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Design Optimization of Small-Scale Horizontal-Axis Wind Turbines Using Genetic Algorithm to Minimize CO_2 Emissions

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Small-scale wind turbines are increasingly relevant in the global effort to reduce CO_2 emissions while meeting growing energy demand, particularly in Philippine off-grid areas with modest energy needs and moderate wind speeds. Still, designing efficient turbines for such conditions remains challenging due to trade-offs between power output, cost, and emissions. To address these, turbine blade designs must be optimized for better performance within environmental and economic constraints. This study introduces a genetic algorithm (GA) to optimize horizontal-axis wind turbine blades tailored to Phillippine off-grid areas' high RPM and low wind speed conditions. Improved aerodynamic performance was attained using a Python-based Blade Element Momentum (BEM) code, with blade geometry parameterized by a conic equation for chord and twist distribution, controlled by an A-coefficient iteratively refined by the GA. Enhanced GA settings—larger parent and population sizes and a higher maximum A-coefficient—yielded improved power coefficients (C_p) and tip speed ratios (TSR). Although initial performance was low under local wind conditions, increasing rotor diameter restored and improved efficiency. The optimized 1-m blade achieved a rated power of 13.91 kW at 4.00 m/s and 496.56 RPM, outperforming the base blade designed for 10 m/s. To assess environmental benefits, CO_2 emissions were estimated by determining blade solidity, scaling for mass, and applying an emissions model. The optimized blade exhibited significantly lower CO_2 emissions than both the baseline design and a comparable diesel generator, underscoring its potential for decentralized renewable energy applications.

1. Introduction

The global energy sector is at a critical juncture as the demand for sustainable and low-carbon energy sources increases. Wind energy, owing to its abundance and minimal environmental footprint, has emerged as a viable alternative to fossil fuels. However, in developing countries like the Philippines, challenges such as high electricity costs, frequent power interruptions, and limited access to energy in remote areas. As global warming intensifies due to the continued reliance on conventional energy sources, and as energy demand rises alongside limited electrification in remote islands, the need for renewable energy solutions grows ever more critical.

In the Philippines, fossil fuels have continued to dominate the energy mix despite ongoing efforts to harness renewable resources over the past years. This highlights a significant opportunity for expanding wind energy utilization, particularly through technologies suited for low-wind-speed environments prevalent across the archipelago.

Large-scale horizontal-axis wind turbines (HAWTs), typically with rotor diameters between 80 and 108 m, are designed for high-wind-speed regions. This presents a mismatch for the Philippine wind conditions since the average wind speeds range from only 4.5 to 7.0 m/s, leading to suboptimal turbine performance and economic inefficiency (Silang et al., 2014). Consequently, there is a pressing need to develop small-scale wind turbines (SWTs) specifically optimized for low-wind-speed applications.

Small-scale wind turbines present a practical solution for off-grid electrification in the Philippines, where approximately 634 islands remain disconnected from the main grid due to geographic and economic constraints (Castro et al., 2021). Unlike large turbines, SWTs benefit from lower production, installation, and maintenance costs, making them suitable for rural and isolated communities.

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Moreover, economic considerations play a pivotal role in SWT deployment. Downsizing generators and simplifying mechanical components can substantially lower manufacturing and operational costs, enhancing the feasibility of wind energy systems in resource-constrained settings (Encarnacion et al., 2019). The correlation between generator size, cost, and turbine performance further emphasizes the need for design optimization to achieve economically viable and environmentally sustainable solutions.

This study aims to optimize blade design for small-scale HAWTs using a Genetic Algorithm (GA), targeting low-wind-speed Philippine conditions. Blade performance—heavily influenced by parameters like tip speed ratio (TSR), chord length, and twist distribution—critically affects energy capture. Metaheuristic methods like GA have grown in prominence in turbine design, due to their capacity to handle complex, multivariable challenges. GA mimics evolutionary processes (selection, crossover, mutation) to efficiently probe large design spaces for optimal solutions. Recent applications include the work of Muhsen et al. (2020), who optimized a small HAWT blade for low-wind-speed conditions using aerodynamic simulations, achieving notable efficiency gains. These findings, combined with location-specific wind resource studies such as Gacu et al. (2024), underscore the potential for tailored, computationally optimized small-scale wind turbine designs in the Philippines.

2. Method

2.1 Validation of the BEM Solver

Encarnacion et al. (2019) used a Python code to evaluate the performance of the different blade configurations using simplified Blade Element Momentum (BEM) Theory. BEM remains an industry-grade tool for preliminary wind turbine design. More advanced methods such as Computational Fluid Dynamics (CFD) can capture complex flow effects but require substantial computational resources, making them less practical for iterative optimization in this work. The same BEM solver was used in this study to calculate different performance parameters of a wind turbine. To validate the BEM solver, a case study using the linear base blade of the experimental study done by (Abdelsalam et al., 2021) was evaluated using the BEM solver. The generated power curve of the BEM solver was compared to the experimental power curve of the base blade. In addition, the base blade was evaluated using QBlade, a design software that calculates the performance of s turbine design. The chord and twist distributions of the base blade was shown on the figure below.

2.2 Design Optimization

Optimizing wind turbine blades was done by altering two parameters only: chord and twist distribution. Both distributions were parametrized by the A-value to generate a smooth geometry along the different sections of the blade. The blade modification was patterned on the study performed by (Encarnacion et al., 2019) where a conic equation, Eq(1), was used to define a distribution.

$$r^2 + A\lambda r + \lambda^2 = 1 \quad (1)$$

The distribution defined by the radial coordinate, r, and the scaling coefficient, λ, were determined by the value of A. The graphical pattern of the distribution varies from Elliptical (A<2), Linear (A=2), and Hyperbolic (A>2). The implementation of the parametrization reduced the number of variables needed to be optimized. A python code was developed to perform the algorithm shown in Figure 1 that optimizes the power coefficient (C_p) and the corresponding TSR (TSR_{cor}) through the application of GA on parametrize A-value of both the twist and chord distribution.

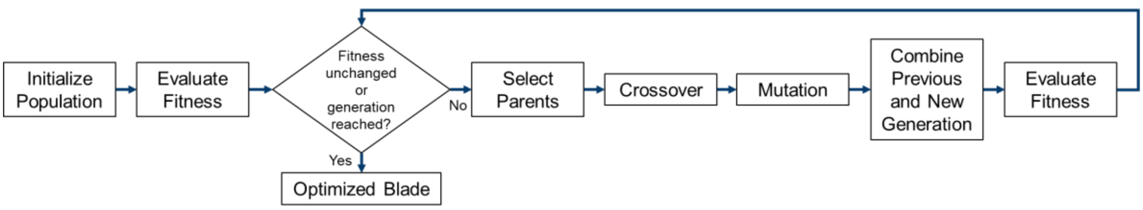

Figure 1: Optimization Algorithm performed in this Study

The initial population of 100 individuals was generated by uniformly sampling 10 points for each A-value parameter and cross-combining them for both chord and twist distributions. Each individual was evaluated using a fitness function based on its aerodynamic performance shown in Eq(2). The Blade Element Momentum (BEM) solver calculated the C_p across a range of tip speed ratios (TSRs), identifying $C_{p_{max}}$ and its corresponding TSR. These were normalized with respect to the Betz limit and the base blade's TSR to compute fitness. New set of population from parents of the previous generation was updated after every generation where crossover and mutation are allowed. The GA was coded to end if the set number of generation has been met or the fitness function is not changing.

$$fitness = \left(\frac{C_{p_{max}}}{C_{p_{Betz}}}\right) \times \left(\frac{TSR_{cor}}{TSR_{Betz}}\right) \quad (2)$$

2.3 Carbon Footprint Assessment

To evaluate the environmental performance of the optimized wind turbine blade (WTB), a carbon footprint analysis was conducted and compared against both the baseline blade and a diesel generator of equivalent rated power. The analysis incorporated real industrial data on commonly used materials for wind turbine blade construction, considering two eco-parameters: embodied energy and carbon footprint. These values accounted for material production, manufacturing processes, transportation, operational use, and final disposal. The mass of the optimized blade was estimated by scaling the results from the study of Algolfilaf et al. (2021), which relates blade solidity to mass. The corresponding carbon footprint, in terms of metric tons of CO_2 (tCO_2), was then estimated using emission factors reported by Morini et al. (2022), based on blade mass.
For comparison, the baseline blade's mass was computed using a 3D CAD model in SolidWorks, assuming a glass fiber composite material. The same emissions estimation method was applied. Additionally, a representative diesel generator with comparable power output was included to benchmark the carbon footprint of the optimized WTB against conventional fossil-fueled power generation.

3. Results

3.1 BEM Solver Validation

The BEM solver developed in this study was validated using the linear blade geometry from Abdelsalam et al. (2021), which employs the E216 airfoil and a rotor diameter of 0.5 m, optimized for a wind speed of 10 m/s and Reynolds number of 100,000. The E216 airfoil was selected for its high lift-to-drag ratio at low Reynolds numbers, making it suitable for small-scale applications.

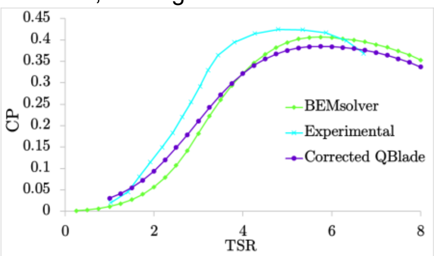

Figure 2: Validation of the BEM solver

Figure 2 compares the power coefficient curves from experimental data, the custom BEM solver, and QBlade with Prandtl's loss correction. The experimental blade reached a peak. C_p of 0.425 at TSR = 4.80, the BEM solver predicted 0.407 at TSR = 5.75, and QBlade gave 0.385 at the same TSR. The BEM solver's rightward shift in peak performance—linked to its steady-state, inviscid assumptions and lack of turbulence modeling—is consistent with Lazzerini et al. (2022). At TSR = 6.25, the BEM solver overestimates power, while QBlade's overestimation begins at TSR = 6.62.
Despite these differences, the BEM and QBlade results show good agreement in curvature from TSR = 5 onwards. Variations are attributed to the different correction models used: QBlade applies Prandtl's correction, while the custom BEM solver incorporates the iterative solution method for blade element momentum equations with guaranteed convergence proposed by Ning (2014), which helps improve accuracy in predicting thrust and torque behavior at high angles of attack.

3.2 Genetic Algorithm's Performance

An important observation during the implementation of the genetic algorithm (GA) is the influence of the number of parents on the generation at which convergence begins. As shown in Figure 3a, varying the parent count significantly affects the convergence behavior of the GA.
The same parameters validated for the BEM solver were used in the GA, with the exception of a higher Reynolds number set to Re = 200,000, to better represent blade sections experiencing flow conditions beyond 100,000.

The number of parents was varied across five cases: 5, 8, 10, 13, and 15. The generations at which convergence began were observed at 12, 33, 3, 22, and 6, respectively. An exponential trendline fitted to the data indicates that as the number of parents increases, the generation at which the GA converges tends to decrease.
This behavior is expected due to the increased population size associated with a higher number of parents, especially under the complete crossover scheme applied. With more parents contributing genetic material, the algorithm explores a broader solution space per generation, thereby accelerating convergence in earlier generations.

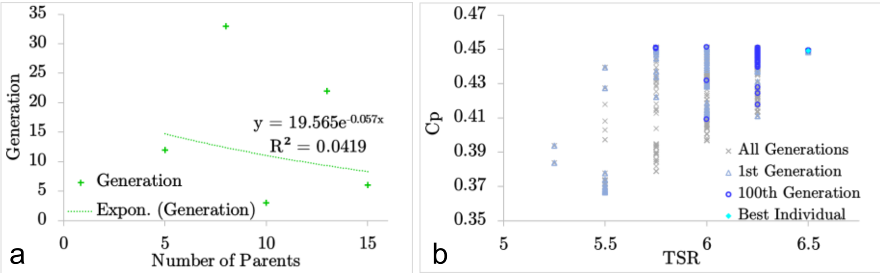

Figure 3: Effect of the Number of Parents on Convergence of GA (a), Generated Individuals (b)

Figure 3b illustrates the distribution of all generated individuals across different parent counts, highlighting the first and final (100th) generation, which includes the optimized blade. The results fall within an acceptable design region, as no maximum C_p values occur at extreme TSR values (i.e., TSR = 1–2 and TSR = 7–8), where physically unrealistic performance often appears. Additionally, all C_p values remain below the Betz limit of 0.593, further validating the acceptability of the generated solutions.
A key trend is evident in the population size across different parent counts. As the number of parents increases, the number of individuals generated per generation also increases, resulting from the combinatorial crossover mechanism used in the algorithm. While this leads to a more extensive exploration of the design space—which is beneficial for identifying high-performing blades—it also increases the computational load and run time.
Notably, with 15 parents, the GA produced a significantly larger population while achieving faster convergence. This suggests a trade-off between solution quality and computational cost that must be considered when tuning the GA parameters.

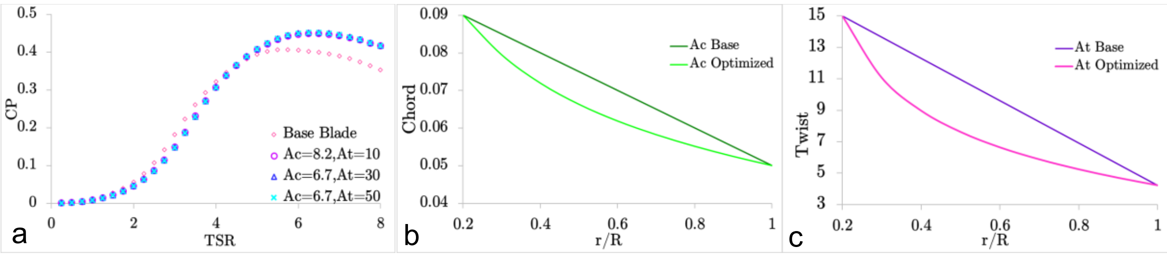

Figure 4: Power Curve of Optimized Blades for Different Maximum A-Coefficients (a), Chord (b) and Twist (c) Distribution of the Base and Optimized Blade

The influence of varying the maximum allowable A-coefficient on the aerodynamic performance of the optimized wind turbine blade was investigated. The resulting optimized A-coefficients tend to approach the higher values of C_p which attributes to higher fitness of the optimized blades. For a maximum A-coefficient (Amax) of 10, the algorithm converged to the chord's A-coefficient (Ac) value of 8.2. When Amax was increased to 30 and 50, the resulting Ac stabilized at 6.7, indicating a threshold beyond which further increases in Amax no longer influence the optimized curvature. This saturation suggests that there exists an optimal range of curvature values that maximize performance within the given design space. Comparison on the optimized blade's geometry to the base blade is shown in Figure 4b and 4c where both the distributions of the optimized blade are hyperbolic in nature.
The corresponding aerodynamic performance of the optimized blades is illustrated in Figure 4a. Blades generated with higher Amax values exhibited superior C_p curves, especially beyond the TSR of 4.5. Among the tested configurations, the blade optimized at Amax = 50 consistently achieved the highest C_p across a broad TSR range. This improvement in performance is particularly beneficial for turbines operating in environments

with variable wind speeds, as it indicates a robust design capable of maintaining high efficiency over a wider range of operating conditions.

Overall, increasing the maximum A-coefficient during optimization enhances both the quality of the geometry and the aerodynamic performance, up to a critical point. Beyond this, the gains in fitness and power output begin to plateau. The blade optimized at Amax = 50 demonstrated the most favorable characteristics in terms of geometry and C_p distribution, and is thus considered the most effective design among those examined.

3.3 Carbon footprint assessment

To analyze the environmental benefits of the optimized wind turbine blade (WTB), a carbon footprint (CFP) analysis was conducted and benchmarked against a baseline blade and a diesel generator of comparable power output. Using the geometry of the NREL 5 MW reference blade from Algolfilaf et al. (2021), the solidity was calculated to be 0.052, and the corresponding total blade mass was estimated at 16,757.1 kg based on its mass per unit length distribution. This served as the basis for scaling the mass of the blades generated through the genetic algorithm (GA). The scaling relation used was:

$$\frac{M_{model}}{\sigma_{model}} = \frac{M_{gen}}{\sigma_{gen}} \quad (3)$$

Applying this relationship, the estimated mass of the generated blades ranged from 4.01 to 5.08 kg, depending on the blade geometry. In comparison, the baseline blade modeled in SolidWorks using glass fiber composite materials had a total mass of 5.58 kg. The lower mass of the optimized blade was expected, as the design was refined to enhance aerodynamic performance while reducing material use through lower blade solidity.

The carbon footprint of the blades was then computed using emission factors reported by Morini et al. (2022), which correlate blade mass to total CO_2 emissions. The following equation was used:

$$\frac{M_{model}}{CFP_{model}} = \frac{M_{gen}}{CFP_{gen}} \quad (4)$$

Using this approach, the estimated carbon footprint of the GA-generated blades ranged from 0.016 to 0.021 metric tons of CO_2 (tCO_2). The optimized blade design corresponded to a carbon footprint of 0.017 tCO_2. In contrast, the baseline SolidWorks model yielded a higher carbon footprint of 0.023 tCO_2 due to its greater mass. For additional comparison, a 13 kW diesel generator—representing conventional fossil fuel-based power generation—from de Melo et al. (2019) was included. Based on published emission factors, the diesel generator had an estimated carbon footprint of 0.109 tCO_2 for equivalent power output. As shown in Figure 5, the optimized blade not only reduced emissions by approximately 22.7 % compared to the baseline blade, but also achieved over 84.0 % lower emissions compared to the diesel generator.

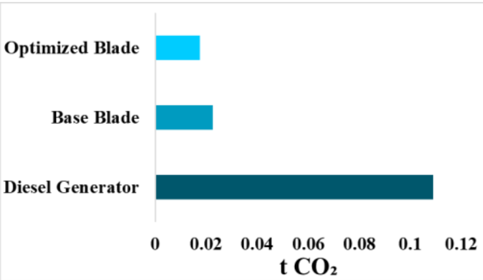

Figure 6 : Carbon Footprint in tCO_2 of the Optimized Blade, Base Blade, and the Diesel Generator

These findings highlight the significant environmental advantages of the optimized wind turbine blade. With an output of 13.91 kW and a minimal carbon footprint, the blade offers a cleaner alternative to traditional fossil fuel systems. Furthermore, the reduction in material usage translates to potential cost savings in manufacturing, transportation, and end-of-life disposal. Taken together, the optimized blade design demonstrates both environmental sustainability and economic viability, reinforcing its applicability in low-emission renewable energy systems.

4. Conclusions

The application of a Genetic Algorithm (GA) in optimizing horizontal-axis wind turbine blades using an A-coefficient-based parameterization showed promising results in increasing the blades performance and minimizing the blade's carbon footprint. Increasing the maximum A-coefficient improved C_p values, particularly beyond TSR = 4.5, with performance gains plateauing at Amax = 50 — where the optimized blade consistently achieved the highest C_p across a wide TSR range. The convergence of designs to a consistent Ac value suggests an optimal curvature zone for efficient energy extraction. The evolution of chord and twist distributions further indicated that higher A-coefficients lead to more aerodynamically favorable shapes — characterized by reduced chord curvature and enhanced twist near the root. These trends are consistent with physical expectations and reinforce the robustness of the GA's search capability.

From an environmental standpoint, the carbon footprint assessment underscored the optimized blade's sustainability advantage. The computed carbon footprint of the optimized blade (0.017 tCO_2) was significantly lower than that of the baseline blade (0.023 tCO_2) and dramatically less than that of a comparable diesel generator (0.109 tCO_2). This highlights the viability of GA-optimized wind turbine blades not only in terms of aerodynamic efficiency but also in minimizing environmental impact.

In summary, integrating GA with curvature-controlled design parameters provides an effective framework for aerodynamic and environmental optimization. While the present study validates the blade's aerodynamic performance using BEM-based methods, further validation can be conducted using higher-fidelity simulations such as (CFD) and experimental testing in a wind tunnel or field conditions. These approaches could serve as valuable extensions for future research to confirm and enhance the real-world performance of the optimized blade.

Nomenclature

λ – scaling coefficient
σ_{gen} – solidity of blade generated
σ_{model} – solidity of model
CFP_{gen} – carbon footprint of blade generated
CFP_{model} – carbon footprint of model
$C_{p_{Betz}}$ – maximum C_p of Betz Limit
$C_{p_{max}}$ – maximum C_p of generated blade
r – radial coordinate
M_{gen} – mass of generated blade
M_{model} – mass of model
TSR_{Betz} – corresponding TSR of $C_{p_{Betz}}$
TSR_{max} – corresponding TSR of $C_{p_{max}}$

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