	CNN-Transformer architecture for nodal voltage prediction and reactive power coordination [55]; data-driven sensitivity-based controller for simultaneous power tracking and voltage regulation [56].	Achieves real-time voltage control without centralized communication; supports both active power delivery and grid voltage support in weak or islanded grids.
Model Calibration and Siting Acceleration	Bayesian framework for wake model calibration using historical power data [52]; random forest proxy model trained on meteorological and terrain data for macro-siting [51].	Corrects site-specific model biases using operational data; drastically reduces the number of expensive CFD evaluations during early-stage siting.
Large-Scale Coordinated Control	Semi-decentralized data-model-driven optimization scheme [57].	Balances total power output, load equity, and communication overhead under bandwidth constraints, achieving near-centralized performance with distributed implementation.

5. Real-Time Uncertainty-Aware Optimization Under Dynamic Inflow

The increasing penetration of wind energy into power systems demands a paradigm shift from static, deterministic optimization to real-time, uncertainty-aware decision-making. As wind resource availability and wake dynamics are inherently stochastic and time-varying, traditional planning approaches fail to capture the full complexity of offshore wind farm operations. This section reviews recent advances in modeling and optimizing wind farm performance under dynamic inflow conditions, focusing on stochastic programming, data-driven adaptation, multi-fidelity modeling, and integrated risk-aware frameworks.

5.1. The Challenge of Stochasticity in Wind Resource and Wake Dynamics

Uncertainty in wind farm performance arises from turbulent atmospheric conditions, dynamic wake effects, and external market or grid signals. Farrell et al. [58] investigated how atmospheric turbulent fluctuations alter wake structures and excite blade vibrational dynamics, highlighting the mechanical implications of small-scale turbulence. Balakrishnan and Hur [59] addressed offshore wind farm power maximization by optimizing both turbine placement and control settings under uncertain wind fields. To enhance operational resilience, Zhang et al. [60] proposed a data-driven optimization model to generate robust maintenance scheduling templates for offshore wind farms, effectively hedging against weather window uncertainty and equipment failures. Complementarily, Lee et al. [61] developed a wake-induced two-phase planning framework using stochastic mixed-integer programming, where maintenance accessibility is dynamically constrained by evolving wake conditions.

5.2. Stochastic Programming and Robust Optimization Frameworks

Modern wind farms are expected not only to generate power but to provide ancillary services. Feng et al. [62] introduced a non-iterative distributed approximate dynamic programming (ADP) algorithm for frequency security-constrained stochastic economic dispatch, enabling scalable real-time coordination across large power systems. Pan et al. [63] extended this paradigm to offshore–onshore integrated energy systems, employing an improved state-space ADP approach to optimize stochastic dispatch while respecting multi-energy coupling constraints. In electricity markets, Dirin et al. [64] formulated an optimal offering strategy for wind-storage systems that accounts for spatially and temporally correlated wind production, reducing bidding risk. Notably, Kayedpour et al. [65] demonstrated that active wake control (AWC) can be leveraged to provide a frequency containment reserve (FCR), transforming aerodynamic adjustments into grid-supportive actions. As wind farms take on increasingly active roles in power system operation and electricity markets, optimization under uncertainty has shifted from deterministic formulations toward stochastic and robust frameworks. Recent studies have employed advanced methodologies, such as approximate dynamic programming, scenario based stochastic offering, and integrated wake control, to address such challenges as wind variability, spatiotemporal correlations, and grid ancillary service requirements. These approaches enable coordinated decisions that jointly consider aerodynamic performance, energy storage dispatch, and frequency support capabilities. A representative overview of these strategies, along with their application contexts and key advantages, is presented in Table 7.

Table 7. Stochastic and Robust Optimization Approaches for Wind Farm Operational Planning.

Methodological Framework	Application Context	Key Advantages
Non-iterative distributed Approximate Dynamic Programming (ADP) [62].	Frequency security-constrained stochastic economic dispatch.	Enables real-time coordination in large-scale power systems without iterative convergence issues.
Improved state-space ADP [63].	Stochastic optimal dispatch of offshore–onshore integrated energy systems.	Handles multi-energy coupling constraints and enhances cross-sectoral synergy.
Stochastic offering strategy with correlated wind uncertainty [64].	Bidding for wind-storage participation in electricity markets.	Accounts for spatiotemporal wind correlations to reduce revenue risk and to improve market competitiveness.
Active Wake Control (AWC) integrated with a Frequency Containment Reserve (FCR) provision [65].	Ancillary service delivery under grid frequency support requirements.	Transforms aerodynamic control actions into grid-supportive services, enhancing operational flexibility.

5.3. Data-Driven Uncertainty Propagation and Online Adaptation

Recent advances have leveraged real-time data and machine learning to adapt to changing inflow conditions. Yu et al. [66] proposed a multi-cluster distributed optimization strategy for collaborative wake environment perception and control, enabling scalable yaw coordination without centralized computation. Sheehan et al. [67] employed deep reinforcement learning (DRL) to achieve optimal wind farm control under time-varying wind conditions, learning control policies that balance power, capture, and structural loads. As illustrated in Figure 7, the proposed WFFC (wind farm flow control) strategy outperforms a greedy baseline across multiple inflow scenarios. The figure compares the yaw configurations and total farm power output between the greedy approach and the trained RL agent under -35° and $+5^\circ$ incoming winds. The results show that WFFC dynamically adjusts turbine yaw angles to actively steer wakes, leading to higher overall power generation in most cases. Notably, the performance advantage persists even in

evaluation directions not seen during training, demonstrating the generalization capability of the learned policy.

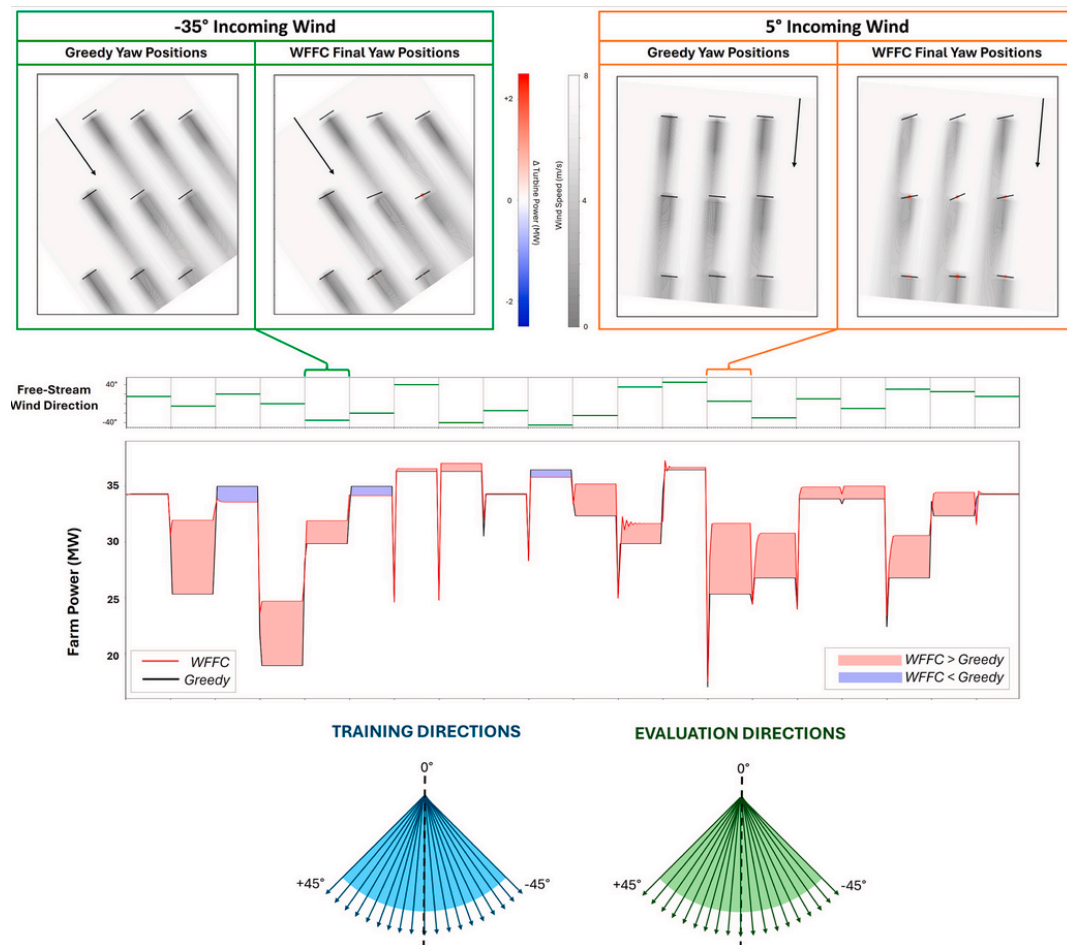


Figure 7. Performance of the final agent under “quasi-dynamic” wind conditions between $\pm 45^\circ$ seen in training. Top to bottom: flow fields under greedy control and the RL agent control scheme, for wind from -35° (left) and 5° (right); FS wind directions; farm power and difference between greedy and RL agent control schemes; training and evaluation wind directions [67].

Sood et al. [68] developed a quasi-static closed-loop control framework that jointly optimizes power output and fatigue loads by continuously updating setpoints based on estimated wind states. The flow of information within this feedback-enabled architecture is illustrated in Figure 8.

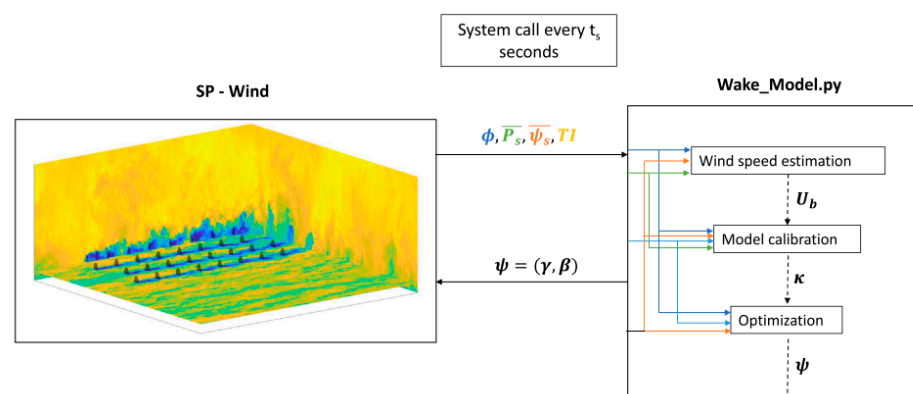


Figure 8. Flow of information in the quasi-static closed-loop control framework [68].

These approaches exemplify the shift toward autonomous, feedback-driven wind farm operations. In parallel with model based planning, data-driven control techniques are gaining traction for enabling real-time adaptation in complex and changing wind environments. By fusing measurements from lidar, SCADA, and other sensing systems with learning enabled algorithms, modern wind farms can continuously adjust yaw angles, power setpoints, and load management policies without relying on perfect forecasts or centralized architecture. Methods such as deep reinforcement learning and multi-cluster distributed optimization exemplify this move toward autonomous, feedback-informed operation. The core features and objectives of these emerging adaptive control strategies are summarized in Table 8.

Table 8. Data-Driven Online Adaptive Control Strategies for Wind Farms.

Approach	Control Objective	Key Technical Features
Multi-cluster distributed optimization [66].	Cooperative wake-aware turbine control.	Decentralized yaw coordination based on dynamic cluster partitioning; scalable to large arrays.
Deep reinforcement learning (DRL) [67].	Optimal power capture under time-varying wind conditions.	Learns trade-offs between energy maximization and structural load mitigation autonomously.
Quasi-static closed-loop control [68].	Joint optimization of power output and fatigue loads.	Updates setpoints in real time using estimated wind states; enables feedback-driven operation.

5.4. Multi-Fidelity Modeling for Computational Tractability

Beyond control, physical reconfiguration offers another degree of freedom. Jard and Snaiki [69] presented a real-time dynamic layout optimization method for floating offshore wind farms, adjusting the turbine positions in response to wave and wind direction changes to maximize energy capture. Cazzaro et al. [70] focused on vertical-axis wind turbines (VAWTs), proposing a novel layout optimization framework that exploits their omnidirectional characteristics. To bridge the modeling fidelity and computational speed, Li et al. [71] utilized the WFSim platform to investigate how inter-field wake and layout design jointly affect average power output, providing insight for large-scale wind farm clustering. Finally, Jahantigh et al. [72] introduced an induction-based wake model for simultaneous wind farm control and power curve optimization, demonstrating improved performance through physics-informed parameter tuning.

Atmospheric stability stratification and wind direction uncertainty are pivotal factors whose effects propagate through every stage of the wind farm optimization pipeline. Input uncertainties such as forecast errors in wind speed or direction introduce bias into wake model predictions. This bias is further amplified by model uncertainty arising from simplifications in engineering models or inaccuracies in data-driven surrogates. As these uncertainties accumulate they significantly undermine the reliability of optimization outcomes. A layout deemed optimal under flawed wake forecasts may deliver substantially lower actual annual energy production (AEP) in practice.

To address this challenge advanced optimization frameworks must explicitly incorporate uncertainty quantification (UQ). Techniques such as Monte Carlo simulation, Bayesian inference, or stochastic programming enable the systematic propagation of both input and model uncertainties through the modeling chain, yielding probabilistic estimates of key performance metrics including the AEP and structural loads. By doing so, UQ facilitates robust optimization ensuring that design and control decisions remain effective across a

wide range of plausible atmospheric conditions rather than being overfitted to a single deterministic scenario.

6. Multi-Objective Collaborative Optimization in Modern Wind Farm Design

The paradigm of wind farm design has undergone a fundamental shift, moving from the singular pursuit of maximizing the annual energy production (AEP) towards a holistic multi-objective collaborative optimization (MOCO) framework. This evolution is driven by the complex interplay of economic pressures, mechanical reliability concerns, grid integration requirements, and the need for sustainable siting practices. As demonstrated across numerous recent studies, the most effective modern wind farms are those whose layout, control strategy, and component selection are co-optimized to balance competing objectives. This section synthesizes these advances, structured around key performance metrics, reliability, grid services, algorithmic innovations, and integrated design.

6.1. Key Performance Objectives in Layout Design

Contemporary layout optimization extends beyond AEP maximization to incorporate economic efficiency and spatial sustainability. Kirchner-Bossi and Porté-Agel [73] introduced novel multi-objective evolutionary algorithms to optimize not only turbine positions but the overall wind farm area shape, enhancing land-use efficiency in constrained sites. Economic considerations are further integrated through levelized cost of energy (LCOE) minimization. Yang et al. [74] combined an analytical wake model with a hybrid optimization strategy to directly target LCOE reduction, showing that cost-optimal layouts often differ significantly from the AEP-optimal ones. For real-world applications, Boucekara et al. [75] employed a parallel collaborative multi-objective algorithm to optimize wind turbine placements, demonstrating improved convergence and diversity in the solution set. Furthermore, Ye et al. [76] developed a novel reliability-oriented assessment method specifically for coastal urban regions, analyzing spatial resources and power yield for offshore wind farms to ensure long-term viability.

6.2. Mechanical Reliability and Structural Load Considerations

Fatigue and extreme loads induced by wake interactions and turbulent inflows are critical constraints in long-term operation. Yang et al. [77] formulated a Pareto-based multi-objective problem that simultaneously optimizes power production and turbine fatigue life, revealing inherent trade-offs between energy yield and structural durability. This approach explicitly includes fatigue life as an objective in layout design, generating configurations that inherently reduce wake-induced cyclic loading. Complementing this, Fu et al. [78] addressed the issue through coordinative optimization considering an improved fatigue load index, thereby providing a more nuanced metric for structural health. For offshore environments, Peng et al. [79] focused on a layout optimization that considers both fatigue damage and power generation, recognizing the unique challenges of marine operations.

6.3. Wake Mitigation and Turbulence Management

Wake-induced effects remain a primary concern for energy capture and turbine longevity. Souaiby and Porté-Agel [80] specifically optimized wind farm layouts to minimize the wake-induced turbulence effect on wind turbines, directly targeting the root cause of performance degradation and increased wear. In the context of offshore wind farms, Ling et al. [81] developed a multi-objective layout optimization approach based on non-uniformly distributed turbulence and a new three-dimensional multiple wake model, providing a more accurate representation of complex offshore flow fields. Chen et al. [82] explored multi-objective optimization for large-scale offshore wind farms based on decou-

pled groups operation, potentially mitigating wake propagation across the entire array. Additionally, Lucas Frutuoso et al. [83] advanced wake mitigation through yaw-based wake steering, employing multi-objective optimization to balance power capture and wake redirection. The spatial arrangement of turbines significantly influences intra-farm performance, particularly in terms of power distribution across rows. As illustrated in Figure 9, the normalized power output of downstream turbines rapidly declines in the initial rows and gradually stabilizes with increasing distance from the front row. This decay pattern is sensitive to both the longitudinal spacing and the layout configuration, with staggered arrangements showing a slightly faster recovery compared to aligned layouts at a spacing five rotor diameters versus seven rotor diameters. These results highlight that optimizing individual farm layouts requires careful consideration of wake evolution dynamics to maximize overall energy capture.

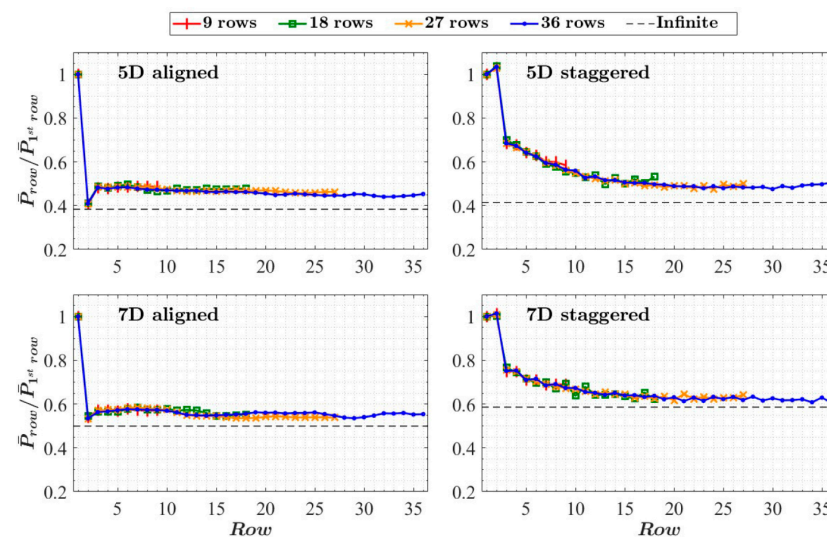


Figure 9. Power output of different turbine rows inside the wind farms normalized by the power output of the first row [80].

The shift toward multi-objective collaborative optimization in wind farm design reflects a growing recognition that performance cannot be measured by energy yield alone. Modern layout strategies must simultaneously address economic viability, structural durability, spatial constraints, and grid compatibility. As summarized in Table 9, recent studies have formalized this paradigm by integrating diverse objectives, ranging from LCOE minimization and land-use efficiency to fatigue-aware placement and active wake control into unified optimization frameworks. These efforts demonstrate that optimal wind farm configurations emerge not from isolated maximization of power output, but from balanced trade-offs across interdependent technical and operational dimensions.

Table 9. Key Performance Objectives and Approaches in Multi-Objective Wind Farm Design.

Objective Category	Specific Goal	Method/Contribution
Energy Production	Maximize the annual energy production (AEP).	Traditional single-objective baseline.
Economic Efficiency	Minimize the levelized cost of energy (LCOE).	Hybrid optimization with analytical wake model to directly target LCOE reduction [74].
Land-use Efficiency	Optimize farm area shape and spatial footprint.	Multi-objective evolutionary algorithms for turbine placement and boundary shaping in constrained sites [73].

Table 9. Cont.

Objective Category	Specific Goal	Method/Contribution
Mechanical Reliability	Maximize fatigue life/minimize structural loads.	Pareto-based co-optimization of power output and turbine fatigue life [77]; improved fatigue load index for health assessment [78]; offshore-specific fatigue-aware layouts [79].
Wake & Turbulence Management	Reduce wake-induced turbulence and power loss.	Layout optimization targeting turbulence mitigation [80]; 3D multi-wake model under non-uniform turbulence for offshore farms [81]; decoupled group operation to limit wake propagation [82].
Grid Integration & Control	Enable active wake steering and flexible operation.	Yaw-based wake redirection via multi-objective control balancing power and wake effects [83].

6.4. Optimization Algorithms and Solution Frameworks

The computational complexity of MOCO demands have advanced algorithmic strategies. Rizk-Allah and Hassanien [84] proposed a hybrid equilibrium optimizer combined with pattern search to enhance local exploitation in layout problems. For handling complex wake interactions, Moreno et al. [85] applied a multi-objective lightning search algorithm, demonstrating its efficacy for wind farm layout optimization. Eikrem et al. [86] introduced ensemble methods for offshore wind farm layout optimization, leveraging collective intelligence for robust solutions. When dealing with non-homogeneous turbines, Ziyaei et al. [87] minimized the LCOE through layout optimization, while de Moura Ribeiro et al. [88] used automatic grouping of wind turbine types via multi-objective formulation, optimizing non-uniform wind farm layouts using an analytical wake model. For large-scale benchmarking, Manikowski et al. [89] conducted multi-objective optimization of the standard wind farm layout problem, establishing methodological baselines. To accurately simulate realistic wind conditions for wind farm performance assessment, high-fidelity turbulent wind fields are essential. As shown in Figure 10, the spatiotemporal characteristics of the turbulent wind field generated by TurbSim are validated against atmospheric turbulence models. Panel a illustrates the three-dimensional distribution of wind speed across lateral and vertical directions over time, capturing the inherent variability and spatial coherence of turbulence. Panel b compares the power spectral density of the simulated wind data with the theoretical Kaimal spectrum under typical wind conditions at a mean wind speed of 11.4 m per second and a turbulence intensity of 15 percent, demonstrating good agreement in both low and high frequency ranges [90]. This validation ensures that the input wind field accurately represents real-world atmospheric turbulence, which is critical for reliable wake modeling and control strategy development.

Addressing the computational and conceptual complexity of multi-objective wind farm optimization has spurred the development of sophisticated algorithmic approaches. Traditional evolutionary methods are increasingly augmented or replaced by hybrid, ensemble-based, or physics-informed strategies tailored to the unique challenges of wake interactions, heterogeneous turbine fleets, and large-scale deployment. Table 10 provides a comparative overview of these advanced algorithms, highlighting their application contexts and key strengths from enhanced convergence in high-dimensional search spaces to improved scalability for real-world offshore projects. Together, they constitute a rapidly evolving toolkit that enables practical implementation of the integrated design philosophy outlined throughout this section.

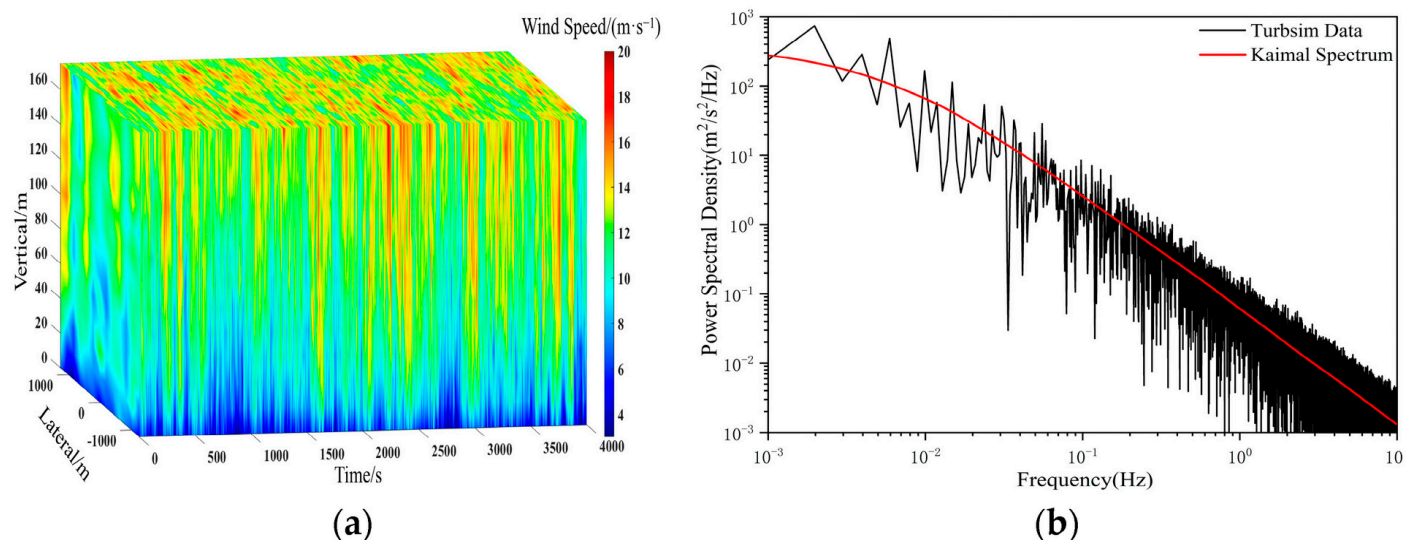


Figure 10. Validation of the turbulent wind field generated by TurbSim: (a) Spatiotemporal distribution characteristics of turbulent wind fields; (b) Comparison of wind velocity spectrum between TurbSim data and the Kaimal spectrum in the case of $U = 11.4$ m/s and $I = 15\%$ [90].

Table 10. Advanced Optimization Algorithms for MOCO in Wind Farm Design.

Algorithm	Application Context	Core Advantage
Hybrid Equilibrium Optimizer + Pattern Search	Layout optimization	Enhanced local exploitation and solution accuracy [84].
Multi-objective Lightning Search Algorithm	Complex wake interaction scenarios	Effective for high-dimensional, nonlinear layout problems [85].
Ensemble-based Methods	Offshore wind farm layout	Robust solutions through collective intelligence and uncertainty handling [86].
Automatic Turbine Grouping + Multi-objective Formulation	Heterogeneous turbine layouts	Enables optimal clustering and placement of non-uniform turbines using analytical wake models [88].
Multi-objective Charged Particles Optimization with Variable Reduction	Large-scale wind farms	Improved scalability and reduced computational burden [90].
Parallel Collaborative Multi-objective Algorithm	Real-world engineering deployment	Better convergence and diversity in Pareto-optimal solutions [75].

Together, these studies illustrate a maturing ecosystem of tools and philosophies that treat wind farm design as an integrated, multidisciplinary challenge where energy, economics, reliability, and environmental factors are optimized not in isolation, but in concert.

6.5. Resources for Advancement: Benchmarks and Open-Source Ecosystem

The progress in wind farm modeling and optimization is inextricably linked to the availability of high-quality validation data and accessible software tools. Community-driven efforts have established several critical benchmarks.

Horns Rev and Lillgrund are early large-scale offshore wind farms that have provided foundational SCADA for validating steady-state wake models and basic layout optimization approaches.

The Scaled Wind Farm Technology (SWiFT) Facility, operated by Sandia National Laboratories, delivers unparalleled high-resolution field measurements of turbine–turbine interactions under controlled conditions, making it the gold standard for validating dynamic wake models and control strategies.

The Perdigão campaign was an intensive field experiment conducted in complex terrain in Portugal, generating a rich dataset for studying atmospheric flows over steep topography—an essential resource for onshore micro-siting studies.

International collaborations under IEA Wind Tasks, such as Task 31 and Task 37, have played a pivotal role in establishing standardized comparison frameworks and promoting best practices in wake modeling and wind farm control.

At the same time, a vibrant open-source ecosystem has significantly lowered the barrier to entry for researchers.

FLORIS (v3.1, <https://github.com/NREL/FLORIS>, accessed on 29 January 2026) is a widely adopted engineering-based framework for rapid wake modeling and layout optimization, now extended with dynamic and control capabilities.

WFSim (v1.0, <https://github.com/TUDELFT-DataDrivenControl/WFSim>, accessed on 29 January 2026) is a medium-fidelity simulation tool specifically designed for control-oriented studies of large wind farms.

OpenFAST (v2.8, <https://github.com/OpenFAST/OpenFAST>, accessed on 29 January 2026) serves as the industry-standard aero–hydro–servo–elastic simulator and is essential for a high-fidelity analysis of individual turbines and floating platforms.

OpenFOAM (v2206, <https://openfoam.org/download/>, accessed on 29 January 2026) and SOWFA (v1.0, <https://github.com/NREL/SOWFA>, accessed on 29 January 2026) are open-source computational fluid dynamics platforms that enable high-fidelity LES and RANS simulations of entire wind farms.

The synergy between these benchmark datasets and open-source tools accelerates model development, enhances reproducibility, and helps bridge the gap between academic research and industrial application.

To contextualize how these resources feed into next-generation design workflows, Figure 11 presents a schematic of a closed-loop, co-design methodology for wind farms under dynamic inflow conditions. This table outlines an integrated framework that links high-fidelity simulation, data-driven surrogates, real-time sensing, and multi-objective optimization—highlighting the critical role played by community benchmarks and open-source tools at each stage. By embedding validation datasets and modular software components into a unified workflow, this co-design paradigm enables the simultaneous optimization of layout, control, and uncertainty management, thereby translating research advances into actionable engineering solutions.

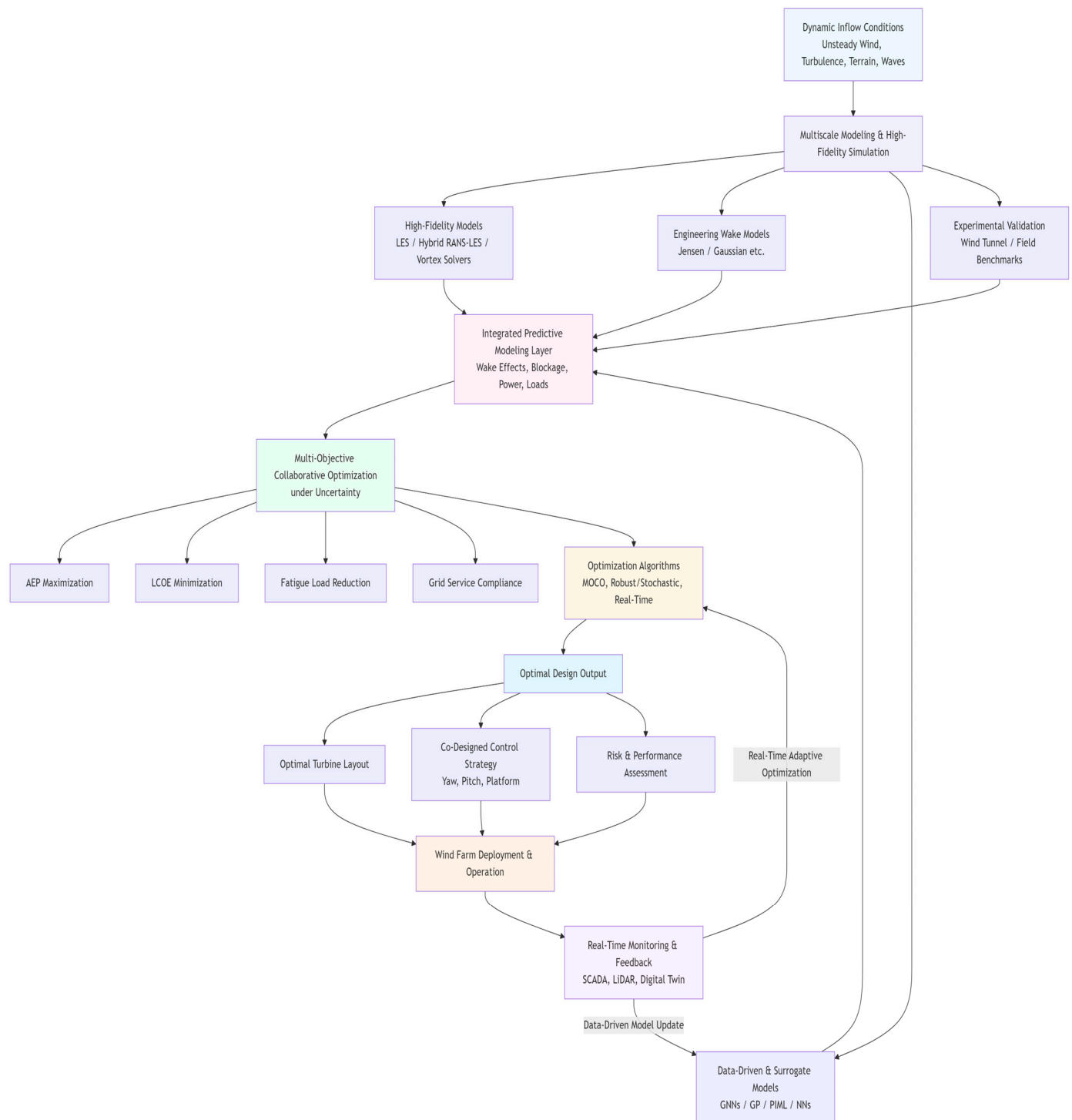


Figure 11. Schematic of a closed-loop, co-design methodology for wind farms under dynamic inflow conditions.

7. Challenges and Future Directions

Despite significant progress in dynamic inflow-aware wind farm layout optimization, several critical challenges remain that hinder the transition from research prototypes to industrial deployment at scale.

First, the controllability of transient wakes under realistic atmospheric conditions is still poorly understood. While LES and wind tunnel studies have elucidated vortex dynamics and meandering mechanisms, translating these insights into robust, real-time

control policies, especially for floating offshore turbines subject to 6-DOF platform motions, requires tighter coupling between hydro–aero–elastic models and farm-level controllers. Current wake steering strategies, though effective in steady or quasi-steady regimes, often degrade under rapid wind direction shifts or high turbulence intensity, exposing a gap between simulation fidelity and operational robustness.

Second, real-time multi-objective optimization under uncertainty remains computationally and algorithmically demanding. Although surrogate models (e.g., ML, POD, Kriging) and multi-fidelity frameworks have reduced evaluation costs, they struggle to simultaneously handle stochastic inflow, component degradation, and grid service constraints within sub-minute decision horizons. Distributionally robust and scenario-based stochastic programming offer theoretical guarantees but face scalability bottlenecks in farms with hundreds of heterogeneous turbines. Moreover, the lack of standardized uncertainty quantification protocols, particularly for wake width growth and power curve drift, limits cross-study comparability and field validation.

Third, integrated co-design across layout, control, and hardware is still fragmented. Most optimization frameworks treat turbine selection, placement, and yaw/induction control as sequential or decoupled tasks, missing the synergistic gains achievable through true joint optimization. The emergence of heterogeneous layouts further complicates this integration, demanding new formulations that balance power density, fatigue life, and control complexity within a unified MOCO (multi-objective collaborative optimization) paradigm.

Fourth, digital twin implementation for operational feedback loops remains nascent. While simulators like WFSim and FOWLTy enable offline validation, closing the loop with SCADA, lidar, and fault diagnostics in real time requires standardized data pipelines, online model recalibration (e.g., Bayesian updating of wake parameters), and edge-compatible inference architectures. Without such infrastructure, even the most sophisticated layout designs risk performance will decay over the turbine lifetime due to unmodeled environmental degradation or sensor drift.

Future directions should prioritize the following:

- (i) Physics-informed reinforcement learning that embeds conservation laws and stability constraints into adaptive controllers;
- (ii) Uncertainty-aware Pareto frontiers that explicitly trade off LCOE, CV (coefficient of variation), DEL (damage-equivalent load), and grid service capacity;
- (iii) Standardized benchmarking suites extending beyond Horns Rev I to include complex terrain, floating platforms, and hybrid HAWT–VAWT arrays;
- (iv) Open-source, modular frameworks that unify CFD, surrogate modeling, and optimization, enabling reproducible, community-driven advancement toward resilient, cost-competitive wind energy systems.

8. Conclusions

This review has systematically synthesized key advances over the past five years in wind farm layout optimization under dynamic inflow conditions, revealing a paradigm shift—from static geometric arrangements toward integrated, intelligent, and resilient design frameworks. This evolution is driven by five interdependent research thrusts: (i) high-fidelity multiscale modeling of transient wake physics; (ii) data-driven prediction of unsteady wake dynamics and power deficits; (iii) multi-objective co-optimization balancing energy yield, structural loads, economics, and grid services; (iv) accurate representation of complex terrain effects, canopy interactions, and large-scale blockage; and (v) stochastic and real-time optimization under inflow and model uncertainty.

First, at the physics modeling level, large eddy simulation (LES), hybrid RANS–LES, and vorticity-based far-wake solvers have successfully captured critical mechanisms such

as wake meandering, counter-rotating vortex instabilities, and turbulent energy cascades under dynamic inflows. These high-fidelity simulations not only correct systematic biases in classical engineering models (e.g., Jensen, Frandsen) under yawed, sheared, or highly turbulent conditions but enable reduced-order representations—via POD mode extraction, spectral wake characterization, or kinetic energy conservation principles—that are computationally tractable for optimization. Wind tunnel experiments further validate the evolution of multiscale structures (tip vortices, hub vortices, shear layers) across varying yaw angles, turbine spacings, and heterogeneous rotor sizes, providing high-quality benchmark data for surrogate model development.

Second, data-driven modeling has emerged as the essential bridge between high-fidelity simulation and practical deployment. Machine learning surrogates, including Gaussian processes, graph neural networks, and bilateral convolutional architectures now enable near-real-time prediction of spatiotemporal wake fields, facilitating rapid evaluation of thousands of candidate layouts. Crucially, these models are evolving from purely empirical regressors toward physics-informed frameworks: by embedding conservation laws, wake superposition rules, or induction-zone dynamics into network architectures or loss functions, they achieve significantly improved extrapolation robustness and physical interpretability.

Third, the optimization objective space has expanded well beyond the annual energy production (AEP) maximization. Modern frameworks now pursue Pareto-optimal trade-offs among levelized cost of energy (LCOE) minimization, fatigue load reduction, grid service compatibility, and operational flexibility. For instance, co-optimizing layout with battery energy storage capacity can mitigate curtailment and enhance frequency response, and incorporating damage-equivalent load constraints extends the drivetrain lifetime while preserving high energy yield. Furthermore, mixed-integer programming approaches for heterogeneous turbine deployment, allowing for variations in hub height, rotor diameter, and control authority, enable farms to better exploit spatial heterogeneity in wind resources, unlocking additional layout efficiency.

Fourth, the modeling of complex environments has gained critical importance. Whether it be flow acceleration over mountain ridges, enhanced turbulence-mixing induced by forest canopies, or momentum starvation caused by global blockage in gigawatt-scale arrays, it is clear that the traditional assumptions of flat, homogeneous inflow are no longer tenable. Recent studies have demonstrated that neglecting blockage can lead to an AEP overestimation by 2 to 5 percent, while machine learning-based feasible region modeling (e.g., SVDD) enables constraint-aware micro-siting in irregular domains, retaining over 96 percent of baseline energy production despite 28 to 37 percent land reduction. These findings underscore that micro-siting must be tightly coupled with terrain-resolved atmospheric dynamics to achieve true resource efficiency.

Building on these four pillars, the field must now address cross-cutting challenges through a prioritized roadmap for future advancement. Most urgently, community-wide standardization—through initiatives like IEA Wind Task 37—is needed to establish unified benchmarks, validation protocols, and open data formats, which form the bedrock for reproducible research and industrial trust. Equally critical is the development of truly integrated modeling frameworks that fuse high-fidelity physics with scalable data-driven surrogates, ensuring both accuracy and computational tractability. Looking ahead, full-system co-design for floating offshore wind farms demands new theories that couple platform dynamics, wake evolution, and control in a unified optimization loop. Ultimately, the vision of intelligent wind farms hinges on closed-loop, self-adaptive architecture—powered by lidar preview, digital twins, and online learning—that transitions from passive layout design to active, coordinated flow control.

In summary, layout optimization under dynamic inflow is no longer a standalone geometric problem but a multidisciplinary system engineering challenge, integrating atmospheric science, fluid dynamics, machine learning, control theory, and power systems engineering. While challenges remain in real-time scalability, industrial standardization, and field validation, the path forward lies in open, modular, multi-fidelity frameworks that unify design, control, and operations. Through such integration, next-generation wind farms will not only deliver higher energy yields but achieve superior economic competitiveness, structural reliability, and grid-support capabilities, providing a cornerstone for the global clean energy transition.

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Abbreviations

The following abbreviations are used in this manuscript:

AEP	Annual Energy Production
ABL	Atmospheric Boundary Layer
AWC	Active Wake Control
ADP	Approximate Dynamic Programming
ARFF	Adaptive Random Fourier Features
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
DRL	Deep Reinforcement Learning
DEM	Digital Elevation Model
DBPDE	Discrete Bi-Population Differential Evolution
ECPO	Electric Charged Particles Optimization
FFT	Fast Fourier Transform
FCR	Frequency Containment Reserve
GA	Genetic Algorithm
GP	Gaussian Process
GIS	Geographic Information System
IGA	Improved Genetic Algorithm
LES	Large Eddy Simulation
LCOE	Levelized Cost Of Energy
ML	Machine Learning

MDAO	Multidisciplinary Design And Optimization
MOCO	Multi-Objective Collaborative Optimization
MPC	Model Predictive Control
PSO	Particle Swarm Optimization
POD	Proper Orthogonal Decomposition
PCE	Polynomial Chaos Expansion
RANS	Reynolds-Averaged Navier–Stokes
TKE	Turbulent Kinetic Energy
VAWT	Vertical-Axis Wind Turbines

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