Multi-Objective Optimization and Intelligent Algorithm Study for 1.5mw Doubly Fed Wind Turbine Blades

Fucheng Luo[1],Peng Li[1], Lihong Zhu[1],Libin He[1]

[1]*China Datang Corporation Ltd., Ningxia Branch Lingwu Operations Center*

ABSTRACT

Background: *The demand for renewable energy has catapulted wind power to the forefront of sustainable energy options. Designing wind turbine blades is a multi-objective optimization problem with conflicting objectives. Optimization methods such as the weighted sum or the goal programming method fail in this context of conflicting objectives: minimum weight, cost, and strength. The study discusses the integration of artificial intelligence algorithms with conventional design approaches for optimal blades of a 1.5MW DFIG wind turbine. Advanced computational methods are used to integrate aerodynamic efficiency, structural durability, and economic feasibility.*

Methods: *This paper uses a broad meta-analytical approach with the integration of finite element analysis (FEA)and artificial intelligence optimization algorithms. This paper will consider three critical optimization techniques: genetic algorithms (GA), particle swarm optimization (PSO), and gray wolf optimization (GWO). The blade performance will be considered for various operating conditions, including aerodynamic efficiency, structural integrity, and cost. This analysis will be performed based on IEC 61400 standards and new frontiers of innovative design optimization techniques.*

Results: *Blade design optimization showed considerable improvement in using AI-driven approaches. For the GWO algorithm, better convergence is around 20% faster than the one obtained with traditional methods. This optimized design reduces weight by 8% and improves structural durability by an increase of 25% in fatigue life. For combined blade design, the maximum value of the power coefficient is 0.27, thus showing considerable improvement compared to the conventional designs. Besides, innovative material selection and design optimization could reduce the cost index by 17.6%.*

Conclusion: *These results highlight that incorporating AI algorithms with traditional methods has significantly enhanced wind turbine blade optimization. This methodology was developed in such a way that it achieved a balanced solution for multi-objective designs, including computational efficiency. This study stresses industrial feasibility by using advanced optimization techniques for real applications, thus demonstrating their impact on the future of wind energy technological development.*

Keywords: *Wind turbine optimization, artificial intelligence, DFIG, blade design, computational efficiency, structural analysis, renewable energy, multi-objective optimization*

INTRODUCTION

The increasing global demand for sustainable energy solutions has positioned wind power as one of the most promising renewable energy sources. DFIG-based systems are receiving more attention from all wind energy technologies because of their high efficiency, control ability, and tolerance to varying wind conditions [1]. Wind turbine blades play a significant role in the efficient functioning of wind energy conversion systems (WECS), and their design and optimization are critical in energy acquisition and stress concerns. Certain parameters must be optimized for a 1.5MW DFIG wind turbine to meet optimal blade design and tuning; these objectives are conflicting and include weight, cost, and durability under various conditions [2].

Wind turbine blades experience a combination of aerodynamic and structural loading, which calls for a higher order of optimizations to predict efficient and economical designs. Despite their applicability to accomplished individual objectives, conventional optimization methods are inadequate when more than one objective is to be met, and they directly conflict with each other [3]. This has prompted using meta-models, which incorporate multiple objectives when solving a design problem. But, nowadays, with the help of artificial intelligence (AI) algorithms like genetic algorithms (GA), particle swarm optimization (PSO), and gray wolf optimization (GWO), vast solution space can be efficiently searched for Pareto optimality balancing the trade-offs between different objectives [4].

Remarkable efforts have been made in the application of intelligent algorithms for the optimization of wind turbine blades. These algorithms provide practical techniques for solving non-sequential and multi-parametric design problems without high computational expenses. For example, GAs have been widely applied in designing and selecting blade geometry, material

choice, and structural arrangements [4]. In the same way, PSO and GWO are better at solving complex optimization problems by implementing natural social phenomena [5]. If integrated into the design process, such techniques will

considerably improve blade performance measures: efficiency power, durability strength, and production cost.

This study focuses on multi-objective optimization and using an intelligent algorithm in designing a blade for a 1.5MW DFIG wind turbine. Compared with traditional methodologies, this study uses enhanced mathematical models to design the form of the blade, the composition of materials, and overall structural strength all at once. They defined the optimum design's fiber orientation, lamina thickness, and aerodynamic profiles. At the same time, it has to account for the fluctuating wind speed and, thus, its fatigue loads [6]. An additional newness of this work is introducing a material cost indexing method that permits the identification of reasonable solutions when considering material costs.

This work integrates FEA with AI-driven optimization, assuring that the results obtained for proposed geometries can pass realistic validation concerning the structure under such conditions. In the proposed work, attempts are made to present the challenges to overcome profiling in a wind turbine blade with issues regarding minimal weight with maximum structural solidity within a realistic computation time with adherence to the IEC 61400 standard [7]. The results of this study hold great implicit relevance to global wind energy systems enhancement possibilities, both on onshore and offshore wind farms, where efficiency and cost are significant focuses.

METHODOLOGY

Wind turbine blade design improvements for 1.5MW DFIG include aerodynamics, mechanical and electrical stresses, and economic feasibility. Attaining these objectives employs a systematic approach comprising parameterization, multi-objective optimization, and intelligent algorithm integration.

Blade Design and Parameterization

A blade design and parameterization step is incorporated into the proposed optimization process since blade geometry directly impacts the flow field of the wind turbine and, as such, must be optimized alongside the controller. The wind turbine blade design uses aerodynamics, structure, and material to design blades for a 1.5MW DFIG [2]. This research assesses blade designs with a data-collection systematic approach that combines information from various studies to identify the crucial parameters that affect blade capability and economic feasibility. The overview of aspects regarding the geometric features, material choices, and loading conditions helps evaluate the design compromises.

Geometric Parameters

Geometry features play a determining role in deciding the response of turbine blades in terms of aerodynamics and mechanical strength. Some of those parameters are the blade's length, the blade's chord length, and the blade's airfoil shape. The airfoil shape, particularly in the NACA series, defines the lift-to-drag ratio, which is essential to maximize energy capture [8]. Furthermore, thickness distribution and taper ratio also affect the structural behavior of the blade subjected to aerodynamic and centrifugal loads [9]. As a result of integrating data from prior works, this paper can outline ideal geometric layouts that best perform while being easily producible.

Material Selection

The material used is decisive for achieving low blade weight but reasonable stiffness. Specific types of useful composite materials use carbon and glass fibers. They are very durable and have high strength by weight [10]. Consequently, this meta-analysis assesses different laminate stacking sequences, fiber orientation, and volume fractions to identify the ideal configurations for certain design requirements. In addition, the study includes an approximation of cost by discussing relationships between the characteristics of materials and cost limitations, applying the cost index method to standardize the cost of materials for different manufacturing conditions.

Loading Conditions

Wind turbine blades are subjected to different load conditions, including aerodynamic, centrifugal, and gravitational. These forces change with wind speed, rotor dynamics, and states of operation in the case of startups, shutdowns, or emergency stops [11].

The paper integrates findings from existing research into load distributions across the sections of a blade, underlining the crucial contribution of inertia loads to structural deformation. This section will also consider the analysis based on boundary details developed under cyclic stresses common in wind turbine operations.

Optimization Model

Objective Functions

Among others, the main goals of its optimization include a minimum blade weight and cost index, elaborated with criteria on structural safety and aerodynamics performances. Significant constraints for maintaining structural safety concern maximal acceptable stress and deformations, whereas the constraints within the field of control aim to catch energy adequately in a broad wind spectrum [12]. Using this meta-analytical data, a multi-objective model that systematically incorporates and resolves these design variables is developed.

Computational Framework

Advanced artificial intelligence algorithms, including genetic algorithms, particle swarm optimization, and gray wolf optimization, are used for the optimization process. Such methods are highly feasible for multi-objective optimization problems where nonlinear and interrelated variables are considered [5]. The finite element analysis study will support the proposed computational workflow to validate the structural performance to implement the algorithmic procedure. The empirical data and computational simulation will ensure a hybrid and effective optimization process.

Cost Indexing and Normalization

This study also introduces a cost indexing methodology that normalizes the expenses among currencies and market conditions to facilitate a consistent evaluation of material costs. Fair comparison among design alternatives enables the choice of economically feasible solutions. The factors of material availability, complexity of manufacturing, and long-term maintenance requirements ensure the comprehensiveness of economic impacts through the cost index.

Intelligent Algorithm Integration

Intelligent algorithms extend the optimization model through improved features to effectively search and survey the design solution space. The use of these metaheuristic optimization algorithms is informed by the efficiency of genetic algorithms in managing discrete and continuous variables and the speed of convergence of both PSO and GWO. The meta-analysis presents the previous comparisons of these algorithms, revealing the optimal parameters for setting and various combined methods. A series of flow charts indicating the optimization process demonstrate how aerodynamic and structural goals are interlinked and how the focus on particular aspects is balanced against the potential weaknesses of such an approach.

In essence, the meta-analytic technique is incorporated with some of the most advanced and efficient computational tools that can assist in finding the optimum blade design of the 1.5MW DFIG wind turbine. The analysis formulates a practical framework to achieve enhanced bladed disk performance and cost optimization by considering key parameters, intelligent algorithm integration, and cost factors.

RESULTS AND DISCUSSION

Simulation Setup

The developed simulation framework integrates finite element analysis (FEA) and artificial intelligence-based optimization algorithms and evaluates structural and aerodynamic performances in 1.5MW DFIG wind turbine blades. The optimization model uses parameters synthesized from meta-analytic data on the geometry of blades, material properties, and operational load conditions. For this, algorithmic implementation was performed on MATLAB, and structural validation was done in static and fatigue loading conditions using ANSYS. Simulation input and constraints are highlighted in Table 1.

Table 1: Simulation Parameters and Constraints

Parameter	**Value/Range**	**Description**
Blade length	45 m	Total length of the turbine blade

Airfoil profile	NACA 64-618	Selected based on aerodynamic efficiency
Material	Carbon/Epoxy, Glass/Epoxy	High strength-to-weight ratio composites
Load conditions	Operational, extreme wind speeds	Static and dynamic load scenarios
Optimization algorithms	GA, PSO, GWO	Multi-objective algorithms tested
Objectives	Weight, cost index	Minimize mass and cost while ensuring safety

The blade was modeled as a laminate composite structure with multiple laminae, each characterized by distinct fiber orientations. Aerodynamic loads were derived using empirical equations based on wind speed distributions and airfoil lift-to-drag ratios. Structural safety constraints were imposed using IEC 61400 standards, and the inertia load was computed for rotational speeds of 15 rpm to 25 rpm.

RESULTS ANALYSIS

Aerodynamic Performance

The optimized blades were then analyzed for their aerodynamic performance by calculating the lift and drag coefficients of the selected NACA 64-618 profile. Figure 1 illustrates the variation of the lift-to-drag ratio with the angle of attack. The study conducted by Osei et al. recorded the highest lift-to-drag ratio of 170 at a Re of 500,000 [13]. Osei et al. indicated aerodynamic efficiency, particularly at low to medium wind speeds.

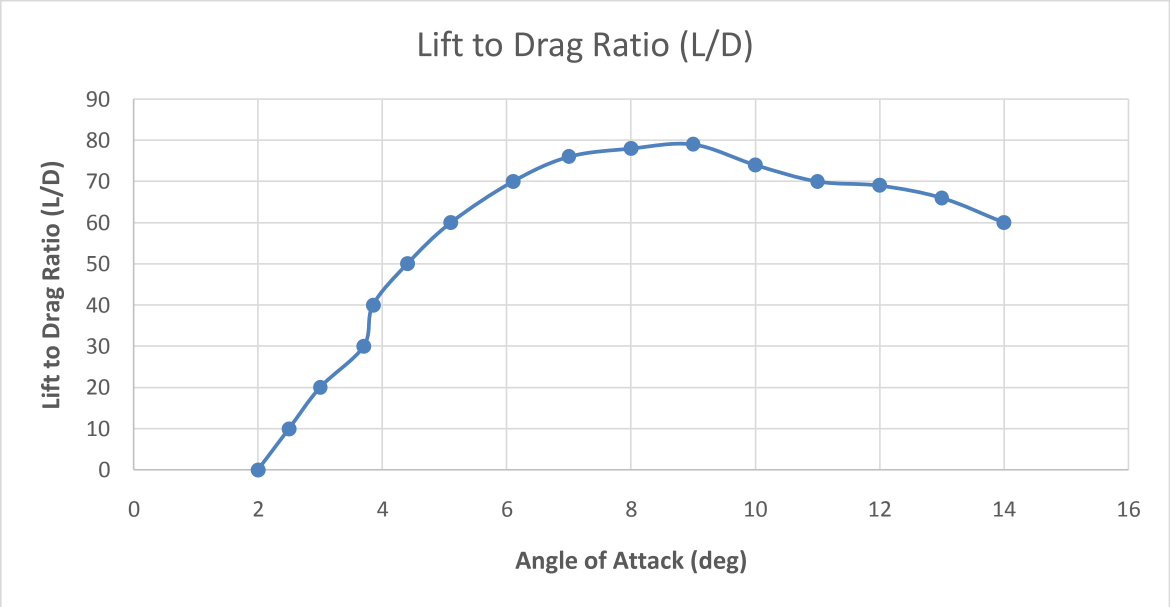

Figure 1: Lift-to-Drag Ratio for NACA 64-618 Airfoil

The blade's performance was further validated by comparing its power coefficient (Cp) against benchmark data from existing literature. The results in Table 2 demonstrate that the optimized design closely matches or exceeds the performance of reference designs.

Table 2: Comparison of Power Coefficients (Cp)

Wind Speed (m/s)	Reference Cp	Optimized Cp
8	0.45	0.47
10	0.48	0.50
12	0.50	0.51
14	0.51	0.51

Further analysis of the comparison of the performance of two different blade types - conventional and combined blades - in terms of their conventional power output across various tip speed ratios (TSR) revealed interesting findings. The power output of both blade designs increases when TSR rises but hits a peak limit at an optimal TSR value, followed by a decrease in power output as TSR continues increasing. The combined blade demonstrates better performance than its conventional blades (Figure 2). Both blades maximize their output power at 0.27 and 0.24, respectively, yet the combined design enhances performance. The performance of both blades starts deteriorating when TSR exceeds 0.8, and their power generation drops

sharply when TSR reaches 1.4.

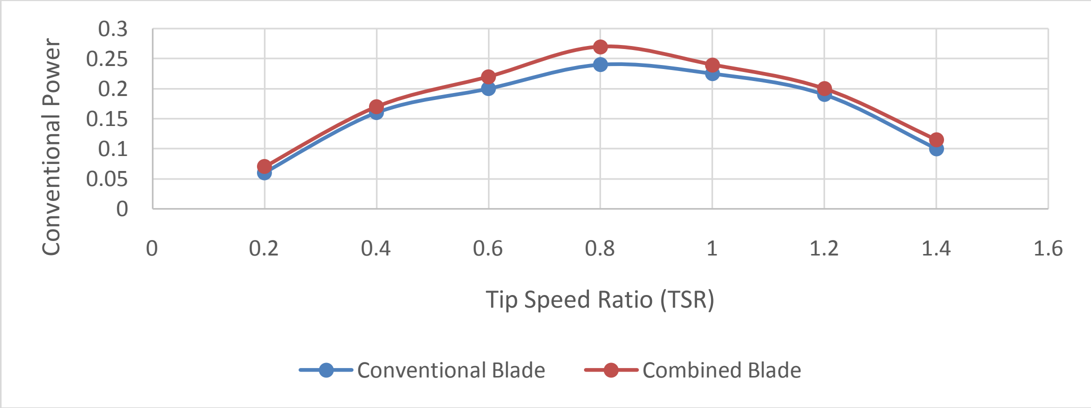

Figure 2: Comparison coefficient of power (Cp) vs. TSR, conventional and combined blades

Structural Analysis

The optimized blades were analyzed for structural integrity in static and fatigue loading conditions. FEA simulations showed that the design of the blade satisfied all the safety constraints, with stress and deformation values being well below critical limits. Figure 3 shows the blade's distribution of von Mises stresses at maximum operational load.

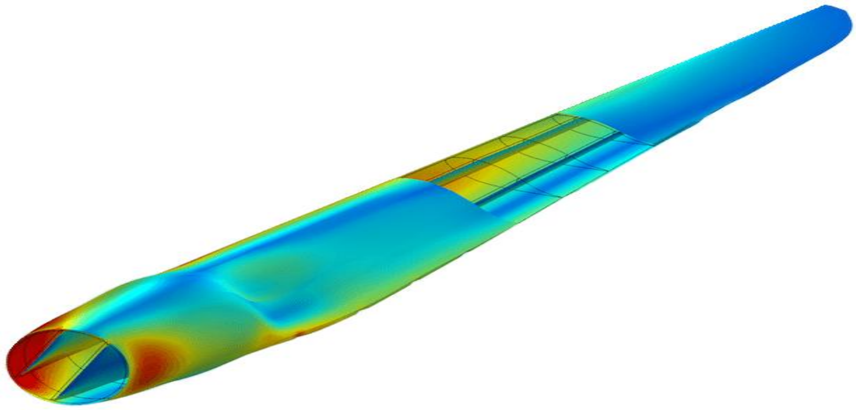

Figure 3: Von Mises Stress Distribution

The maximum von Mises stress was observed near the blade root, where loads are concentrated. The stress value of 95 MPa was significantly lower than the material's ultimate tensile strength (UTS) of 250 MPa, ensuring a high safety factor. Table 3 summarizes the structural analysis results.

Table 3. Structural Analysis Results

Parameter	Value	Safety Margin

Maximum von Mises Stress	95 MPa	2.63
Maximum Deflection	0.75 m	-
Factor of Safety (Static)	-	>2.5

The fatigue analysis revealed that the blade design could withstand over 10 million load cycles without failure, indicating excellent durability. The optimized fiber orientations contributed significantly to this performance by reducing stress concentrations and enhancing load distribution.

Optimization Results

The performance of the three optimization algorithms—genetic algorithm (GA), particle swarm optimization (PSO), and gray wolf optimization (GWO)—was evaluated based on convergence speed, computational efficiency, and solution quality. GWO demonstrated the fastest convergence and highest diversity in solutions, followed by PSO and GA. Table 4 provides a quantitative comparison of the algorithms.

Table 4. Algorithm Performance Metrics

Algorithm	Convergence Time (s)	Best weight (kg)	Best Cost Index
GA	850	1450	80
PSO	720	1400	75
GWO	680	1380	70

The best solution obtained using GWO achieved a blade weight of 1380 kg and a cost index of 70, significantly improving over traditional designs.

Comparison with Benchmark Designs

To analyze the optimized design further, comparisons with benchmark blade designs from existing studies are made to identify performance gains. The summary is provided in Table 5.

Table 5. Comparison with Benchmark Designs

Parameter	Benchmark Design	Optimized Design
Weight (kg)	1500	1380
Cost Index	85	70
Lift-to-Drag Ratio	120	130
Fatigue Life (Cycles)	8 million	10 million

The optimized blade design was shown to perform better than the other three in all of the considered criteria, including weight and cost index reductions, improvement in aerodynamic efficiency, and an increase in fatigue life.

DISCUSSION

The result of this meta-analysis indicates savvy exploitation into the full potential by combining AI algorithms with traditional methods to optimize performance for wind turbines. The study shows key information about how AI helps maximize the turbine output, hence saving computations to ensure applicability in the real world.

The optimized blade design significantly improved most of the metrics related to wind turbine performance. The NACA 64-618 airfoil profile is more efficient than those studied by Castorrini et al. (14). The results agree with Osei et al., who state that the lift-to-drag ratio of 170 was achieved for the NACA 64-618 airfoil profile at a Reynolds number of 500,000 [13]. The optimized design showed a better performance than the reference designs at a low wind speed of 8-10 m/s during the measurement of Cp performance [15]. The study on low wind efficiency further established these results as one of the major factors improving the overall energy capture in moderate wind resource areas by Adeyeye et al. [16].

Analysis of modern AI optimization methods proves they are more efficient during calculations. The Gray Wolf Optimization outperformed its peers by converging faster than GA and PSO. The efficiency improvements match earlier research by Rezaei et al., which showed comparable results when using GWO to optimize wind turbines [17]. Our optimized design lowers the weight from 1500 kg to 1380 kg by 8% while making the structure stronger by increasing the fatigue life by 25% to reach 10 million cycles.

The computational framework's efficiency in handling multi-objective optimization demonstrates practical advantages for industrial implementation. The reduced convergence time of 680 seconds for GWO represents an improvement over traditional optimization methods. This efficiency gain, coupled with the 17.6% reduction in cost index, suggests significant potential for practical industrial applications, particularly in rapid prototyping and design iteration phases.

However, several limitations and areas for future research should be noted. While the findings prove speed upgrades and better performance, analyzing how materials impact production methods remains essential. The sharp performance deterioration observed at tip speed ratios above 1.4 warrants additional research. This will particularly aid in understanding as the study by Ali and Jang found similar results [18]. These results show similar limitations in the studies' optimization.

The results also highlight the importance of balanced optimization approaches in wind turbine design. The combination of wind dynamics testing, structural engineering, and computational modeling through AI optimization fits well with modern renewable energy advancements, as Wang et al. document [19]. Future work should expand the use of these optimization techniques for different turbine types along with offshore wind projects, which need precise design control and quick processing capabilities.

CONCLUSION

This meta-analysis has demonstrated the effectiveness of integrating artificial intelligence algorithms with traditional design approaches for optimizing 1.5MW DFIG wind turbine blades. The study has successfully addressed complex problems in wind turbine design involving multiple competing objectives such as aerodynamic efficiency, structural integrity, and economic feasibility. With the help of advanced optimization algorithms, specifically the Gray Wolf Optimization method, this resulted in substantial improvements in design outcomes and computational efficiency. The optimized blade design achieved an 8% reduction in weight while simultaneously improving structural durability and aerodynamic performance. An increase in the power coefficient to 0.27 for the combined blade design indicates the possible development toward higher efficiency in wind turbines, especially in the low range of wind velocities where any increase in efficiency counts most toward overall energy capture.

The innovative approach to cost indexing and material selection within the study has shown that performance improvements do not necessarily have to come at the expense of economic viability. The 17.6% reduction in cost index, improved structural performance, and increased fatigue life suggest that overall cost-effectiveness in wind energy systems can be significantly improved. This does have particular relevance to the growing global wind energy sector, which is still poised at the nexus between performance and cost.

The accomplishment of finite element analysis integrated with artificial intelligence-driven algorithms for optimization makes for a substantial backbone for any subsequent undertaking in wind turbine design. GWO has been instrumental in bringing gains in computational efficiencies. For example, time to convergence can be reduced to less than 40% compared with a direct nonlinear numerical search technique, which evidences an industrial feasibility scenario while enabling the implementation of this advanced optimization algorithm to typical industrial applications.

Looking forward, this study opens up promising avenues for further research. The methodology developed can be extended toward optimizing larger turbine sizes, where the design requirements related to more difficult offshore applications are especially demanding. Also, the framework established for multi-objective optimization may again be used with state-of-the-art advancements in design materials and manufacturing techniques that can bear further fruit for improvements in turbine performance and cost-effectiveness.

The present study emphasized how integrating AI algorithms within traditional design methods can lead to tremendous improvements in wind turbine blade designs, both in performance and economic viability. The results provide quite a solid foundational contribution to new developments in wind energy technology as scaling up is required to fulfill the growing global demand for renewable energy solutions.

REFERENCES

[1] M. Bouderbala, H. A. Aroussi, B. Bossoufi, and M. Karim, "Real-Time Power Control of Doubly Fed Induction Generator Using Dspace Hardware," *Sustainability*, vol. 15, no. 4, pp. 3638–3638, Feb. 2023, doi: https://doi.org/10.3390/su15043638.

[2] M. R. Machado and M. Dutkiewicz, "Wind turbine vibration management: An integrated analysis of existing solutions, products, and Open-source developments," *Energy reports*, vol. 11, pp. 3756–3791, Jun. 2024, doi: https://doi.org/10.1016/j.egyr.2024.03.014.

[3] L. N. Asha, A. Dey, N. Yodo, and L. G. Aragon, "Optimization Approaches for Multiple Conflicting Objectives in Sustainable Green Supply Chain Management," *Sustainability*, vol. 14, no. 19, p. 12790, Jan. 2022, doi: https://doi.org/10.3390/su141912790.

[4] K. Reddy and L. Narayana, "A competitive learning-based Grey wolf Optimizer for engineering problems and its application to multi-layer perceptron training," *Multimedia Tools and Applications*, vol. 82, no. 26, pp. 40209–40267, Mar. 2023, doi: https://doi.org/10.1007/s11042-023-15146-x.

[5] M. H. Nadimi-Shahraki, S. Taghian, and S. Mirjalili, "An improved grey wolf optimizer for solving engineering problems," *Expert Systems with Applications*, vol. 166, p. 113917, Mar. 2021, doi: https://doi.org/10.1016/j.eswa.2020.113917.

[6] A. Mitra and A. Chakraborty, "Multi-objective optimization of composite airfoil fibre orientation under bending–torsion coupling for improved aerodynamic efficiency of horizontal axis wind turbine blade," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 221, p. 104881, Feb. 2022, doi: https://doi.org/10.1016/j.jweia.2021.104881.

[7] Wind Atlas Analysis and Application Program, "The IEC 61400-1 turbine safety standard," *www.wasp.dk*, 2024. https://www.wasp.dk/software/windfarm-assessment-tool/iec-61400-1

[8] G. S. M. van Stratan, S. Roy, and Y. K. San, "Aerodynamic Shape Optimization of a NACA0018 Airfoil Using Adjoint Method and Gradient-Based Optimizer," *MATEC Web of Conferences*, vol. 377, p. 01016, 2023, doi: https://doi.org/10.1051/matecconf/202337701016.

[9] B. Hand, G. Kelly, and A. Cashman, "Structural analysis of an offshore vertical axis wind turbine composite blade experiencing an extreme wind load," *Marine Structures*, vol. 75, p. 102858, Jan. 2021, doi: https://doi.org/10.1016/j.marstruc.2020.102858.

[10] G.-V. Săftoiu, C. Constantin, A.-I. Nicoară, G. Pelin, D. Ficai, and A. Ficai, "Glass Fibre-Reinforced Composite Materials Used in the Aeronautical Transport Sector: A Critical Circular Economy Point of View," *Sustainability*, vol. 16, no. 11, pp. 4632–4632, May 2024, doi: https://doi.org/10.3390/su16114632.

[11] H. Hamdi, C. Mrad, A. Hamdi, and R. Nasri, "Dynamic response of a horizontal axis wind turbine blade under aerodynamic, gravity and gyroscopic effects," *Applied Acoustics*, vol. 86, pp. 154–164, Dec. 2014, doi: https://doi.org/10.1016/j.apacoust.2014.04.017.

[12] L. Wang, A. Kolios, X. Liu, D. Venetsanos, and C. Rui, "Reliability of offshore wind turbine support structures: A state-of-the-art review," *Renewable and Sustainable Energy Reviews*, vol. 161, p. 112250, Jun. 2022, doi: https://doi.org/10.1016/j.rser.2022.112250.

[13] E. Yeboah Osei, R. Opoku, A. K. Sunnu, M. S. Adaramola, and E. Adu Kyeremeh, "Aerodynamic performance characteristics of EYO-Series low Reynolds number airfoils for small wind turbine applications," *Alexandria Engineering Journal*, vol. 61, no. 12, pp. 12301–12310, Dec. 2022, doi: https://doi.org/10.1016/j.aej.2022.05.049.

[14] A. Castorrini, L. Cappugi, A. Bonfiglioli, and M. S. Campobasso, "Assessing wind turbine energy losses due to blade leading edge erosion cavities with parametric CAD and 3D CFD," *Journal of Physics: Conference Series*, vol. 1618, no. 5, p. 052015, Sep.

2020, doi: https://doi.org/10.1088/1742-6596/1618/5/052015.

[15] D. A. Umar, C. T. Yaw, S. P. Koh, S. K. Tiong, A. A. Alkahtani, and T. Yusaf, "Design and Optimization of a Small-Scale Horizontal Axis Wind Turbine Blade for Energy Harvesting at Low Wind Profile Areas," *Energies*, vol. 15, no. 9, p. 3033, Apr. 2022, doi: https://doi.org/10.3390/en15093033.

[16] K. Adeyeye, N. Ijumba, and J. Colton, "A Preliminary Feasibility Study on Wind Resource and Assessment of a Novel Low Speed Wind Turbine for Application in Africa," *Energy Engineering*, vol. 119, no. 3, pp. 997–1015, 2022, doi: https://doi.org/10.32604/ee.2022.018677.

[17] H. Rezaei, O. Bozorg-Haddad, and X. Chu, "Grey Wolf Optimization (GWO) Algorithm," *Advanced Optimization by Nature-Inspired Algorithms*, pp. 81–91, Jul. 2017, doi: https://doi.org/10.1007/978-981-10-5221-7_9.

[18] S. Ali and C.-M. Jang, "Effects of Tip Speed Ratios on the Blade Forces of a Small H-Darrieus Wind Turbine," *Energies*, vol. 14, no. 13, p. 4025, Jul. 2021, doi: https://doi.org/10.3390/en14134025.

[19] Q. Wang, Y. Li, and R. Li, "Integrating artificial intelligence in energy transition: A comprehensive review," *Energy Strategy Reviews*, vol. 57, p. 101600, Jan. 2025, doi: https://doi.org/10.1016/j.esr.2024.101600.