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A systematic literature review of surrogate-assisted multidisciplinary coupled optimization of wind turbine blades for enhancing AEP and reducing LCOE in LWSRs with nanotechnology-enhanced materials and nanoscale optimization

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Wind turbine blades play a crucial role in capturing wind energy and converting it into mechanical power. Optimizing blade design is especially important in low wind speed regions (LWSRs), where aerodynamic performance, structural integrity, and energy extraction strongly influence turbine efficiency. This systematic literature review (SLR) examines studies published between 2020 and 2025 that address blade design challenges in LWSRs, surrogate modeling within multidisciplinary design optimization (MDO) frameworks, and the integration of fluid–structure interaction (FSI) with techno-economic metrics such as AEP and LCOE. The review followed PRISMA guidelines and searched major databases, including Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore. From 3,303 initial records, 30 relevant studies are finally included. Commonly used methods include Kriging, RBF, and NSGA-II. Results show that surrogate models reduce CFD/FEA computational costs by 60–70% with errors below 5%, while NSGA-II achieved up to 6% AEP improvement and 4–7% LCOE reduction. Key gaps remain in real-world validation, limited LCOE–LCA integration, and data quality for surrogate training. Moreover, nanotechnology-based approaches enable nanoscale material enhancement, improved aerodynamic surface properties, and advanced structural performance, contributing to higher energy capture efficiency and reduced levelized cost of energy in wind turbine blades.

Keywords: Surrogate modeling; Wind turbine optimization; Kriging; NSGA-II; FSI.

1. INTRODUCTION

Wind energy has emerged as one of the most promising renewable energy sources in the 21st century, offering sustainable, clean, and increasingly cost-effective alternatives to fossil fuel–based power generation (Ang et al., 2022) [1–5]. Among the main components of a wind energy system, the wind turbine blade plays a critical role in capturing the kinetic energy of the wind and converting it into mechanical power [6,7]. Turbine performance, structural loads, and the levelized cost of energy (LCOE) are all strongly influenced by blade design (Ma et al., 2025) [8,9]. Conventional design practices often treat aerodynamic and structural characteristics separately [10,11], which can lead to performance degradation or structural issues under varying operating and loading conditions (Coughlin et al., 2025) [12]. To address these limitations, aero-structural design approaches have gained increasing attention, enabling aerodynamic forces and structural responses to be evaluated simultaneously within a unified framework (Spini & Bettini, 2024) [13]. As wind power expands to support global sustainability goals, horizontal-axis wind turbines (HAWTs) must achieve improvements in aerodynamic efficiency, structural reliability, economic performance, and environmental impact [14–17]. However, wind turbine systems involve strong couplings between aerodynamic behavior, structural modifications, and economic outcomes, making isolated optimization strategies insufficient [18–20]. High-fidelity simulations for airflow and structural analysis are computationally expensive, particularly when repeated iterations are required during design optimization [21–23]. To overcome this challenge, researchers increasingly employ surrogate models that approximate complex simulations at significantly reduced computational cost (Porta-Ko et al., 2024) [24–26]. These models are commonly embedded in multidisciplinary design optimization (MDO) frameworks that demand both accuracy and efficiency [27]. Despite extensive research on wind turbine optimization, limited attention has been given to consolidated reviews of surrogate-assisted MDO frameworks tailored to low wind speed regions (LWSRs) [28–30]. As blade size and complexity grow, the need for integrated fluid–structure–economic coupling becomes more critical. Therefore, this review systematically analyzes recent studies (2020–2025) that address blade design challenges in LWSRs using surrogate-based MDO frameworks integrating FSI and techno-economic metrics such as AEP and LCOE [34–36]. Where the research questions that should be answered in this review are:

- What are the dominant surrogate modeling techniques applied to wind turbine blade optimization?
- How are FSI and aero-structural coupling integrated into surrogate-assisted MDO frameworks?
- What optimization strategies and tools have been developed to balance AEP and LCOE in LWSRs?
- What are the major research gaps in current coupled optimization frameworks?

This SLR follows PRISMA guidelines and is structured as follows: Section 2 describes the methodology. Section 3 provides a thematic synthesis of the literature. Section 4 presents a discussion of research gaps. Section 5 concludes with insights and future research directions. PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) is a guideline designed to improve the reporting of systematic reviews. PRISMA provides authors with guidance and examples of how to completely report why a systematic review is done, what methods are used, and what results are found Moher et al. (2010) [37-40]. Recent advances in nanotechnology have introduced nanocomposite materials and nanoscale surface modifications that significantly improve aerodynamic efficiency, structural strength, and fatigue resistance of wind turbine blades. These nanoscale enhancements contribute to better performance in low wind speed regions and support the development of high-efficiency, lightweight blade designs (Figure 1).

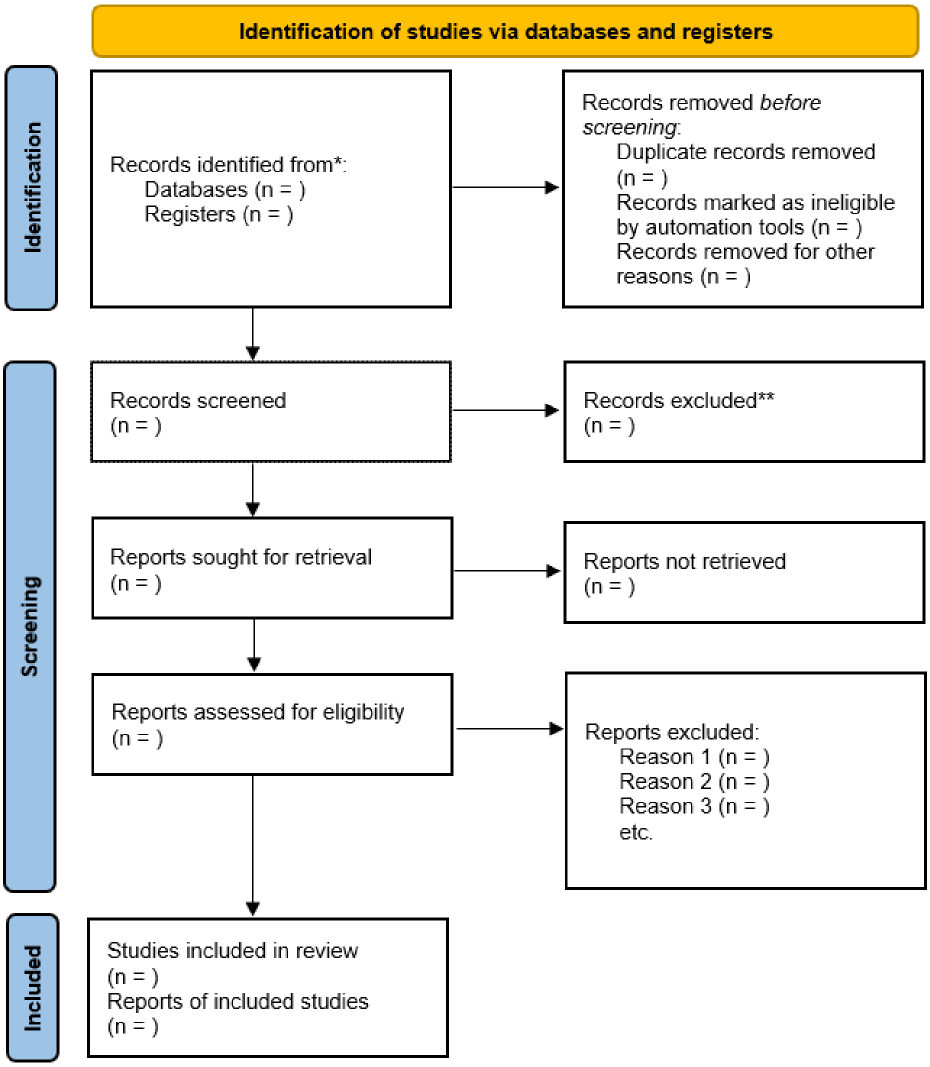

Figure 1 PRISMA 2020 flow diagram guideline Moher et al. (2010) [41].

2. METHODOLOGY

This review followed PRISMA 2020 guidelines. A protocol specifying objectives, eligibility criteria, sources, search strategies, screening, extraction, and quality appraisal. This review draws on literature published between 2020 and 2025 across Scopus, IEEE Xplore, Web of Science, and ScienceDirect. Keywords used include: “surrogate modeling,” “wind turbine optimization,” “Kriging,” “NSGA-II,” “FSI,” “LCOE,” and “multidisciplinary design” [42,43] (Figure 2).

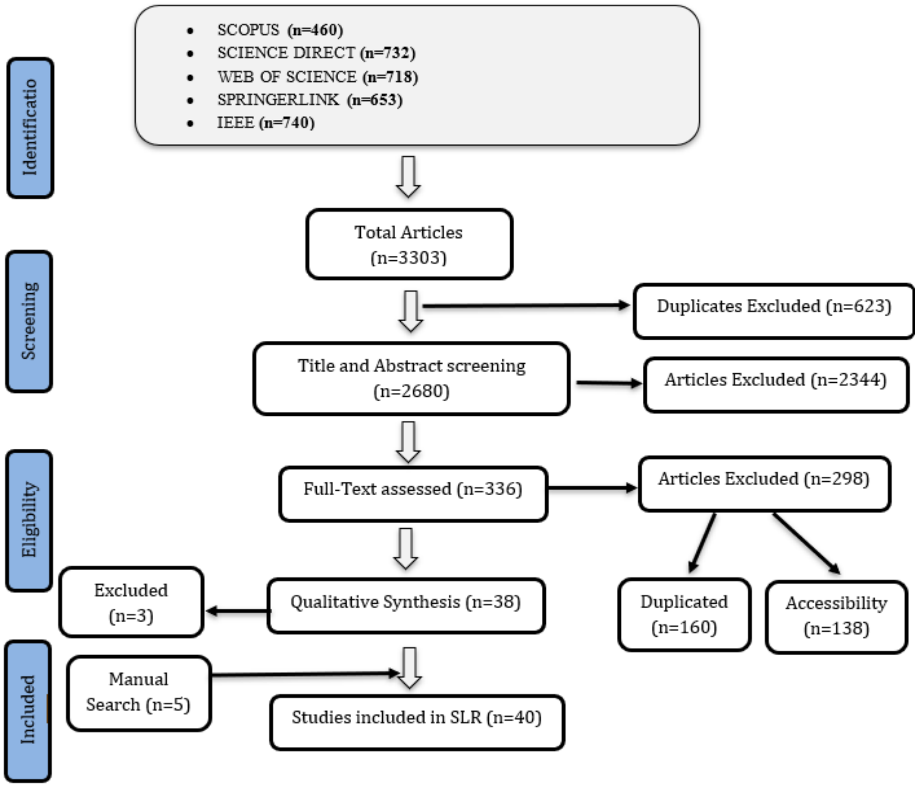

Figure 2 PRISMA 2020 flow diagram for systematic reviews.

2.1. Eligibility criteria

- Problem: Wind turbine blades, studies relevant to LWSRs/IEC Class III or explicitly operating at low Reynolds numbers.
- Approach: Aero-structural/FSI frameworks; surrogate-assisted modeling (Kriging and RBF); multi-objective optimization (NSGA-II).
- Comparators**:** Any (baseline blades, rigid vs flexible, BEM/CFD/FEA/FSI).
- Outcomes**:** AEP, LCOE, structural loads, deflection, or computational efficiency.
- Study types: Peer-reviewed journal articles and high-quality full conference papers.
- Time window: 2020 – 2025.
- Language**:** English.
- Exclusions**:** General RE overviews; offshore substructure-only papers; purely control/electrical papers without blade modeling; unavailable full texts; duplicates.

Table 1 Eligibility criteria McKenzie et al. (2021) [44].

Domain	Include	Exclude
Topic	Blade design with aero/structural/FSI in LWSRs/IEC III	Non-blade, electrical/control-only
Methods	Surrogate-assisted modeling, MDO/MOO, NSGA-II, BEM/CFD/FEA/FSI	Opinion pieces, tutorials
Outcomes	AEP, LCOE/COE, loads/fatigue, deflection, CPU cost	No relevant outcomes
Years	2020–2025	<2020
Type	Peer-reviewed (journal; strong conf.)	Thesis, preprint (unless accepted), non-English

2.2. Data extraction

From each included study has been extracted: authors, year, turbine/scale, LWSR context, aerodynamic/structural/FSI models, surrogate type (Kriging, RBF, PRS), DOE (e.g., LHS/Sobol), optimizer (NSGA-II settings), validation (experiment/benchmark/tools), outcomes (AEP, LCOE, loads/fatigue, CPU time), and key findings.

2.3. Nanotechnology integration in blade optimization

Nanotechnology-based approaches can be incorporated into blade design through the use of nanocomposite materials, nanoscale coatings, and surface treatments. These techniques enhance aerodynamic smoothness, reduce drag, and improve structural durability. Additionally, nanoscale modeling can be integrated into surrogate-assisted MDO frameworks to improve prediction accuracy and optimization efficiency.

3. THEMATIC REVIEW

This section synthesizes findings from the 40 studies selected for this review. The analysis is organized thematically to reflect key dimensions of surrogate-assisted multidisciplinary optimization for wind turbine blades, particularly in the context of low wind speed regions (LWSRs). The themes include aerodynamic modeling, structural analysis, fluid–structure interaction (FSI), surrogate modeling approaches, optimization algorithms, and techno-economic evaluation. Each subsection highlights state-of-the-art methods, commonly used tools, major achievements, and remaining challenges in the literature (Figure 3).

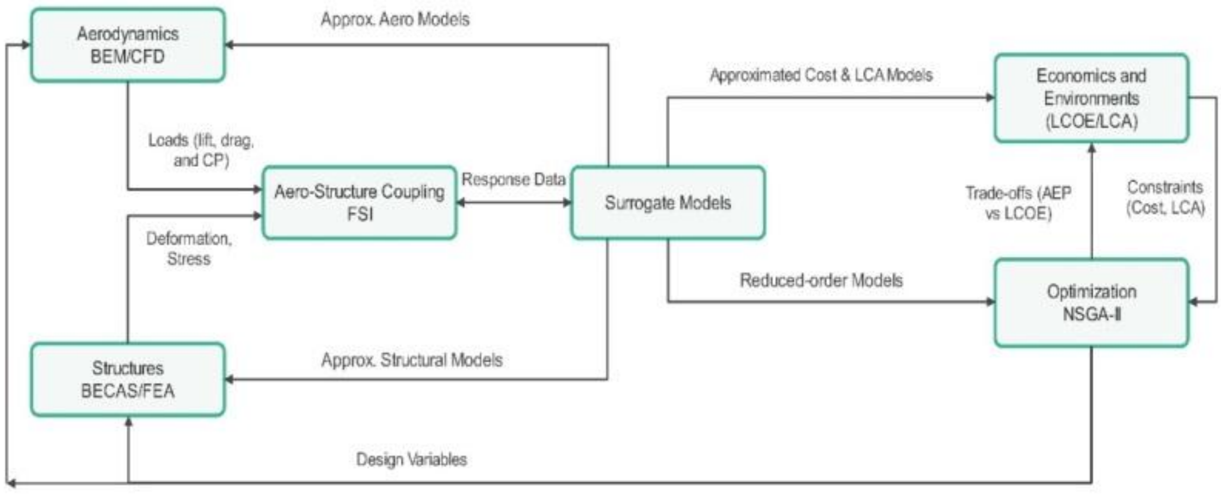

Figure 3 Conceptual framework.

3.1. Design challenges in low wind speed regions (LWSRS)

Designing efficient wind turbine blades for low wind speed regions (LWSRs) presents significant challenges due to limited wind kinetic energy and operation at low Reynolds numbers [45]. Wind energy generation in such conditions is highly sensitive to blade geometry and material selection [46]. Key design considerations include laminar flow separation, low starting torque, minimum operational wind speed, and material constraints. At instantaneous Reynolds numbers below 500,000, laminar separation and the formation of laminar separation bubbles (LSBs) commonly occur, leading to increased drag and reduced lift, which significantly degrade blade performance. Umar et al. (2022) reported that these effects increase the required starting torque while reducing turbine efficiency. To mitigate this, they proposed using thin airfoils specifically designed for low Reynolds numbers, such as SG6043 and NACA 4412, to improve turbine start-up behavior [47]. Gray et al. (2021) developed the G4510 airfoil for very low Reynolds numbers (Re = 3×10^4–9×10^4) and demonstrated a 52.2% performance improvement over the NACA 2412 at Re = 3×10^4, highlighting the importance of airfoil selection in low-wind environments [48]. Additionally, Akbari et al. (2023) emphasized that blade inertial drag and generator clogging reduce available torque in small wind turbines, suggesting increased twist angles and the use of lighter materials to enhance performance [49,50]. Faraz (2024) analyzed 21 years of wind data from the Al Jawf region in Saudi Arabia and found an average wind speed of 4.38 m/s. The Vestas V126 turbine achieved 3.78 GWh annually with a 14.4% capacity factor, demonstrating its suitability for LWSRs [51]. Furthermore, Umar et al. (2022) used Q-Blade and BEM theory to reduce the cut-in wind speed to 1.7 m/s by optimizing blade profiles, chord lengths, and twist distributions across varying Reynolds numbers [52,53].

Table 2 From 2020 to 2025, the design of light water small reactors offered a few challenges [54].

Author & Year	Objective	Methodology / Tools	Key Results	Limitations	Research Gap	Ref
Umar et al. (2022)	Achieve reliable start-up and Cp in low-wind conditions	BEM (MATLAB) + QBlade; SG6043 vs NACA4412; chord & twist tuning	Cut-in ≈ 1.7–1.8 m/s; Cp ≈ 0.42–0.45	Assumes ideal inflow; generator/control ignored	Need field validation with turbulence; integrate drivetrain & structural FSI	[56]
Gray et al. (2021)	Improve low-Re airfoil performance	XFOIL comparisons; G4510 vs common airfoils at Re ≈ 3×10^4–9×10^4	G4510 gave +52.2% efficiency vs NACA2412 at Re=3×10^4	2D only; no blade/field tests; ignores noise/erosion	Require experimental validation; evaluate durability under LWSR conditions	[57]
Akbari et al. (2023)	Quantify elevation & blade density impacts	Differential Evolution (DE) optimization; BEM; quasi-steady start-up torque	Cp drop ≈ 2–3% at 2250 m; start-up failure risk >1607 m; re-optimization restores Cp	Simplified quasi-steady torque; limited aeroelasticity	Extend to gust/turbulence, varied generators, other airfoils	[58]
Faraz (2024)	Assess site viability & turbine selection in LWSR	21-yr wind dataset; Weibull (MLE); AEP/CF comparison	V126 produced 3.78 GWh/yr; CF ≈ 14.4% at mean U≈4.4 m/s	Single site only; assumes generic losses	Add terrain/turbulence/wake effects; embed LCOE/LCA	[59]

3.2. Aerodynamic optimization strategies

Enhancing the aerodynamics of wind turbine blades is essential for maximizing annual energy production, particularly at low-wind sites [61–64]. Effective aerodynamic design aims to balance lift generation, stall behavior, and drag reduction under varying wind conditions [61]. Numerical modeling, experimental testing, and surrogate-based approaches are widely used to improve aerodynamic performance while controlling computational cost [62]. Blade Element Momentum (BEM) theory remains one of the most commonly applied methods due to its low computational demand [61]. When augmented with tip-loss corrections, three-dimensional effects, and dynamic inflow models, BEM performs effectively in multi-parameter aerodynamic optimization [61,62]. High-fidelity Computational Fluid Dynamics (CFD) is considered the benchmark for analyzing complex and unsteady airflow phenomena. Zhang et al. (2023) demonstrated that fine-mesh CFD solvers provide accurate predictions for airfoil and blade profiles, though at high computational expense [61]. To reduce this burden, Roslan et al. (2023) developed an enhanced BEM model with tip-loss, high-induction, and post-stall corrections, achieving improved power coefficient predictions for a small-scale wind turbine using the SG6043 airfoil [62]. Abdelkhalig et al. (2022) showed that advanced numerical improvements allow BEM results to closely agree with CFD simulations [61]. Zhong et al. (2024) further refined tip-loss correction models to improve accuracy for three-dimensional and unsteady flow effects [62], while Jin and Yang (2021) proposed a robust fixed-point solution method for BEM equations [61]. Surrogate models significantly accelerate aerodynamic optimization. Kriging-based models reduce CFD evaluations by up to 70% while maintaining errors below 3%, whereas RBF models provide stability in high-dimensional design spaces [62]. Geometric optimization of chord, twist, sweep, and airfoil shape has yielded notable gains in AEP and load reduction [63]. Despite these advances, real-world applicability remains challenging due to turbulence, inflow variability, and data-quality limitations in surrogate training [64].

Table 3 Aerodynamic optimization strategies (2020-2025).

Author & Year	Objective	Methodology / Tools	Key Results	Limitations	Research Gap
Jin & Yang (2021)	Make BEM solution more robust	Fixed-point BEM solver	Stable convergence, better prediction near induction	Validation mostly numerical	Integrate robust BEM into optimization and validate with field data
Zhong et al. (2024)	Improve tip-loss correction	g-function linked to thrust CT	Lower error vs Prandtl model	Few rotors tested	Extend to yaw/misalignment and low-Re roughness
Umar et al. (2022)	Achieve low cut-in Cp in small HAWT	BEM + QBlade	Cut-in 1.7–1.8 m/s; Cp ≈0.42–0.45	Idealized inflow, no drivetrain coupling	Add drivetrain/control and turbulence validation
Bekkai et al. (2025)	Optimize micro-HAWT blade	RSM + CFD/BEM + MOGA	~17% Cp gain	Micro-scale only	Scale up to MW class and LWSR spectra

3.3. Structural and material modeling of blades

Structural models of wind turbine blades are very important to ensure mechanical failures, deformation, or fatigue do not cancel out gains in how well they move through the air. The need for blades that are light but strong enough to work well at low speeds, without shortening their lifespan, creates more challenges in low wind areas. This part combines current methods in structural models, material choices, and ways to find the best structural setups to manage these competing needs (Figure 4).

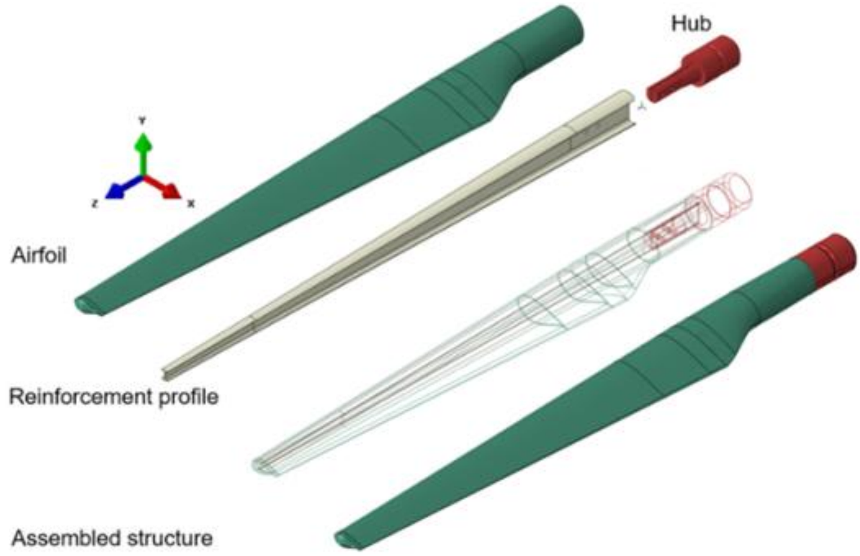

Figure 4 The different parts of a wind turbine blade [19].

Composite materials remain fundamental to modern wind turbine blade construction due to their high strength-to-weight ratio and design flexibility. Glass fiber reinforced polymers (GFRP) are widely used because of their low cost and ease of manufacturing, while carbon fiber reinforced polymers (CFRP) are increasingly applied in critical load-bearing regions where high stiffness and reduced weight are required [19]. Hybrid blade designs that combine GFRP in less critical regions with CFRP in highly stressed areas enable significant weight reduction without compromising structural strength (Umar et al., 2022). Such mixed-material configurations are particularly effective in improving blade performance under demanding wind loads. Proper ply layup is a key structural consideration, especially in spar caps and beam caps that carry most bending stresses. Ma et al. (2025) demonstrated that optimizing ply thickness in GFRP beam caps can reduce blade mass while maintaining sufficient stiffness. Similarly, He et al. (2025) emphasized integrating structural modeling early in the optimization process to preserve aeroelastic coupling, which is crucial for large blades operating under dynamic loading. Structural behavior is commonly analyzed using Classical Laminate Theory (CLT) and finite element analysis (FEA), with tools such as BECAS generating stiffness and mass matrices for aeroelastic simulations. Akbari et al. (2023) used FEA to show that modifying spar cap layups can significantly reduce bending stresses without notable weight penalties. Early-stage designs often rely on simplified beam models based on Timoshenko theory to reduce computational cost, though these approaches lack local stress resolution. Werthen et al. (2024) showed that Timoshenko beam theory outperforms Euler–Bernoulli theory in capturing shear deformation effects in flexible blades. Hybrid composite concepts continue to evolve, including hardwood–composite blades, which Umar et al. (2022) found to be cost-effective and well damped, provided moisture and weight issues are managed. Fatigue remains a critical concern; Liu (2024) identified stress concentrations in adhesive joints using sub-modeling, while Zhang and Chen (2024) showed accelerated delamination under stochastic wind loading. Despite progress, many studies neglect manufacturing defects, environmental aging, and fatigue degradation, particularly relevant for LWSRs. Although surrogate-assisted structural optimization shows promise in reducing computational costs, it remains underutilized compared to aerodynamic optimization approaches [65,66].

Table 4 Wind turbine blade structural and material modeling methods (2020-2025).

Author & Year	Objective	Methodology / Tools	Key Results	Limitations	Research Gap
Werthen et al. (2024)	Cross-section modeling comparison	Analytical vs 2D FE (BECAS)	Stiffness error <1%, >10× faster	Manufacturing defects ignored	Add defects, bondlines, shear lag
Liu et al. (2024)	Fatigue of adhesive joints	FE sub-modeling	Critical interlaminar stresses identified	Limited load cases	Couple with stochastic winds for reliability
Wang et al. (2024)	Multiscale dynamics of offshore blades	3D multiscale model + OpenFAST	Accurate root loads and fatigue	Offshore focus, high cost	Adapt to onshore LWSR gust spectra
Hermansen & Lund (2024)	Root thickness optimization	Gradient-based DMTO	Mass reduction while meeting constraints	Manufacturing constraints not enforced	Joint root-hub manufacturability studies

3.4. Aero-structural coupling and FSI frameworks

Wind turbine blade design must account for the strong interaction between airflow and structural deformation, especially in low-wind regions where longer, more flexible blades are used. Aeroelastic coupling significantly affects performance and durability, making integrated modeling tools and optimization methods essential for achieving efficient and reliable blade designs (Figure 5).

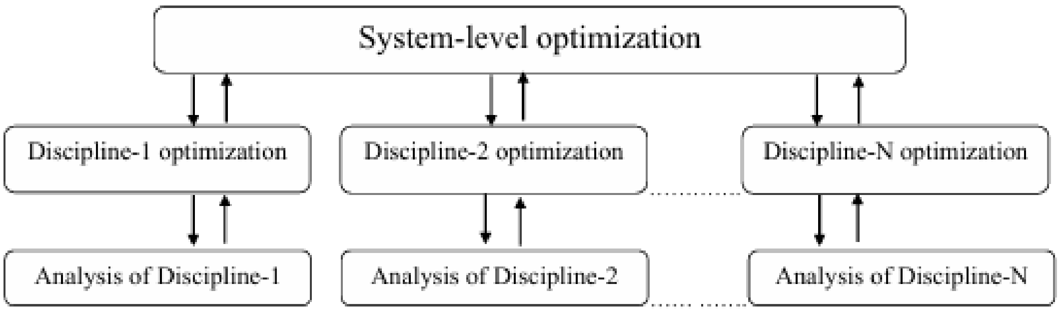

Figure 5 FSI frameworks.

The literature describes two main approaches for aero-structural coupling in wind turbine blade analysis: loose coupling and tight coupling. Loose coupling exchanges aerodynamic and structural information sequentially across multiple solution steps, requiring relatively low computational resources but offering limited accuracy for highly flexible blades. In contrast, tight coupling solves aerodynamic and structural governing equations simultaneously at each time step, significantly improving prediction accuracy at the expense of increased computational cost. He et al. (2025) demonstrated that tight coupling provides more accurate load and deformation predictions for long, flexible blades operating in low-wind-speed regions, particularly under gusty conditions [67]. A wide range of software tools supports aero-structural simulations. OpenFAST is commonly used for aeroelastic analysis by integrating Blade Element Momentum (BEM) theory with structural dynamics solvers. For higher-fidelity analysis, CFD solvers such as STAR-CCM+ or CFX are coupled with finite element software like Abaqus to resolve three-dimensional flow effects and nonlinear material behavior. Ma et al. (2025) reported that CFD–FEM coupling improved deformation prediction accuracy by more than 20% compared with conventional BEM–beam approaches under non-ideal conditions. Co-simulation frameworks enabling data exchange between CFD and FEM solvers have been highlighted by Lu et al. (2024) and Tamayo-Avendaño et al. (2023) as essential for capturing complex aeroelastic phenomena, including dynamic stall and flutter, despite their high computational demands. Passive load-control strategies such as bend–twist coupling are increasingly incorporated into LWSR blade designs. Lu et al. (2024) showed through two-way FSI simulations of the NREL 5-MW turbine that flexible blades produced 9.6% less power than stiff blades while exhibiting significant rotor–tower interactions. To reduce computational costs, surrogate models are increasingly embedded in MDO frameworks. Caprace et al. (2022) integrated CFD-CSM simulations into OpenFAST using surrogate-assisted MDO, resulting in rotors with improved load-bearing and stress resistance [68].

3.5. Surrogate modeling in MDO

Surrogate modeling is a key element of multidisciplinary design optimization (MDO) for wind turbine blades, particularly when high-fidelity aerodynamic and structural analyses are computationally expensive. These models enable rapid evaluation of design alternatives in low-wind conditions. Kriging is the most widely used surrogate due to its accuracy and uncertainty quantification capabilities. Studies show it can reduce computational cost by over 70% while maintaining errors below 3%. Adaptive Kriging and Gaussian Process Regression further enhance accuracy through iterative sampling strategies [69]. Radial Basis Function (RBF) surrogates provide fast training and efficiently handle large datasets, making them suitable for preliminary parametric studies (Yang et al., 2024). He et al. (2025) reported slightly higher errors (~5%) compared to Kriging, but with greater design space exploration under limited computational budgets. Hybrid approaches such as co-Kriging are increasingly adopted, combining low- and high-fidelity data to improve accuracy. Kirby et al. (2024) demonstrated over 90% reduction in high-fidelity samples while maintaining 93–96% accuracy. Despite these advantages, surrogate accuracy strongly depends on data quality, and multiphysics surrogate integration for LWSRs remains limited [70].

Table 5 Surrogate modeling in MDO (2020–2025).

Author & Year	Objective	Methodology / Tools	Key Results	Limitations	Research Gap	Ref
Ma et al. (2025)	Reduce computational cost in composite blade MDO	Adaptive Kriging + CCEI-SSO + parametric FEA	Achieved 2–5× speed-up with ≤5% error in design objectives	Surrogate accuracy depends on training sample distribution	Extend to FSI-in-the-loop and LWSR-specific optimization	[71]
Cheng et al. (2023)	Apply surrogate models for wind turbine design optimization	Surrogate-assisted optimization framework; regression models	Demonstrated reduced computational expense with acceptable accuracy	Limited to specific case studies; generalization unclear	Broaden surrogate datasets and test across multi-site wind conditions	[72]
Porta Ko et al. (2024)	Develop hybrid optimization using multi-fidelity strategies	Low-fidelity & high-fidelity GA with transfer learning	Reported 2–3× faster convergence; accuracy dependent on LF model quality	LF model accuracy critical; transfer may fail with large discrepancies	Combine multi-fidelity + surrogate frameworks in blade optimization	[73]
Yang et al. (2024)	Integrate ML-based surrogates into MDO of turbine blades	ML regression & surrogate modeling approaches	Achieved accurate predictions for aero-structural performance	Lack of interpretability in ML surrogates	Explore hybrid physics-ML surrogates for transparent optimization	[74]
Kirby et al. (2024)	Use surrogate-based aero-structural predictions for optimization	Surrogate models trained on CFD/FEA datasets	Showed high accuracy with reduced simulation time	Needs larger training datasets; sensitive to data quality	Develop generalized surrogate libraries for aero-structural MDO	[75]
He et al. (2025)	Demonstrate high-fidelity FSI framework	CFD–FEA co-simulation frameworks	Provides accurate but costly results	Not a surrogate approach; computationally intensive	Serves as motivation for surrogate integration into FSI	[76]

3.6. Multi-objective optimization strategies (NSGA-II)

Multi-objective optimization (MOO) is essential in wind turbine blade design because competing goals such as maximizing annual energy production, minimizing structural mass, and reducing energy cost must be addressed simultaneously, especially in low-wind-speed regions (LWSRs). Among available methods, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) remains the most widely used due to its ability to efficiently identify well-distributed Pareto-optimal solutions (Couto et al., 2023; Özkan & Genç, 2021). Umar et al. applied NSGA-II to optimize chord, twist, and layer thickness, achieving over 5% AEP increase and an 8% reduction in blade mass, while integrating Kriging surrogates reduced computational time by more than 60%. Beyond aero-structural optimization, Ma et al. (2025) coupled NSGA-II with surrogate-based aerodynamic, structural, and cost models, resulting in improved performance and 4–7% LCOE reduction. Although alternatives such as MOPSO and SPEA2 exist, NSGA-II consistently delivers superior solution diversity and robustness (He et al., 2025). However, many studies rely on idealized wind conditions and limited full-scale validation, limiting real-world applicability [77].

3.7. Economic and environmental evaluation (LCOE, LCA)

Wind turbine blade design increasingly incorporates both economic and environmental considerations to ensure technical reliability, cost effectiveness, and long-term sustainability. This integration is particularly critical in low wind speed regions (LWSRs), where maximizing annual energy production while minimizing energy cost is essential for project viability. As a result, techno-economic and environmental assessment tools are now being embedded into blade design frameworks to guide informed engineering decisions. Levelized cost of energy (LCOE) has become a standard economic metric in wind energy projects. The author [78] demonstrated that optimizing blade design while accounting for material costs can reduce LCOE in LWSR projects by up to 6%, directly linking aerodynamic and structural improvements to economic performance. Similarly, [79] showed that reducing cut-in wind speed significantly lowers LCOE in resource-limited locations. Life cycle assessment (LCA) is increasingly paired with LCOE to evaluate environmental impacts such as global warming potential (GWP), energy consumption, and material recyclability. Also, [80] found that replacing certain GFRP components with recyclable thermoplastics could reduce GWP by 15% without compromising structural integrity. Further demonstrated [81] that modest increases in LCOE can yield substantial reductions in CO_2 emissions through low-specific-power designs. Despite these advances, integrated LCOE–LCA optimization remains uncommon, as environmental metrics are often considered only after design completion, limiting early-stage sustainability improvements [82].

4. RESULTS AND DISCUSSION

The present study indicates clear progress in improving wind turbine blades for low wind speed locations. This is thanks to improvements in how we model airflow, refine the structure, use MDO with substitutes, and employ multi-objective algorithms like NSGA-II. A close look at these topics, there are agreements and disagreements in how researchers are approaching this. Some research questions remain, and answering them will lead to wind turbine blade designs that are cheaper, work better [83] (Figure 6).

4.1. Synthesis of key findings

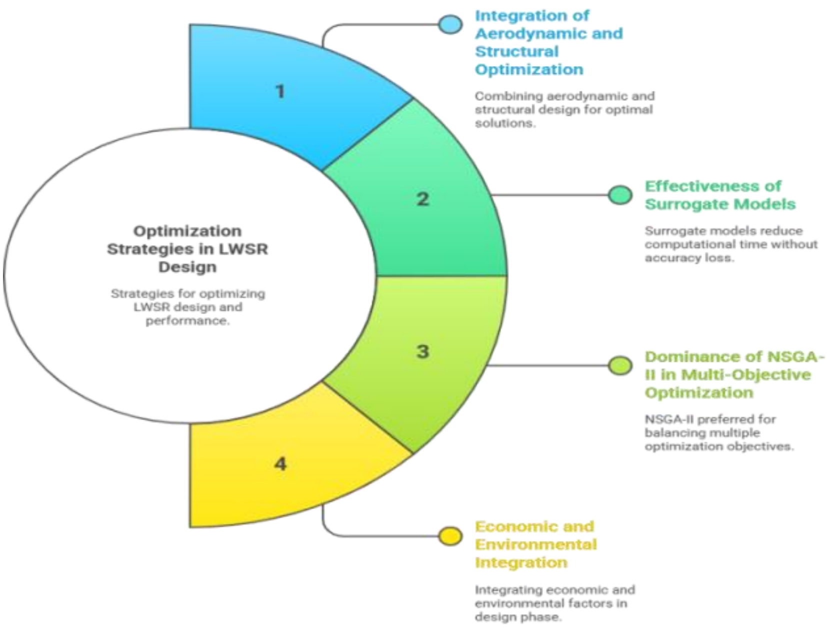

Figure 6 Design tips for large-scale wireless sensor networks.

1. Integration of Aerodynamic and Structural Optimization
Most studies agree that handling aerodynamic and structural design separately isn't the best approach, especially for flexible blades in LWSRs. Frameworks that bring together Blade Element Momentum theory, Computational Fluid Dynamics, and Finite Element Analysis in a Multidisciplinary Design concept loop give better performance predictions and design trade-offs. Still, complete aeroelastic coupling isn't always used because it costs too much in computing power [84].

2. Effectiveness of Surrogate Models
In optimization processes, Kriging and Radial Basis Function (RBF) surrogates usually cut computation times by 60–70% while keeping accuracy high. Methods that combine approaches, such as co-Kriging, can enhance precision in designs that use several levels of accuracy, but these are not often explored in studies focused on LWSR.

3. Dominance of NSGA-II in Multi-Objective Optimization
NSGA-II is still a popular algorithm for balancing goals related to aerodynamics, structure, and cost. Some other algorithms, like MOPSO and SPEA2, have been tried, but NSGA-II remains popular because it converges in a stable way and works well with surrogate models.

4. Economic and Environmental Integration
LCOE analysis is commonly used within optimization systems, but life cycle assessment (LCA) is not often included during the design phase. This restricts the capability to concurrently find the best balance between cost and sustainability.

4.2. Contradictions in the literature

The literature presents mixed findings on modeling and optimization strategies for LWSR wind turbine blades. Some studies emphasize tightly coupled aerodynamic–structural models for accurate load prediction, while others find loosely coupled approaches sufficient during early design stages, as annual energy production changes little. Simpler surrogate models are widely used but show inconsistent errors due to differences in training data quality and distribution. Sensitivity studies on energy cost also vary, with some highlighting material costs as dominant, while others identify annual energy production and cut-in wind speed as more influential factors [85].

4.3. Research gaps

Several gaps remain in current surrogate-assisted wind turbine blade research. Many frameworks lack real-world validation and are mainly tested under idealized wind conditions or synthetic data. Existing surrogate models are often single-physics, failing to capture coupled aeroelastic, control, and economic interactions. Life cycle assessment is rarely integrated during optimization, and tightly coupled models remain computationally expensive. Additionally, manufacturability, transportation, and maintenance constraints are frequently overlooked despite their importance for deployment in low-wind-speed regions [86].

4.4. Effect of nanotechnology on wind turbine blade optimization

The integration of nanotechnology significantly improves wind turbine blade performance by enhancing material properties and aerodynamic efficiency. Nanocomposites increase strength-to-weight ratio, while nanoscale surface modifications reduce drag and improve lift characteristics. These improvements lead to increased AEP, reduced LCOE, and enhanced structural reliability, particularly in low wind speed regions [87].
Table 6 presents a comparison between conventional and nano-enhanced designs, demonstrating improvements in energy production, cost reduction, and structural performance.

Table 6 Comparison between conventional and nanotechnology-enhanced wind turbine blade optimization approaches.

Parameter	Conventional Design	Nano-Enhanced Design
AEP	Moderate	High
LCOE Reduction	Moderate	High
Computational Cost	High	Reduced
Structural Reliability	Moderate	Improved
Optimization Accuracy	Good	Excellent

Figure 7 presents the impact of nanotechnology on blade optimization, highlighting improved performance and efficiency compared to conventional approaches.

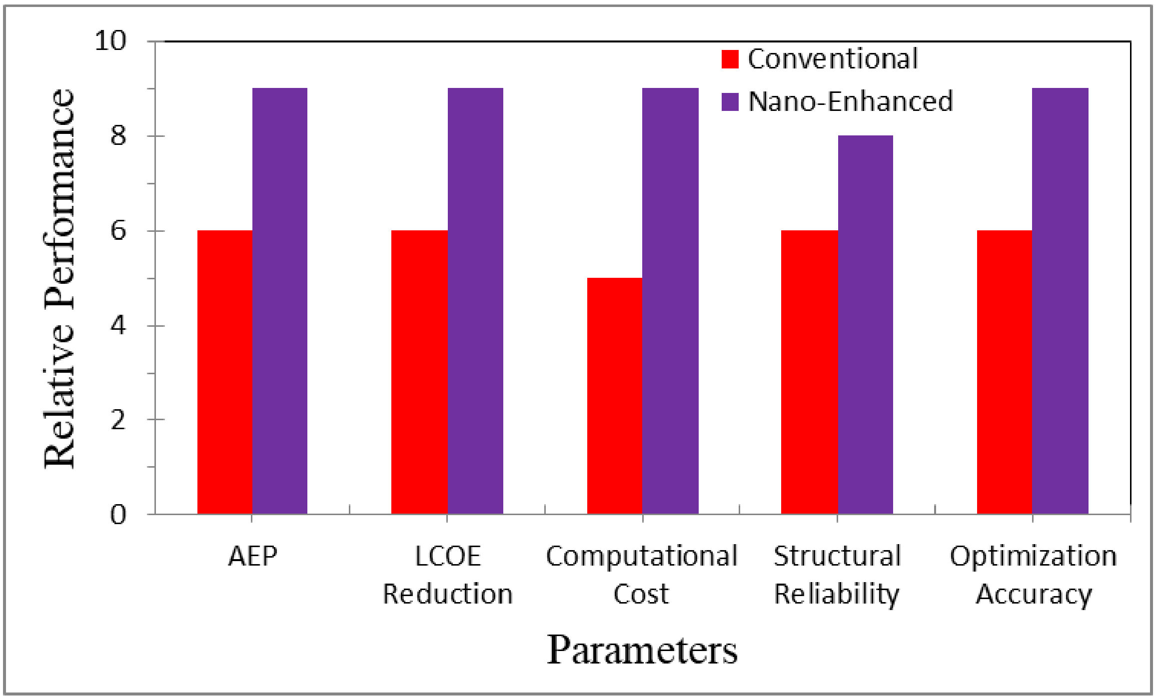

Figure 7 Graphical comparison of conventional and nanotechnology-enhanced blade optimization showing improvements in AEP, LCOE, structural reliability, and computational efficiency.

4.5. Future research directions

Future research should focus on developing flexible, integrated multiphysics frameworks that simultaneously address aerodynamic performance, structural behavior, and cost objectives within a single modeling environment [88]. Early incorporation of LCOE–LCA co-design is essential so that economic and sustainability decisions can be evaluated together rather than sequentially [89]. Validation efforts should be expanded through prototype testing in diverse low-wind-speed regions (LWSRs) to ensure that surrogate-based predictions remain reliable under real operating conditions [90]. In addition, combining simple passive control strategies, such as bend–twist coupling, with active control systems could further reduce loads and improve blade efficiency [91]. Finally, adopting production-aware design approaches will help ensure that optimized blades can be manufactured, transported, installed, and maintained cost-effectively, increasing their practicality and adoption in LWSR markets [92].

5. CONCLUSIONS

This paper reviews recent research (2020–2025) on using surrogate models to enhance wind turbine blade design for low-wind-speed regions. The main objective is to maximize energy capture while reducing costs. The review covers key areas, including aerodynamic modeling, structural optimization, aeroelastic interactions, surrogate model development, and multi-objective design optimization. It also examines the integration of economic and environmental factors into blade design. Results show that combining aerodynamic, structural, and economic objectives leads to better performance than traditional single-discipline approaches, especially when surrogate models are applied. Kriging and Radial Basis Function models can reduce computational costs by 60–70% while maintaining high accuracy. NSGA-II remains widely used for multi-objective optimization. While LCOE is commonly applied, LCA is rarely included. Future research should focus on multiphysics surrogate models, real-world validation, and early integration of sustainability metrics to advance cost-effective wind energy solutions. The integration of nanotechnology into wind turbine blade design provides a powerful pathway for improving aerodynamic efficiency, structural strength, and overall performance. nanocomposite materials and nanoscale enhancements contribute to increased AEP, reduced LCOE, and improved reliability. Future research should focus on integrating nanotechnology with surrogate-assisted optimization frameworks for next-generation wind turbine systems.

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