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Review

A Review of Yaw Optimization Strategies for Wind Farms with Complex Terrain

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Abstract

Considering the global shift towards clean energy, advancing wind power generation technology is crucial. In complex terrain, turbines face significant challenges, such as increased fatigue loads from turbulent airflow, which reduce efficiency and structural integrity. Yaw optimization has emerged as a key solution to enhance performance in these environments. By dynamically adjusting the nacelle orientation, it improves wind capture, mitigates load fluctuations, and alleviates stress on turbine components. This not only boosts energy output but also extends equipment lifespan and reduces operational costs, supporting the economic feasibility of wind projects in complex terrain. This paper reviews current research and development trends in yaw optimization for wind farms in such settings, focusing on adaptive control strategies and the balance between load management and power efficiency. It examines the impact of different yaw optimization approaches on both individual turbines and overall wind farm performance. In conclusion, tailored yaw optimization strategies are proposed to maximize wind resource utilization in complex terrain, providing a reference for more resilient and efficient wind energy systems.

Keywords: clean energy; wind power generation technology; fatigue load; complex terrain; yaw optimization

1. Introduction

Driven by the global carbon neutrality goal and the transformation of the energy structure, the use of clean and renewable energy is becoming more and more urgent. The global demand for electricity is increasing, and wind energy, as a clean and renewable energy source, is considered a viable solution to this growing demand [1]. According to key figures from the International Energy Agency (IEA), headquartered in Paris, France, photovoltaics account for more than three-quarters of new renewable energy installations, followed by wind power (17%) and hydropower (4%), and bioenergy, geothermal, concentrated solar power and ocean energy account for the rest. The annual new installed capacity of wind power remained stable at about 120 GW. Together, photovoltaic and wind power accounted for 95% of the total renewable energy installed capacity growth in 2024. China has once again achieved record-breaking expansion, accounting for nearly two-thirds of the total renewable energy capacity connected to the grid in 2024. Wind power growth remained steady and strong, reaching 80 GW. By mid-2024, China had already surpassed

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its 1200 GW target for total solar photovoltaic and wind power capacity, six years ahead of schedule [2,3]. According to the data, Figure 1 displays solar PV and wind net capacity additions for key markets. Figure 2 illustrates the corresponding changes in energy demand for selected regions between 2023 and 2024.

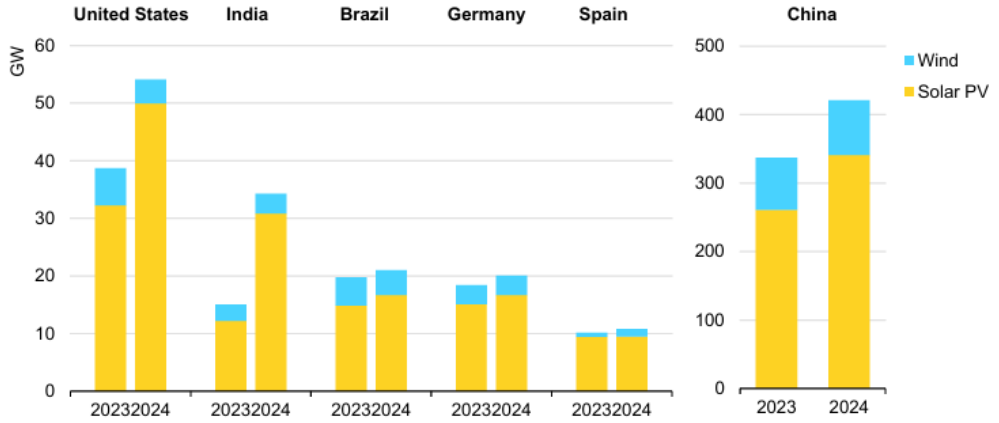


Figure 1. Solar PV and wind net additions in selected markets [3].

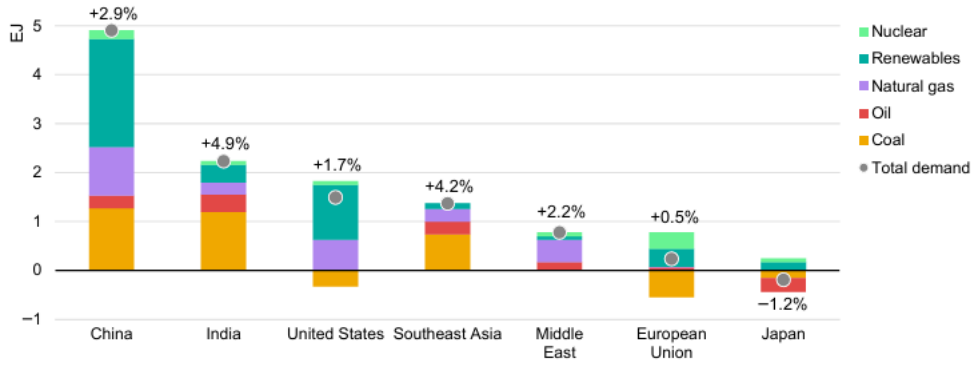


Figure 2. Change in energy demand, selected regions, 2023–2024 [3].

Nowadays, wind power has become the core pillar of global renewable energy development, and wind power also has the advantages of high technological maturity and low carbon emissions. Its industrial scale and single-unit capacity continue to expand, which plays an irreplaceable role in reducing dependence on fossil energy and addressing climate change [4,5]. As a key link in industrial development, wind farm site selection needs to fully consider the reshaping of wind farm characteristics by factors such as terrain undulations and surface roughness, which not only determines the resource potential of the project but also directly affects the subsequent unit layout and operation efficiency [6–8].

Although the complex terrain contains rich wind energy resources, it significantly changes the structure of the atmospheric boundary layer through the dual mechanisms of "roughness enhancement" and "terrain diversion", resulting in vertical wind profile distortion, increased spatiotemporal heterogeneity of wind speed, and increased turbulence intensity, which brings multiple challenges to the efficient operation of wind farms. Based on complex terrain optimization, a literature search was conducted, and the VOSviewer (version 1.6.18) software was used to create a network map of the related field, as shown in Figure 3.

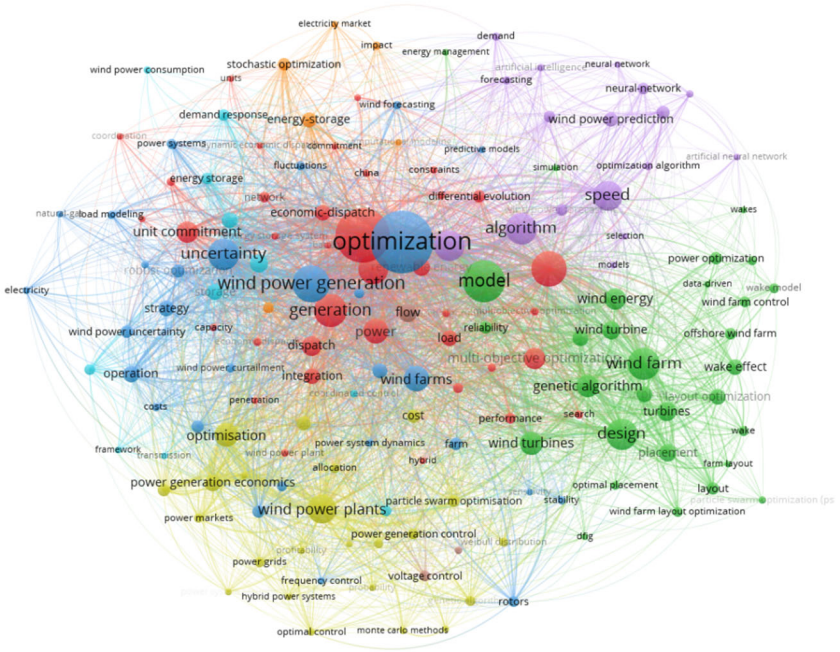


Figure 3. Complex terrain optimization network diagram.

This bibliometric analysis was conducted using VOSviewer software. The input data consisted of titles, abstracts, and keywords from the peer-reviewed articles identified in a literature search (Section 3). The network displayed represents co-occurrence of keywords, where nodes correspond to keywords and the size of each node indicates its frequency in the dataset. Links between nodes represent co-occurrence relationships, with thickness indicating the strength of the relationship. Clusters were automatically generated by VOSviewer based on the similarity of the keyword co-occurrence patterns, identifying thematic groups within the research field.

For example, through the study of large eddy simulation (LES), it is found that every order-of-magnitude increase in the length of aerodynamic roughness in complex terrain will increase the friction velocity and thin the thickness of the atmospheric boundary layer, which will directly lead to a higher fluctuation of wind speed at the height of the hub than on flat terrain [9]. However, the interference effect of parked wind turbines on the wind field in complex terrain is significantly weaker than that of the terrain itself, which further confirms that the terrain is the dominant factor in reshaping the characteristics of the wind field. As the "initial incoming flow condition" generated by the wake, this modified wind farm will cause problems such as wake asymmetric diffusion and path deflection, making the wake overlap rate of downstream units higher than that of flat terrain, which seriously affects the overall power output of the wind farm [10].

In view of the particularity of wind farms with complex terrain, accurate wind energy resource assessment and power prediction are the prerequisites for ensuring the efficiency of wind farms. Traditional power law models or empirical statistical methods based on flat terrain have been difficult to adapt to the strong spatiotemporal heterogeneity of complex terrain wind fields, so researchers have tried to combine physical models and data-driven methods to improve prediction accuracy. For example, the Wind Spatial Extrapolation (WiSpEx) model is constructed by computational fluid dynamics (CFD), the wind field space of complex terrain is realized by combining the measured data of Light Detection and Ranging (LiDAR), and the Symmetric Mean Absolute Percentage Error (SMAPE) of ultra-short-term power prediction symmetry can be as low as 8.44–9.26% [11]; another example is a convolutional neural network (CNN) combined with DeepSHAP

interpretability analysis to identify key terrain features that affect the prediction accuracy (such as terrain ruggedness index and elevation standard deviation), so that the prediction error of wind power generation in complex terrain areas is significantly reduced [12]. These technological advances provide support for the early evaluation of wind farms with complex terrain, but there are still greater challenges in wake regulation and yaw optimization in the operation stage of wind farms [13–15].

As the core technology of adjusting the wind direction of wind turbines, guiding the wake path, and alleviating wake interference, the performance of yaw control directly determines the operating efficiency of wind farms with complex terrain [16]. Most of the traditional yaw control aims to maximize the wind accuracy of a single machine, relying on a fixed threshold and the assumption of wake in flat terrain, and does not consider the characteristics of wind direction fluctuation amplitude expansion and wake deflection due to slope in complex terrain, resulting in an increase in wind hysteresis time and an increase in the power loss of a single machine [17,18]. In order to make up for the shortcomings of traditional strategies, existing research has carried out multi-directional explorations: From the hardware level, the yaw control system developed based on PLC technology can improve the response speed and stability, and adapt to the harsh operating environment of complex terrain [19]. From the control strategy perspective, LiDAR is employed to measure upstream wind field parameters in real time. By integrating these measurements with active wake control theories, the yaw angle of paired wind turbines can be optimized to enhance annual power generation and improve energy yield. Figure 4 presents a comparison of the daily averaged wind speed data collected over one year from SCADA systems at hub height and corresponding LiDAR measurements. The results show a high degree of consistency between the two datasets, validating the reliability of LiDAR in capturing long-term wind speed trends at the turbine hub level.

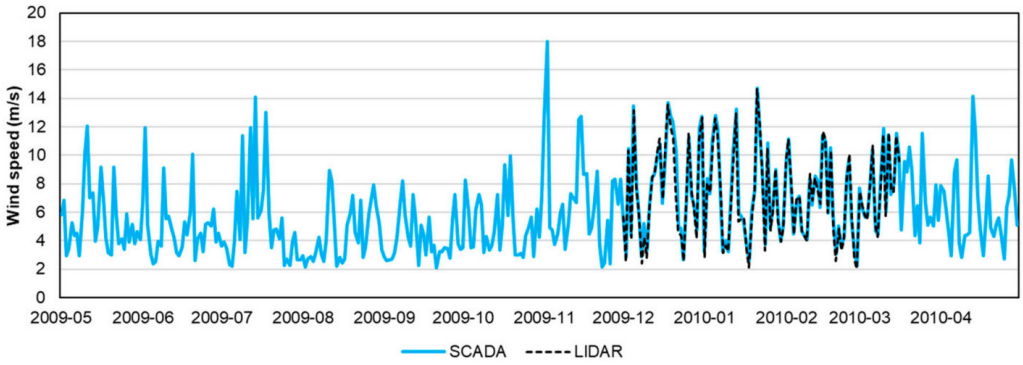


Figure 4. Comparison of the daily-mean wind speed between SCADA and LiDAR data at the hub height [20].

From the dynamic modeling level, a graph-based dynamic yaw model is developed, which integrates wake curl deformation and inter-machine time delay, which can accurately capture the transient response of the wind field to the yaw action and provide support for real-time control [21]. From the level of fleet coordination, the coordinated and optimized scheduling of wind turbine groups can be realized through active wake control, which can reduce the superposition effect of multi-machine wake and improve the overall output of the wind farm [22]. Anagnostopoulos et al. built a wake proxy model based on a deep feedforward neural network for offshore wind farms, which is trained on the high-fidelity wake data generated by FLORIS software (version 3.1.0), which can accurately predict the wake velocity loss of a single wind turbine with an order-of-magnitude improvement in computational efficiency [23].

Although existing research has made progress in modeling, prediction, and yaw control of wind farms in complex terrain, there are still many bottlenecks to be broken through, the refined mechanism of the coupling evolution of wind fields and wakes in complex terrain has not been fully elucidated, the adaptability of dynamic yaw models and actual wind fields needs to be further verified, and the yaw optimization system with multiple goals such as power maximization and load minimization still needs to be improved [24–26]. In the context of new energy power generation, the coordinated operation of wind power generation and power grid puts forward higher requirements for the real-time use and flexibility of yaw control. Therefore, it is important to analyze the coupling influence of complex terrain on wind farm–wake coupling, reveal the adaptability defects of traditional yaw control, integrate advanced measurement technology, dynamic modeling, and multi-objective optimization methods, and construct a refined yaw control system suitable for complex terrain, which is of great theoretical value and engineering significance for improving the energy capture efficiency of wind farms with complex terrain, reducing operation and maintenance costs, and promoting in-depth development of the wind power generation industry in high-potential complex terrain areas. Based on the above, this paper will conduct in-depth research on the basic characteristics of wind farms and wakes in complex terrain, the limitations of traditional yaw control, and new optimization strategies, so as to provide a reference for the efficient and stable operation of wind farms with complex terrain.

2. Adaptability of Wind Farm Characteristics and Yaw Control in Complex Terrain

2.1. Coupling Influence of Complex Terrain on Wind Field and Wake

If a wind field with complex terrain is studied, its core basic characteristic is the change in vertical wind profile, which can reflect the regulatory effect of surface roughness on the wind field; this is a classic characterization method for wind fields with complex terrain, and its expression is:

$$\overline{u}(z) = \frac{u_*}{k}\ln\left(\frac{z}{z_0}\right) \tag{1}$$

In the formula, $\overline{u}(z)$ is the average wind speed at height z, and u_* is the characteristic velocity scale, which is used to characterize the shear stress strength of the surface. k is the Carmen constant, with a value of 0.41, and z_0 is the length of the aerodynamic roughness which is the core of the terrain parameters [9].

However, the applicability of the classical log law is challenged in complex terrain and under non-neutral atmospheric boundary layers. Terrain disturbances violate its foundational assumptions of horizontal homogeneity and local equilibrium. Therefore, in practical applications, it is often modified, for instance, by introducing stability functions, or replaced by CFD-based local wind field simulations. In this review, such classical models are regarded as baseline references for understanding wind field characteristics in complex terrain.

If the wake is studied, its core characterization is velocity loss; this is the difference between the wind speed at a certain point downstream and the wind speed of the incoming flow. In complex terrain, most of the wakes show an asymmetric distribution; the Gaussian wake model has become a basic characterization tool by virtue of its simplicity and adaptability, and its velocity loss formula is:

$$\frac{u_G(x,y,z)}{U_\infty} = 1 - C\cdot\exp\left(-\frac{(y-\delta)^2}{2\sigma_y^2} - \frac{(z-z_h)^2}{2\sigma_z^2}\right) \tag{2}$$

In the formula, U_∞ is the free-flow wind speed and C is the contrail attenuation constant. σ_y and σ_z represent the contrail width parameter in the y and z directions, respectively, z_h is the hub height, and δ is the Wade deflection [24].

Analogously, the standard Gaussian wake model assumes flat terrain and uniform inflow. In complex terrain, phenomena such as asymmetric diffusion, curvature, and accelerated recovery of the wake lead to significant prediction biases. Consequently, various extended models have been developed, such as those incorporating terrain-induced deflection terms and asymmetric variance parameters or constructing fully three-dimensional wake representations. Recognizing the limitations of these baseline models is the starting point for developing more accurate wake models and optimization algorithms for complex terrain.

2.1.1. Influence Mechanism of Terrain Relief (Slope and Curvature): Flow Deformation and Speed-Up

The core mechanism of the wind turbine is that the wind speed gradient and turbulence characteristics of the wind field directly regulate the wake deflection, diffusion and recovery law. The wake superposition changes the aerodynamic characteristics of the local wind field in reverse, which ultimately significantly affects the power output and load distribution of the wind farm.

The transformation of wind fields by complex terrain is the initial link of the coupling effect, which is mainly achieved by changing the spatial distribution of wind speed, turbulence intensity and wind shear characteristics. Based on field measurements at Campo Formoso I wind farm in Brazil, the wind speed in the slope area is 15–20% higher than that in the flat area, and the increase under stable atmospheric conditions is an additional 8–10% higher [27]. Literature [28] Experiments have shown that, when the geographical roughness increases from 0.5 to 1.5, the wind speed at 10 m altitude decreased by 30%, and the turbulence intensity increased by more than 50%. Ref. [29] developed a backpropagation neural network model (BPNM) for predicting topographic amplification effects, incorporating key input parameters such as terrain roughness (α), height (H), fetch (f_r), slope (λ), and normal distance (N). As illustrated in Figure 5, the network architecture consists of an input layer, a hidden layer with a tanh activation function, and an output layer that predicts the maximum amplification ratio (AR_h,max). This data-driven approach enables accurate estimation of terrain-induced wind enhancement under complex topographies.

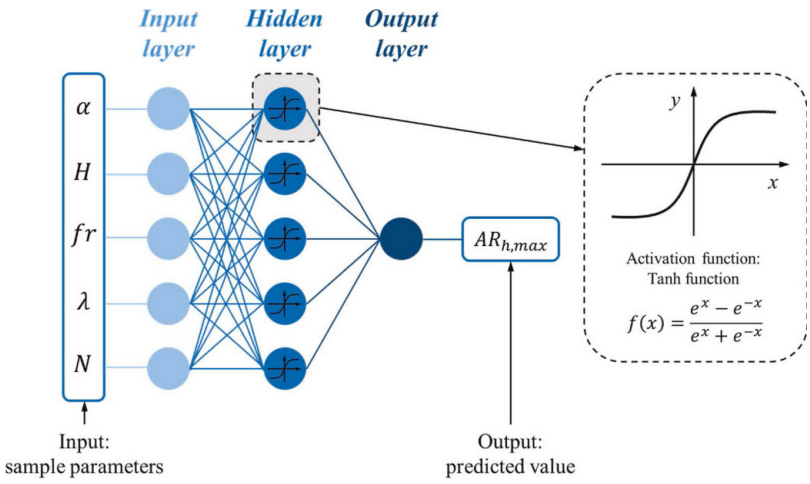


Figure 5. Structure of the BPNNM for topographic amplification prediction [29].

The performance of a special wind turbine in a wind farm in Zhangbei, China, was verified using LIDAR. According to the measured results, the horizontal wind speed

deviation caused by complex terrain can reach up to 0.8 m/s, and the initial deflection direction of the wake is offset by 10–15° [30]. Literature [10] used field data from hilly wind fields showing that terrain obstacles can cause local wind speed attenuation and also reduce the turbulence integral scale.

The regulation of wake evolution by topography is the core of the coupling effect, which directly changes the wake trajectory and energy attenuation law. Ref. [31] used the measured LIDAR in the three terrain complexity regions to show that the effective influence distance of the wake in complex terrain is about 7D, and rapid recovery of the wake will reduce the downstream turbulence intensity. Regarding the robustness index, RIX = 0.8%. The wake width expansion rate is twice that of flat terrain, and the velocity loss at 5D is 30–40% lower. Also, Ref. [29] used the LES simulation to reveal that the wake is deflected by 1.2D when the slope is 0.50, which is 3-times higher than that of flat terrain, and the pressure gradient forms a positive feedback with deflection. CFD simulation shows that when the terrain curvature radius <500 m, the wake "curling" effect is enhanced, and the vertical diffusion angle increases by 15° [32]. Literature [33] used the verification and application of the model to an actual onshore wind farm in the complex terrain of Inner Mongolia, where China is located, the actual measurement shows that the vertical wind shear induced by the terrain will shift the wake center, resulting in an increase in the power fluctuation amplitude of the downstream unit. Other than that, wind tunnel experiments confirm that when the geographical roughness increases, the attenuation rate of wake velocity loss increases, and the turbulent mixing effect is significantly enhanced [34]. Dezhi et al. conducted a study on the NREL 5MW unit array through large eddy simulation (LES), which shows that under the stable boundary layer in complex terrain, the Coriolis force will naturally deflect the wake to the left, and the terrain-induced vertical wind shear will aggravate the center offset of the wake, which in turn increases the power fluctuation amplitude of the downstream unit, which verifies the topography-positive feedback effect of wake coupling, strengthening the empirical support of the regulatory mechanism of terrain during wake evolution [35].

2.1.2. Coupling and Feedback of Multiple Factors: Forming a Dynamic Closed Loop

The coupling feedback between the wind field and wake further amplifies the terrain influence and forms a dynamic closed loop. Literature [28] analyzed the influence of topographic complexity on the characteristics of near-surface wind fields through wind tunnel experiments; it was found that when the geographical roughness increases, the wind speed of the wind field will gradually decrease in the future. As shown in Figure 6, the complex heterogeneous terrain of 1:100 scale was reproduced by the researchers. A micro-scale flow model considering the influence of topography, atmospheric stability, and wind turbine wakes was proposed and validated using data from the Iwaya Wind Farm in northern Japan [36]. The error is much lower when this effect is included.

According to the research on complex terrain with atmospheric formation and ground roughness, the coupling of the wake and terrain acceleration effect can make the downstream unit power overtake the upstream (stable atmospheric conditions) [37]. Sun et al. [38] conducted a comprehensive study on wind speed and wake effects in complex terrain, leading to the proposal of a three-dimensional wake model that accounts for terrain-induced speed-up phenomena. In their work, the wake characteristics were investigated through field experiments, which verified the effectiveness of the proposed model [38].

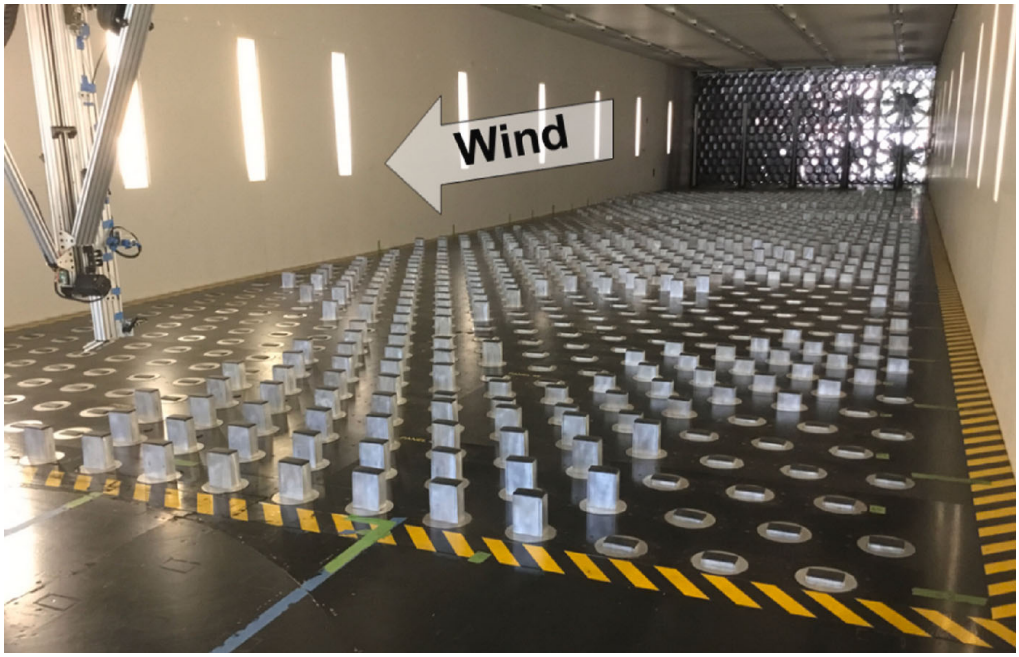


Figure 6. Implementation of complex heterogeneous terrain in Terraformer [37].

In order to present the research basis of wind fields and wakes in complex terrain, the following table summarizes the literature, research objects, methods, and core conclusions of related studies, as shown in Table 1.

Table 1. Research methods used for complex terrain.

Research Methodology Category	Specific Experimental Methods
On-site measurement	① Weather tower [27], SCADA data [30,39], wind direction measuring rod [40,41]
	② LiDAR measured [30,31,37,42–44]
Wind tunnel experiments	① Complex terrain simulation [30,45–47]
	② Boundary layer wind tunnel [10,28,34]
Numerical simulation class	① Large eddy simulation (LES) [29,33,34,37,48–51]
	② CFD simulation [11,36,41,43,52,53]
Machine learning	① Multi-objective optimization (yaw parameter optimization and layout optimization) [32,50,54]
	② Predictive models [28,30,55]
Theoretical models	① Analyzing wake models (Gaussian model [50])
	② Contrail overlay model [29,31,44]

2.2. Adaptability Defects of Traditional Yaw Control

Traditional yaw control mostly relies on the weather vane at the tail of the engine room to measure the wind direction, and simple PID (Proportional–Integral–Derivative) adjustment is used to achieve alignment with the wind direction. However, several studies have shown that such a method has obvious limitations in complex and rapidly changing wind conditions. The traditional yaw system generally assumes that the wind direction sensor in the engine room can accurately reflect the free-flow wind direction, but because the wind passes through the fan blades and the engine room first, there is obvious disturbance in the wake area where the sensor is located, and the measured wind direction is often

affected by wind shear, turbulence, and wake, resulting in a large deviation. Figure 7 is a schematic diagram of the wind direction measurement.

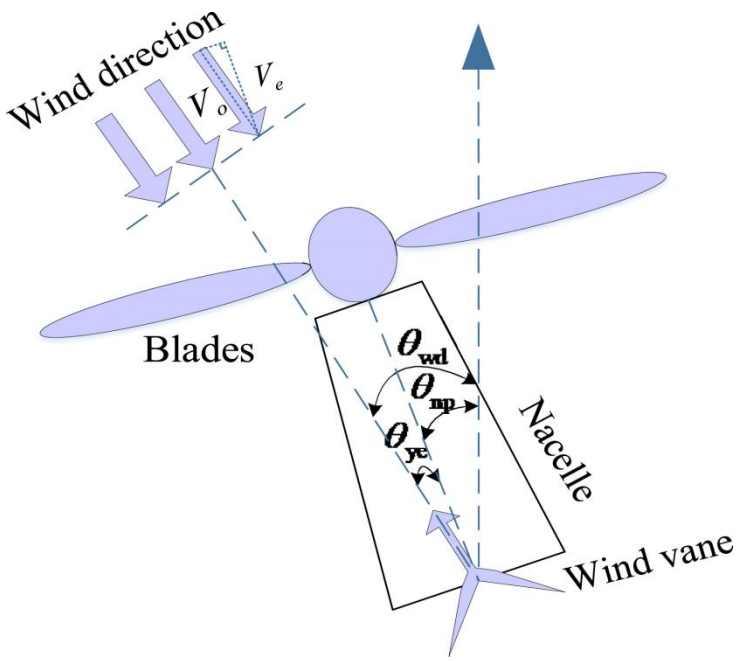


Figure 7. Schematic diagram of wind direction measurement [56].

Through the statistics of Supervisory Control and Data Acquisition (SCADA) data generated by the actual operation of the unit, it is found that the static yaw error of the 3.6MW unit is still about 5° in the high-wind-speed area, while the error can reach 10° at low wind speed. This shows that it is difficult for traditional wind direction measurement methods to accurately track the real wind direction under severe wind direction changes or complex terrain conditions, which is one of the fundamental reasons for the lack of yaw control performance [56].

Based on the measured data of the Horns Rev offshore wind farm and the verification of the 3D wake model, Dou et al. found that the traditional yaw control-dependent 2D or centimetric 3D wake model could not capture the non-centric kidney-shaped wake caused by yaw in complex terrain and did not consider the wake deflection mechanism dominated by the anti-rotating vortex pair, resulting in the power increase in the layout with 7D unit spacing not being high, but the increase rate continuing to decrease when the spacing increased to 10.4D, and the adaptability decreasing significantly with the change in layout parameters [57]. Literature [58] used the WindSE actuator line method (ALM) combined with large eddy simulation (LES) to generate high-fidelity data, and the symbolic regression model was trained and compared, and it was found that the traditional analytical wake model had significant limitations: the Jiménez model overestimated the wake deflection and underestimated the maximum velocity loss, and the Bastankhah model did not fully consider the influence of turbulence intensity [56] further confirmed in field experiments in wind farms with complex terrain in Italy that traditional yaw control assumes that the power curve is symmetrically distributed, and the goal is to maximize the power of a single unit, ignoring the asymmetric yaw of the actual unit-power characteristics. The power loss of the unit is minimal or even slightly increased when the unit is at the negative yaw angle, while the positive yaw angle leads to a significant power drop, which is not considered by the traditional strategy, so that the wake avoidance effect of the downstream unit is not good, and the power loss occurs in some wind conditions [59].

The coupling influence of traditional yaw control on turbulent evolution and fatigue load under complex terrain is also a key defect. Sun et al. carried out multi-working aeroelastic simulation using FAST software (v8.16) and found that the influence of yaw angle offset and wake superposition on fatigue load was not quantified by the traditional strategy, and the turbulence intensity was 15–25%. In the complex terrain wind field, the damage equivalent load (DEL) of blade edge bending damage is 20–30% higher than that of the optimization strategy, and the bending load increases by 15–25% before and after the tower, without considering the critical characteristics of a 50% increase in the peak load when the horizontal wake offset is 0.5D [60]. The results of Ref. [61] show that traditional control ignores the modulation effect of the yaw angle on the turbulence integral scale, and the vertical turbulence integral scale fluctuates by 0.2 at 15° yaw, resulting in a prediction deviation of more than 30% of wake recovery speed, which further aggravates the blindness of yaw adjustment. Macrí et al. studied the wake and load dynamics of the yaw maneuver process through wind tunnel experiments and found that the positive and negative yaw direction will significantly affect the time lag of wake deflection (wake stabilization time is shortened when there is negative yaw), and the response delay of downstream wind turbine load fluctuation is positively correlated with the yaw action duration [62]. In addition, the traditional fixed parameter strategy of yaw control cannot adapt to the dynamic changes in wind conditions in complex terrain. Liu et al. found in a study of wind farms with complex terrain in northern Hebei that the traditional strategy adopts a fixed yaw response threshold and delay time and does not take into account the frequent switching of wind direction and turbulence intensity induced by the terrain, resulting in yaw action and wind condition changes in the wind speed range of 5–15 m/s; the average number of invalid yaw times per day of the unit reaches more than 80 times, accounting for 35% of the total yaw times, which not only wastes energy consumption but also increases mechanical wear [63]. Figure 8 is a schematic diagram of the wind turbine trail.

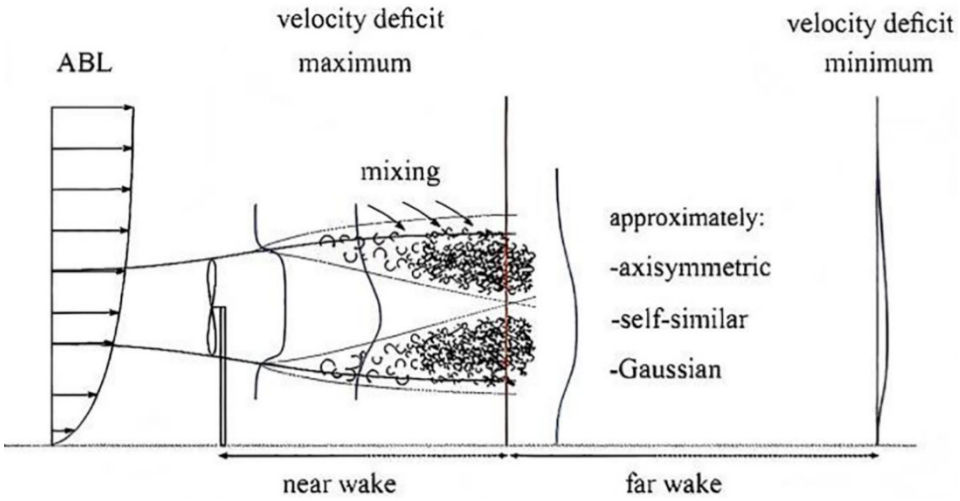


Figure 8. Schematic diagram of wind turbine trails [63].

To sum up, the adaptability defects of traditional yaw control in wind farms with complex terrain are concentrated in multiple dimensions; traditional yaw strategies rely on single-point wind direction measurement, ignore terrain-induced wind field characteristics, adopt fixed threshold logic control, and regard "yaw error minimization" as the only goal; and these assumptions are no longer valid in complex terrain, resulting in amplified wind direction measurement deviations, lag in control response, increased yaw system fatigue, and possible yaw–load relationship mismatch. In addition, traditional yaw control relies on the two-dimensional or centrically symmetrical wake model, which cannot capture

the effect of kidney-shaped wake and counter-rotating vortex pairing, and the spacing of the power boost randomized group increases significantly decreases. Assuming that the yaw angle–power curve is symmetrical, it is contrary to the asymmetry characteristics of the actual unit with small negative yaw loss and large positive yaw loss. The fixed control parameters are difficult to adapt to the heterogeneity of wind direction switching and turbulence, and the proportion of invalid yaw exceeds 35%. Without considering the influence of fatigue load of yaw–wake coupling, the equivalent load of the blade and tower damage is 20–30% higher. These defects lead to large power prediction deviations, increased energy consumption and mechanical wear, and difficulty meeting the operational needs of wind farms with complex terrains.

3. Yaw Optimization Technology System and Application of Complex Terrain

3.1. Core Technology for Yaw Optimization in Complex Terrain

In recent years, research on wind turbine yaw control has emphasized the importance of reducing yaw error in complex terrain conditions, as wind shear and turbulence significantly affect power capture and structural load [64]. In this context, optimizing yaw control strategies to improve aerodynamic efficiency and reduce mechanical fatigue has become a core issue for wind farm performance improvement [65]. This section reviews key techniques for yaw optimization in complex terrain, including advanced wind field modeling, real-time yaw error correction, and multi-objective control frameworks.

The refined perception technology breaks through the limitations of traditional coarse-grained perception and lays the data foundation for yaw optimization. Based on the SCADA system data of the 2MW permanent magnet direct drive unit of the mountain wind farm in southern China, the data binning method and turbulence intensity calculation reveal the key characteristics of wind fields with complex terrain: the wind speed of 3.0–8.0 m/s accounts for 42.6%, the turbulence intensity varies significantly between different wind speed ranges, and the influence of yaw error angle on output power is heterogeneous [66]. In addition, for the dynamic flow field perception of wind fields in complex terrain, by comparing the measured data of Horns Rev wind farm, Ref. [67] verified that the method can accurately capture the frequent wind direction switching and wake deflection law induced by the terrain and provide flow field support for the real-time adjustment of yaw strategy. While refined perception technologies provide the data foundation for optimization, their engineering feasibility faces several challenges. Real-time perception based on LiDAR involves expensive equipment, often costing hundreds of thousands of RMB per unit, and it is highly sensitive to harsh environmental conditions such as dust, rain, snow, and vibration in complex terrain, leading to high maintenance costs. Meanwhile, high-fidelity numerical simulations like CFD or LES can deliver detailed flow field information, but a single simulation may take hours to days, which cannot meet real-time control requirements. Therefore, a hybrid strategy is often adopted in practical applications: high-cost methods such as initial LiDAR measurements or high-fidelity simulations are used to establish a wind farm characteristic database or train surrogate models, while daily operations rely on lower-cost SCADA data combined with lightweight models for state perception and decision-making. The sensing technology based on Reynolds-averaged Navier–Stokes coupled with an actuator line model (RANS/ALM) can accurately output the turbulence intensity distribution at different terrain locations by simulating the non-uniform inflow conditions of mountain wind fields, providing a basis for the differentiated setting of yaw angle [68]. As shown in Figure 9, the power prediction comparison chart based on the LES and RANS/ALM models is shown.

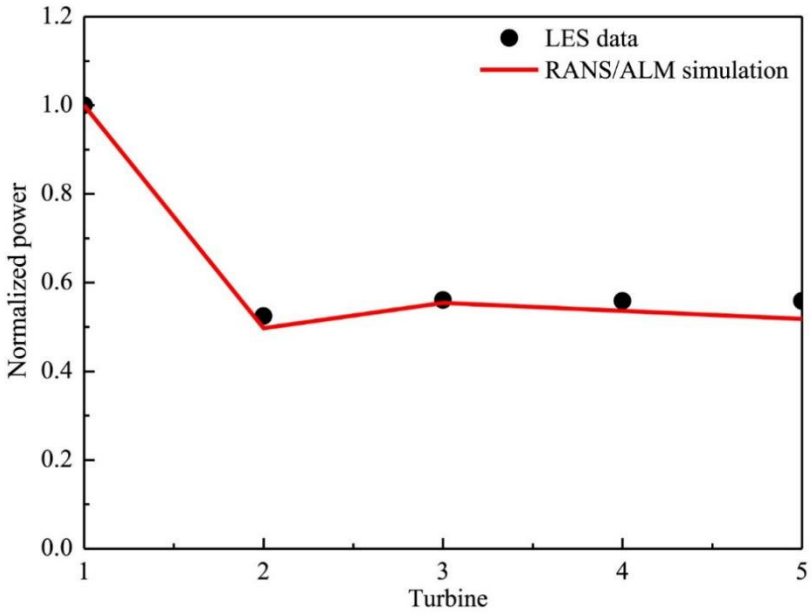


Figure 9. Comparison of power prediction based on LES and RANS/ALM models [68].

The multi-objective optimization algorithm realizes efficient parameter optimization. Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) takes "minimum yaw times" and "maximum power generation" as the target optimization parameters for the three wind speed intervals and, after Technique for Order of Preference by Similarity to an Ideal Solution (TOPSIS) screening, the yaw number is greatly reduced, accompanied by only a 3.5% decrease in power generation [66]. In the face of high-dimensional scenarios, the covariance matrix adaptation evolution strategy (CMAES) algorithm dynamically adjusts the covariance matrix, and the convergence speed is 3-times faster than that of the genetic algorithm in the optimization of 80 units, achieving a power increase of 6.53% [57]. While advanced optimization algorithms such as CMA-ES and DLSSA exhibit excellent convergence rates and optimization outcomes in simulation studies, their real-world deployment must address two critical challenges: computational real-time capability and engineering reliability. For an eighty-turbine wind farm, even with a threefold improvement in computational speed, performing a full-farm optimization remains time-consuming and thus inadequate for responding to wind conditions that evolve over seconds or minutes. Moreover, the optimized yaw-angle sequences generated by these algorithms must be translated into executable control commands, accounting for pertinent physical constraints including yaw bearing speed and acceleration limits, mechanical wear, and the additional energy consumption associated with frequent actuation. A commonly adopted and engineering-feasible approach integrates offline optimization with online lookup. This entails the offline computation of optimal yaw strategies for typical sets of wind conditions, defined by wind direction, speed, and turbulence intensity, using high-performance computing or cloud platforms. The results from pre-computed lookup tables are embedded within the site controller. During online operation, the controller selects the appropriate strategy from these tables based on real-time wind measurements and incorporates straightforward feedback mechanisms for fine-tuning.

The dynamic Levy Sparrow Search Algorithm (DLSSA) introduces heuristic initialization of the engineering layout, accounting for 58% of the initial feasible solution, and the power is increased by 1.70% by jointly optimizing the unit height and yaw angle, far exceeding the 1.01% of sequential optimization [69]. Aiming from the computational efficiency bottleneck of large-scale wind field yaw optimization, Fleming et al. proposed a Serial-Refine rapid optimization method, which improves the computational efficiency

by more than 10 times compared with traditional sequential least squares programming (SLSQP) optimization through the two-step strategy of "upstream to downstream serial traversal of candidate yaw angle and local angle refinement", and achieves a power gain of 4.53% (0.26% higher than SLSQP) in the grid wind field of 81 wind turbines, which has provided an engineering scheme for the real-time yaw control of large-scale wind farms with complex terrain [70].

Song et al. proposed the Fuzzy Deduction Weight Coefficient Evaluator (FDWE)—combined with improved Adaptive Grid Algorithm Multi-Objective Particle Swarm Optimization (AGA-MOPSO) to optimize the fuzzy rules and membership functions—to achieve a dynamic balance between the energy capture loss rate and the yaw actuator utilization rate, which increases the annual power generation by 3% and reduces the actuator loss by 12% compared with the fixed-weight Model Predictive Control (MPC) [71]. Aiming at the computational bottleneck of traditional optimization algorithms in large-scale wind farms, a DDPG (deep deterministic policy gradient)-based reinforcement learning collaborative yaw control strategy is proposed by Ref. [72], and the total power of the wind field below the rated wind speed (5 m/s) is increased by 32.63% compared with the optimized strategy, while the wake steering (low wind speed) and wind alignment (high-wind-speed) modes can be adaptively switched according to the wind conditions.

Rak et al. showed that the Gauss-Curl Hybrid (GCH) model achieved a power increase of 14.66% in an array of 8 units due to the inclusion of yaw-induced wake recovery and secondary steering effects, which was much higher than the benefit of the Gaussian-shaped Bastankhah model, and its angular distribution strategy of "high yaw upstream and decreasing downstream" could balance the loss of a single unit and the gain of the whole field [73]. The traditional Gaussian model assumes that the wake is an axisymmetric distribution and cannot adapt to the elliptical shape of the yaw wake in complex terrain. The wake expansion rate of vertical differentiation has a wake deflection prediction error of only 0.14 in the downstream region of 0–7D, which is better than that of the Jimenez model and the Qian model [74]. Figure 10 shows the error comparison between our model and the Jimenez and Qian models.

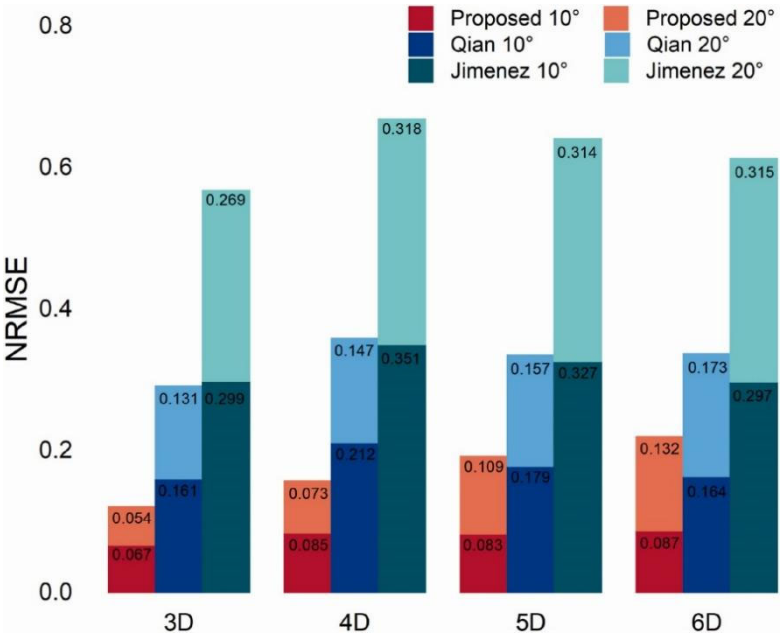


Figure 10. The error of the contrail distribution predicted by the proposed yaw contrail model and the comparable model [74].

In addition, the traditional Gaussian wake model is difficult to adapt to the asymmetric distribution of yaw wake in complex terrain. An improved yaw-wake model is proposed by literature [18], which distinguishes the near deflection law of the far wake region and the introduction of the nonlinear wake expansion hypothesis to reduce the wake deflection prediction error by more than 20% compared with the Bastankhah model, and the prediction accuracy of the velocity loss distribution is improved by 10%.

Yaw-multi-factor collaborative control further taps the optimization potential. For the terrain windshear effect, the combination of differentiated height and yaw angle is determined by DLSSA, which optimizes the power generation by 0.45% compared with the fixed height and reduces the turbulent load of the downstream unit by 9.13% [52]. "Yaw–TSR" was synergistically optimized by the Particle Swarm Optimization (PSO) algorithm to achieve a 4.85% annual power generation increase at the Lillgrund wind farm in Sweden, which is 0.92 percentage points higher than yaw optimization alone, while reducing TSR (tip speed ratio) by 7.6% and yaw angle by 20%, balancing energy efficiency and safety [75]. Duan et al. verified through wind tunnel experiments that when the yaw angle is in sine fluctuation with a Strouhal number of 0.09–0.22 and an amplitude of 10–35°, the power gain of the wind field can reach 10–15.2%, and this strategy can make the wake velocity loss distribution smoother, increase the wake recovery rate by 40%, and reduce the turbulence load of downstream units by 5–10% [76].

Except for yaw–altitude and yaw–TSR coordination, Zhao et al. proposed an optimal method of combining yaw offset and pitch control (CYOPC) that was verified by the simulation of three wind turbines in the coastal offshore wind farm by FAST. OpenFAST (v3.0.0); this method can increase the total power of the wind farm by 2.8% below the rated wind speed and reduce the equivalent load of the upstream wind turbine blade bending damage by 9.94%, and the downstream wind turbine load is reduced by 10.29%. This achieves synergistic optimization of power and load [77].

To sum up, the core technology of complex terrain yaw optimization revolves around accurate perception, accurate modeling, and precise optimization. The complete system is accurately coordinated to solve the problems of terrain-induced wind heterogeneity, wake asymmetry and multi-objective balance. Refined perception for yaw optimization relies on a hierarchy of data sources and models. High-fidelity numerical simulations, such as large eddy simulation (LES) and Reynolds-averaged Navier–Stokes (RANS) models coupled with actuator lines, provide detailed, physics-based insights into the complex flow mechanisms in terrain-distorted wind fields. These simulations, though computationally expensive, serve as a virtual testbed for understanding phenomena like asymmetric wake diffusion. In parallel, data-driven approaches mine operational data from Supervisory Control and Data Acquisition (SCADA) systems to establish empirical relationships between environmental conditions, yaw errors, and power output. Together, high-fidelity simulations and operational data analysis provide complementary support for optimization, with the former elucidating physics and the latter capturing site-specific operational patterns. Yaw-wake modeling advances along two complementary paths: physics-based refinement and data-driven approximation. Physics-based models, such as the three-dimensional cosine distribution model, incorporate terrain-induced modifications into their analytical framework to better describe asymmetric wake behavior. On the other hand, data-driven models, like Artificial Neural Networks (ANNs), learn the input–output relationships from existing datasets. It is crucial to note that the predictive capability and generalizability of an ANN are intrinsically tied to the quality and scope of its training data. For instance, an ANN trained exclusively on outputs from an engineering model like FLORIS acts as a computationally efficient surrogate for that model, inheriting its limitations and not replicating the fidelity of high-fidelity simulation or field data. The multi-objective optimization

algorithm realizes an efficient balance between power generation and equipment loss through improved strategies such as NSGA-II, CMAES, DLSSA, etc., and the convergence speed and optimization effect are better than the traditional algorithms. Yaw–altitude and yaw–TSR cooperative control further taps the gain potential, which effectively reduces the turbulent load of downstream units while increasing power generation. According to the above literature summary and analysis, a core technology and literature support table of complex terrain yaw optimization is created as shown in Table 2. The above technologies realize the deep adaptation of yaw strategy and complex terrain and provide key technical support for wind farm power improvement and operation and maintenance optimization.

Table 2. The core technology and literature support of yaw optimization in complex terrain.

Core Technology Category	Key Technical Approaches	Technical Advantages
Refined perception technology	① Utilizing SCADA high-resolution data and IEC standard turbulence calculations [66].	It can determine the wind speed range is large, and the difficulty of segmentation optimization is low. The error is small.
	②LES simulation and FLORIS model coupling refined power optimization method [67].	The wind direction capture accuracy is high, and the power prediction error in the full wake direction is small.
Yaw-wake modeling technology	① Cosine distribution 3D wake model [67].	The wake deflection prediction error is small. Predicted velocity loss and trail deflection are better than those of the Jiménez model.
	② Yaw contrail model of artificial neural network (ANN); sum of square (SOS) wake superposition algorithm [68].	The power prediction error of multiple units is smaller than that of the traditional model.
Multi-objective optimization and parameter optimization technology	① NSGA-II +TOPSIS (combination of multi-objective optimization and optimal solution screening) [66].	The number of yaws has been greatly reduced, and the power generation has only decreased slightly.
	② CMAES algorithm [57].	The convergence speed is 3 times faster than traditional algorithms.
	③ DLSSA algorithm [69].	The proportion of initial feasible solutions is high.
Yaw multi-element collaborative control technology	① Yaw—High degree of joint optimization (DLSSA algorithm) [69].	The total power generation is more than the fixed height optimization.
	② Yaw—Synergistic optimization of blade tip speed ratio [75].	The annual power generation is higher than the results of yaw alone or blade tip velocity ratio optimization.

3.2. Key Influencing Factors and Regulatory Laws of Optimization Effect

Although yaw optimization technology shows significant gain potential in wind farms with complex terrain, its actual effect is not universal but highly dependent on the synergy of multiple environmental and system factors [78,79]. The results show that the performance of yaw control is modulated by multiple variables such as wind dynamics, unit space layout, wake evolution characteristics, and terrain–wake coupling mechanisms, and the optimization benefits may vary from significant to almost absent under different conditions. Therefore, an in-depth understanding of the mechanism of action and regulation of these key influencing factors is a prerequisite for achieving accurate adaptation and maximization of the benefits of the yaw strategy.

Turbulence intensity and wind direction stability are the core wind condition factors that determine the yaw optimization effect, which directly affects the wake diffusion rate and the response efficiency of yaw adjustment. Zong and Porté-Agel found that the turbulence intensity was monotonically negatively correlated with the relative power

gain of yaw optimization through the wind tunnel experiment of three rows of micro wind farms, and when the turbulence intensity was increased from a low level to 18%, the power gain tended to be close to zero, because the strong turbulence accelerated the mixing of the wake and ambient airflow, weakening the targeted effect of the yaw deflection wake [80]. Gambier proposed to use a nonlinear PI (NPI) controller to replace the traditional PI control in order to synchronize the yaw control and multi-yaw actuator of large wind turbines and balanced the wind direction incoming flow tracking accuracy and actuator loss through an adaptive dead zone design [81]. Khan and Tüfekci focused on the structural optimization of composite wind turbine blades and achieved a mass reduction of nearly 50% while maintaining the aerodynamic shape of the blades through the two-path topology optimization strategy of static deformation constraints and modal frequency enhancement, while improving the bending stiffness and modal stability of the blades, effectively reducing the risk of resonance [82]. In terms of wind direction characteristics, a yaw-related parameter tuning method based on the Gaussian process is proposed by Ref. [83], as shown in Figure 11. The study of the Horns Rev wind farm shows that the angle between the wind direction and the unit line significantly affects the upper limit of the gain, and the peak power gain reaches 18% under some wake conditions, while the full wake condition is only 5.4%, which becomes the local minimum value of gain. In addition, Xu et al. conducted research based on the CFD high-fidelity database validation of the DTU 10 MW unit [84]. Frequent switching of wind direction in complex terrain will lead to an uneven wake deflection effect, and it is necessary to dynamically adjust the yaw response threshold to adapt to the change in wind conditions.

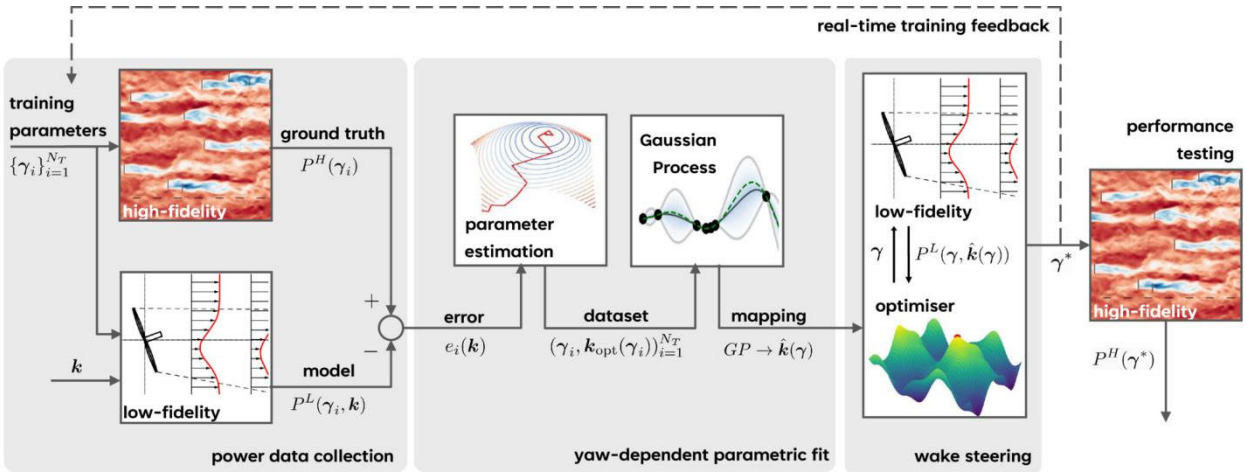


Figure 11. Yaw correlation parameter tuning method based on Gaussian process [66].

The spacing and number of rows directly affect the marginal benefit of yaw optimization by changing the overlap degree and interaction intensity of the wake. The wind tunnel experiments and analytical model analysis of Zong and Porté-Agel show that when the streamwise spacing (S_x) increases, the relative power gain of yaw optimization decreases monotonically, and the gain effect in the range of 3D-5D spacing is the best, while the gain amplitude drops to less than 2% after exceeding 10D [80]. He et al. proposed a cost function based on the comprehensive fatigue load of leaf root, tower base and yaw bearing, through which the optimal yaw angle determined by this function is concentrated in the positive yaw range (0–15°), and the optimal angle with the flow wind speed increases from 5° to 10° from 9 m/s to 17 m/s, realizing the synergy between energy efficiency and equipment life [85]. In terms of the influence of column number, the analytical model predicts that with the increase in the number of rows in the wind farm, the peak power gain and the optimal yaw angle of the front row unit both show an asymptotic increase trend, and when the

number of rows exceeds 5 rows, the gain increase is less than 3%, which tends to be stable. The three-dimensional wake model verification further confirms that the yaw optimization can achieve a power increase of 6.53% when the spacing of the units is small in complex terrain, while when the spacing is increased to 10.4D, the increase is reduced to 2.86%, and the adaptability defect is significantly highlighted [86].

The spatial distribution mode and collaborative control strategy of yaw angle directly determine the global power maximization effect, and the relevant studies clarify the core regulatory principle of "high yaw in the upstream and low yaw in the downstream". The single-row wind farm experiment found that the optimal yaw angle distribution always showed a monotonically decreasing trend from upstream to downstream, which was related to the wake secondary steering effect [80]. Gori et al. further verified in the study of the 5×5 wind farm and the Horns Rev wind farm that the yaw strategy of Gaussian process (GP) dynamic parameter adjustment can enable the low-precision model to capture complex physical effects such as secondary steering, and achieve a power increase of 62% under the 270° wind direction condition of the Horns Rev wind farm, which is completely consistent with the results of the GCH model [83]. Aiming at the computational complexity issue in large-scale wind farms, a grouping strategy based on wake interaction strength was proposed to reduce the training burden. By applying the multi-agent deep deterministic policy gradient (MADDPG) algorithm to control groups of turbines, the training load was reduced by 34% compared with the non-grouping approach, while maintaining a wind farm-level power gain of 12% [87]. The training convergence behavior of the "best" agent under baseline hyperparameters is illustrated in Figure 12, showing the evolution of cumulative reward, noise standard deviation, learning rate, actor loss, and critic loss over training episodes. As observed, the mean total reward increases steadily after an initial phase of random exploration, indicating effective learning progress. The decreasing noise and learning rate reflect the transition from exploration to exploitation, while the stabilization of both actor and critic losses suggests convergence of the policy and value function.

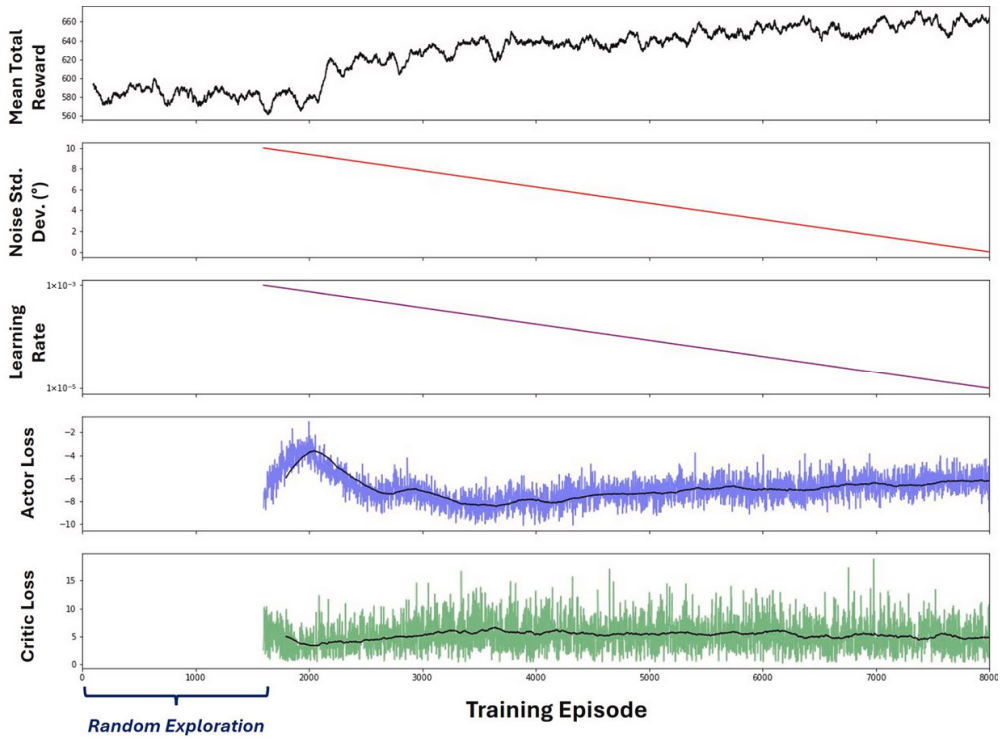


Figure 12. Training curves for the "best" agent with the baseline hyperparameters. Top to bottom: cumulative reward per episode; action noise std. dev. (°); LR; actor loss curve; critic loss curve [87].

The wake asymmetry and special vortex structure induced by complex terrain put forward higher requirements for the accuracy of yaw optimization, and the key control is to adapt to the three-dimensional evolution characteristics of the wake [71]. Wang et al. used ALM combined with unsteady Reynold-averaged Navier–Stokes equations (URANS) simulation and found that the wake of the yaw unit showed a significant asymmetric kidney-shaped distribution, and the flow to the vortex flux carried by the blade tip vortex formed a counter-rotating vortex pair, which is the key mechanism leading to wake deflection and deformation [69]. Xu et al.'s CFD high-fidelity database study further confirmed that there is asymmetry in the influence of positive and negative yaw angles on the wake, and the downstream turbulence intensity is lower during positive yaw, which is more conducive to improving the power of subsequent units, and this asymmetry is more significant due to the terrain blocking effect in complex terrain [67]. As summarized in Table 3, several key factors influence the optimization effect of yaw control in complex terrain.

Table 3. Key influencing factors and literature support for the optimization effect of yaw in complex terrain.

Influencing Factors	Research Methodology	Core Conclusions
Turbulence intensity, wind direction angle, number of unit columns	Wind tunnel experiments and analytical model modeling [80].	The turbulence intensity is negatively correlated with the power gain. The gain of some wake conditions is optimal. The increase in the number of columns brings the gain to near-saturation.
Wind direction, yaw angle distribution, grouping strategy	Gaussian Process (GP) adjusts the parameters, SLSQP optimization, FLORIS framework simulation [83].	Wind direction determines the upper limit of gain. "Upstream high yaw" is the best distribution. Grouping is combined with column-independent strategies to reduce computational complexity.
Grouping strategy and intelligent algorithm adaptability	Multi-agent deep deterministic policy gradient (MADDPG) algorithm and comparative experiment [87]	Grouping by wake interaction reduces computational complexity.
Wake asymmetry, yaw angle direction	High-resolution CFD simulation, fifth-order Fourier fitting, and FLORIS model comparison [84].	The influence of positive and negative yaw angle wake is asymmetrical. Complex terrain aggravates wake asymmetry. Fifth-order Fourier fitting can accurately characterize wake.
Wake vortex structure, unit spacing	ALM, URANS simulation, 3D wake visualization [86].	Counter-rotating vortex pair (CVP) dominates the wake deflection. The marginal benefit of yaw optimization is improved by reducing the spacing.

Engineering feasibility remains a pivotal concern when translating the theoretical gains of advanced optimization strategies, such as reported power increases of 6 to 15 percent, into tangible engineering benefits. This translation is constrained by multiple real-world factors. The substantial costs associated with sensing and control present a primary challenge. Implementing active yaw control based on LiDAR technology necessitates equipping individual turbines or turbine clusters with advanced sensing devices and establishing a reliable, low-latency communication network, the return on investment for which requires meticulous evaluation. A second major factor is system integration complexity. Novel control algorithms demand deep integration with existing industrial systems, including SCADA networks, main turbine controllers, pitch systems, and grid dispatch interfaces. This process involves complex software development and stringent cybersecurity validation. Furthermore, considerations of operation, maintenance, and long-term reliability are critical. Frequent and precise yaw maneuvers may elevate mechanical loads on yaw gears and bearings, potentially compromising their operational lifespan. Concurrently, diag-

nosing and recovering from failures within complex, often opaque intelligent algorithms poses significant practical difficulties. Consequently, future technological development must extend beyond purely pursuing performance limits. It should equally prioritize algorithm lightweighting, deployment simplification, enhanced decision interpretability, and robust fail-safe degradation mechanisms. These efforts are essential to elevate the overall Technology Readiness Level and foster broader industrial acceptance.

In conclusion, the yaw optimization effect of complex terrain is affected by the multi-dimensional coupling of wind conditions, layout parameters, control strategies, and wake–terrain coupling characteristics, and the regulation of each factor has been clarified through experimental and simulation studies. At the wind condition level, the turbulence intensity is monotonically negatively correlated with the power gain, some wake conditions are the optimal gain range, and the yaw response threshold needs to be dynamically adjusted when the wind direction is frequently switched. At the layout level, the spacing optimization effect of 3D-5D units is the best, the marginal benefit is significantly attenuated after exceeding 10D, and the gain tends to be saturated after the number of columns exceeds 5 rows. At the control level, "high yaw in the upstream and low yaw in the downstream" is the optimal distribution mode, and the dynamic parameter adjustment of the packet collaboration and Gaussian process can reduce the complexity of the calculation and improve the gain stability. At the wake–topographic coupling level, the asymmetric influence of the anti-rotation vortex on the dominant wake deflection and positive and negative yaw angles needs to be adapted accordingly. These laws reveal the core regulation logic of yaw optimization: by adapting to the dynamics of wind conditions, optimizing layout parameters, implementing collaborative control, and adapting to the three-dimensional evolution of wake, the benefits of yaw optimization under complex terrain can be maximized and theoretical support for strategy formulation and parameter adjustment in engineering practice can be provided.

3.3. Comparative Analysis and Applicability Discussion of Different Optimization Methods

The preceding review reveals a multi-technical-path landscape for yaw optimization in complex terrain. However, significant differences exist among various methods in terms of mechanism, performance, cost, and applicability, necessitating careful trade-offs based on specific scenarios.

From physical mechanisms to data-driven approaches, there exists a fundamental trade-off between predictive accuracy and computational efficiency. Physics-based models enhance accuracy in complex environments by integrating domain-specific corrective terms, thereby maintaining strong physical interpretability [42,45,87,88]. For instance, models incorporating terrain-modified flow dynamics can demonstrate significant performance gains by capturing key mechanisms such as secondary steering effects. However, their development and validation demand a deep understanding of the underlying multi-system couplings, and their computational cost often precludes real-time application in large-scale systems [40,46,52]. To systematically compare the characteristics of different methods in complex terrain, Table 4 provides a systematic comparison of mainstream yaw optimization methods across dimensions such as method category, core principles, advantages and challenges in complex terrain, and typical applicable scenarios.

In contrast, data-driven methods learn mappings directly from high-fidelity simulation or experimental datasets [48]. This bypasses explicit mechanistic modeling and grants high computational efficiency for online deployment. A primary limitation is their inherent black-box nature. These models may fail under operating conditions not represented in their training data and typically cannot provide physically meaningful explanations for their outputs, which raises significant concerns for safety-critical applications [39,43,49,55].

Table 4. Comparative analysis of yaw optimization methods for wind farms in complex terrain.

Method Category	Core Principle	Advantages in Complex Terrain	Limitations/Challenges in Complex Terrain	Applicable Scenarios
Physics-Based Models (e.g., GCH, 3D Cosine Wake)	Based on fundamental fluid equations with terrain-modified parameters	① Clear mechanism, strong physical interpretability ② Captures key phenomena like terrain-induced wake deflection & asymmetric diffusion ③ Parameter adjustment has clear physical meaning	① Simplifications of terrain–atmosphere–wake coupling may still be inadequate ② High computational cost, especially for real-time control of large farms ③ Requires accurate terrain parameters & atmospheric boundary layer conditions	① Micro-siting and layout optimization in planning phase ② Offline validation & mechanism analysis of control strategies ③ Benchmark studies for medium-scale farms
Data-Driven Models (e.g., ANN, CNN, Deep Learning)	Trains black/grey-box models based on historical/simulated data	① Captures strong nonlinear wind–wake relationships in complex terrain ② Fast online prediction once trained ③ Can fuse multi-source heterogeneous data (SCADA, LiDAR, and simulation)	① Relies on large amounts of high-quality training data (costly) ② Weak model interpretability ("black box") reduces engineering trust ③ Uncertain generalization beyond training data scope	① Power prediction & anomaly detection for operational farms ② Online performance optimization based on SCADA data ③ Supplement or replacement for physics models
Traditional Multi-Objective Optimization (e.g., NSGA-II, PSO)	Population-based global search strategies	① Effectively handles power-load trade-offs ② Mature algorithms with many successful cases ③ Decision methods like TOPSIS aid in selecting compromise solutions	① Slow convergence for high-dimensional problems (>50 turbines) ② Limited adaptability to dynamically changing wind conditions ③ Usually requires full system model, limiting real-time capability	① Offline parameter optimization (e.g., optimal yaw angle lookup tables) ② Medium-scale farm optimization combined with dimensionality reduction ③ Coupled with fast models (e.g., FLORIS)
Modern Optimization Algorithms (e.g., CMA-ES, DLSSA)	Self-adaptive search strategies balancing exploration & exploitation	① Faster convergence in high-dimensional problems than traditional GA (3× faster [57]) ② Algorithms like DLSSA handle engineering constraints well ③ Suitable for parameter tuning in dynamic environments	① Algorithm parameter setting requires expertise ② Still faces real-time computation bottlenecks ③ Less strict theoretical convergence guarantees than classical algorithms	① Offline optimization for large-scale wind farms ② Joint multi-parameter optimization (yaw, height, and TSR) ③ Quasi-real-time applications requiring fast response
Reinforcement Learning/Intelligent Control (e.g., DDPG, MADDPG)	Learns optimal control policy through interaction with environment	① Adapts to strong dynamics & uncertainty of complex terrain wind ② Enables end-to-end control, reducing reliance on precise models ③ Multi-agent architecture suitable for farm-level cooperative optimization	① High computational cost for training, requires vast simulation/real data ② Complex verification of policy safety & robustness ③ Real deployment needs reliable simulators or careful online learning	① Real-time adaptive control in complex dynamic environments ② Global optimization for multi-turbine cooperative yaw

From offline optimization to online learning, this progression reflects a fundamental shift in the capacity to adapt to static versus dynamic operational environments. Traditional multi-objective optimization algorithms are proficient at resolving trade-offs such as that between power generation and structural load [53]. However, their nature is inherently offline, typically yielding static solutions like pre-computed lookup tables or fixed control strategies. The spatiotemporal heterogeneity of wind resources in complex terrain makes such static strategies poorly adaptive [41].

Modern optimization algorithms improve search efficiency through adaptive mechanisms, yet they remain dependent on iterative evaluations of objective functions. In contrast, reinforcement learning represents a paradigm shift toward online learning. By continuously interacting with a simulated environment, it can develop control policies that dynamically adapt to changing wind conditions. Multi-agent architectures extend

this potential, demonstrating a capability for large-scale cooperative control and achieving significant reductions in computational burden through strategies like grouping [47,50,51]. Despite these advances, key challenges for engineering application persist, including training stability, sample efficiency, and the development of reliable safe exploration mechanisms for real-world wind farm deployment.

Strategic selection of methodologies is recommended according to the specific requirements of different operational phases [44]. For the planning and design phase of a wind farm, where physical insight is crucial and computational time is a secondary concern, it is advisable to integrate physics-based models with multi-objective optimization algorithms to conduct comprehensive offline analysis and parameter optimization. To enhance the performance of operational wind farms, data-driven models are suitable for analyzing historical operational data to construct a digital twin for subsequent strategy validation and optimization. Regarding future-oriented real-time adaptive control, reinforcement learning and lightweight hybrid models represent key research directions; however, they require extensive validation within simulated environments prior to real-world deployment, implemented through cautious incremental learning strategies [54]. Notably, hybrid modeling, which integrates physical equations with data-driven components, and hierarchical control architectures, where offline optimization provides baseline strategies for online fine-tuning, offer pragmatic pathways to balance system performance, computational efficiency, and operational safety.

4. Conclusions

This review has systematically analyzed the challenges and advancements in yaw optimization for wind farms located in complex terrain. It is evident that flow distortions induced by topography such as non-uniform velocity profiles, elevated turbulence, asymmetric wake development, and flow separation significantly degrade the performance of conventional yaw control methods. These traditional approaches relying on local anemometry, fixed logic thresholds, and simplified wake models fail to capture the dynamic and heterogeneous nature of complex terrain flows. In contrast, emerging strategies integrating high-fidelity sensing technologies, advanced wake modeling techniques, and intelligent optimization algorithms show promising potential in enhancing power production while reducing structural loads.

Despite these advances, critical research gaps remain. To guide future work toward practical implementation and holistic performance improvement, several specific and well-defined open questions are identified.

First, a unified framework coupling yaw control with structural load prediction and system stability remains an unresolved challenge. Current optimization paradigms often treat yaw adjustment independently from dynamic response. Developing integrated models that explicitly link yaw commands to fatigue accumulation, tower torsion, and blade bending under varying inflow conditions is essential. This requires embedding high-fidelity aeroelastic simulations into real-time control architectures to enable proactive management of both energy capture and mechanical integrity.

Second, effective coordination across multiple spatial and temporal scales is crucial for optimal farm operation. While individual turbine yaw decisions influence downstream wakes, their impact must be evaluated within the context of farm-wide objectives such as total power output and load distribution over extended periods. Future research should focus on hierarchical or distributed control frameworks capable of synchronizing local actions with global goals. This includes designing adaptive control laws that dynamically adjust priorities based on evolving flow states and operational constraints.

Third, the generalization and robustness of data-driven models in unobserved environments require deeper investigation. Although machine learning-based approaches demonstrate strong predictive capability, their performance is highly dependent on training data quality and representativeness. A key question is how to ensure reliable operation when deploying these models in new sites or during extreme events not captured in training datasets. Advancing transfer learning, online adaptation, and hybrid modeling that combines physical principles with data-driven components will be vital for achieving trustworthy and scalable solutions.

Fourth, the cost-effectiveness of sophisticated optimization systems needs rigorous evaluation. The integration of advanced sensors and computational infrastructure increases complexity and operational expenses. Future studies must quantify the trade-offs between performance gains and added costs, establishing clear economic and technical benchmarks. This analysis will inform the development of practical, scalable solutions suitable for widespread deployment in commercial wind farms.

In conclusion, the path forward for yaw optimization in complex terrain lies in transitioning from isolated technological improvements to integrated, intelligent, and resilient control systems. Addressing the identified challenges, particularly the coupling of control with structural dynamics and the design of cross-scale coordination mechanisms, will be fundamental to maximizing wind energy potential in challenging topographies and advancing sustainable power generation.

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Abbreviations

The following abbreviations are used in this manuscript:

AGA-MOPSO	Adaptive grid algorithm multi-objective particle swarm optimization
ALM	Actuator line method
ANN	Artificial neural network
CFD	Computational fluid dynamics
CMAES	Covariance matrix adaptation evolution strategy
CNN	Convolutional neural network
CVP	Counter-rotating vortex pair
CYOPC	Combing yaw offset and pitch control
DEL	Damage equivalent load
DLSSA	Dynamic Levy sparrow search algorithm
FDWE	Fuzzy deduction weight coefficient evaluator

GCH	Gauss-curl hybrid
GP	Gaussian process
IEA	International Energy Agency
LES	Large eddy simulation
LiDAR	Light detection and ranging
MADDPG	Multi-agent deep deterministic policy gradient
MPC	Model predictive control
NPI	Nonlinear PI
NSGA-II	Non-dominated sorting genetic algorithm-II
PSO	Particle swarm optimization
RANS/ALM	Reynolds-averaged Navier–Stokes coupled with actuator line model
SCADA	Supervisory control and data acquisition
SLSQP	Sequential least squares programming
SMAPE	Symmetric mean absolute percentage error
TOPSIS	Technique for order of preference by similarity to an ideal solution
URANS	Unsteady Reynold-averaged Navier–Stokes equations
WiSpEx	Wind spatial extrapolation

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