Optimization of Wind Turbine Design Parameters Using Particle Swarm Optimization

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1. Abstract

With the growing interest in renewable energy sources as a solution to the problems of energy dependence and limited resources associated with conventional energy sources, there have been efforts to optimize renewable energy. Wind energy is a powerful energy resource available in every nation of the world, yet ongoing research is necessary to find methods of increasing power production and decreasing its levelized cost of energy (LCOE). Current literature has demonstrated various tools for design optimization, balancing multiple objectives such as wind turbine aerodynamic performance, structural rigidity, mass, and cost. This paper explores a straightforward yet useful algorithm for finding an optimal wind turbine design that maximizes energy generation and costs over a three-year period for given wind conditions. Using particle swarm optimization (PSO), the algorithm obtained an optimal set of wind turbine design parameters, notably a rotor diameter of 18.58 meters and a gear ratio of 22, with a rated speed of 17.8 meters per second, producing 2.14 million MJ of energy at a peak power of 100 kW and an estimated system cost of $470,231. The algorithm is adaptable to any set of wind conditions, making it a powerful tool for analyzing wind turbine performance in different geographic regions of the world. Improvements to the algorithm might include the addition of more detailed cost breakdowns such as maintenance or financing, like those found in the Department of Energy's System Advisor Model tool.

2. Introduction

There exists a growing awareness of the finiteness of the earth's conventional energy resources. Subsequently, there have been efforts to economize and optimize renewable energy sources. One such energy source is wind, which is a significant renewable resource fundamentally available in every nation of the world.[1] Its power lies in its promise to reduce fuel costs and the dependency on other countries for fuel. Still, the irregularity of the wind resource is a main drawback.[1]

The increase in the power capture and reduction of the levelized cost of energy (LCOE) of wind energy has been an ongoing goal of research and development.[2] Several factors contribute to the power production of wind turbines such as rotor diameter, hub height, gear ratio, and blade pitch. Larger rotor diameters capture more wind energy and usually correspond to higher power outputs. Still, mass and cost increases with rotor diameter, and design optimization is often necessary to select a design that balances power production with mass and costs.[2] Figure 1 demonstrates visually the comparative size of large capacity wind turbines.

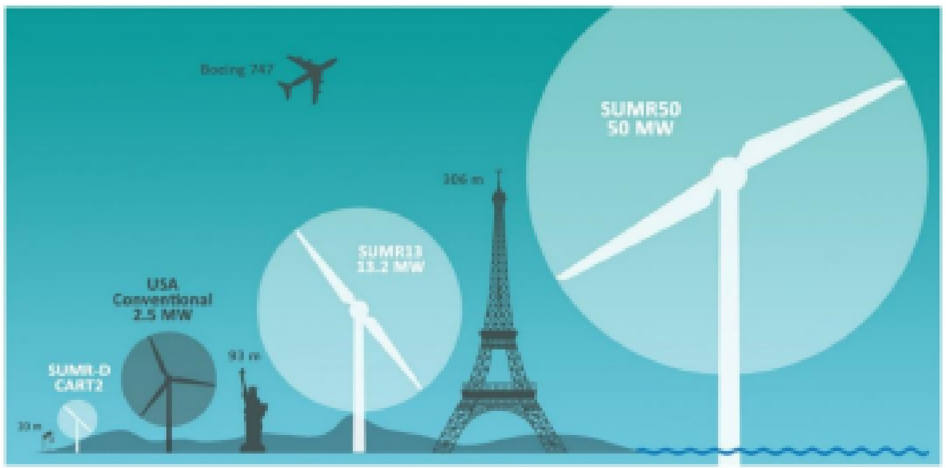


Figure 1. Comparative size of wind turbines of different capacities.[2]

Yao et. al propose an aerodynamic optimization procedure for determining optimal blade cross section properties that reduce blade mass and cost while providing the best aero-structural performance.[2] While the aerodynamics are often the most salient aspect of wind turbines to be analyzed, from which the performance coefficient and efficiency can be obtained, it is important also to analyze the structural loading on the turbine blades, since the stresses will guide material selection and blade geometry. Tools such as the blade element methods and computational fluid dynamics can be used in calculating the forces and moments on the turbine blades.[3] Aslam Bhutta et al. discuss several of these tools in the application of vertical-axis wind turbine analysis, noting that there has been promising agreement between theoretical results and experimental results.[3] These tools can be used in optimization algorithms to streamline wind turbine design, balancing multiple objectives.

For the case of horizontal axis wind turbines (HAWTs), equations have been developed that are used in aerodynamic analysis to calculate wind turbine efficiency and power production as a function of wind speed and turbine geometry.[4] This paper explores a design optimization algorithm utilizing the conventional analytical equations for HAWTs to obtain an optimal design that maximizes energy generation over a period of three years.

3. METHODOLOGY

This paper presents a computational design approach that can be used for modeling and optimizing a wind turbine rated at 100 kW. The chosen optimization focuses are two main design variables: gear ratio (GR) and rotor diameter (D). The third variable that influences power output, pitch angle (β), is held constant at 2.2 degrees throughout this analysis. This methodology uses measured wind data and a turbine performance model to identify the GR and D combination that maximizes energy output while minimizing the cost per turbine; the model must also satisfy constraints on tip speed and power generation.

The power output of a wind turbine at a given wind speed is calculated using the aerodynamic power equation (1):

(1) $$P = \frac{1}{2}\rho A_R V^3 C_p$$

where:

- (P) is the instantaneous power output [W],
- (ρ) is the air density [kg/m³], assumed to be 1.27 kg/m³,
- (����) is the swept area of the rotor [m²],
- (V) is the wind speed [m/s], and
- (����) is the power coefficient

The rotor swept area is defined as:

$$A_R = \frac{\pi D^2}{4} \quad (2)$$

The power coefficient (����) is modeled using the formula derived by Heier (1998); this formula captures the nonlinear behavior related to tip speed ratio and pitch angle:

$$C_p = c_1 \left(\frac{c_2}{\lambda_i} - c_3\beta - c_6 \right) e^{-c_7/\lambda_i}$$

(3) where the modified tip speed ratio (����) is calculated as:

$$\lambda_i = \left(\frac{1}{\lambda + c_8 \beta} - \frac{c_9}{\beta^3 + 1} \right)^{-1}$$

(4) and the tip-speed ratio (λ) is given by:

$$\lambda = \frac{\omega_{\text{gen}}}{GR} \cdot \frac{D}{2V}$$

(5)

In equation 5, �������� is the generator angular speed in rad/s which is held constant at 1800 rpm. All constants ��1 through ��9 are based on values provided in the Heier model and are summarized in Table 1.

Table 1: Heier Model Constants

c_1	0.5
c_2	116
c_3	0.4
c_4	0
c_5	0
c_6	6
c_7	21
c_8	0.08
c_9	0.035

To solve and optimize the turbine design a Particle Swarm Optimization (PSO) algorithm is used to explore the possible GR and D combinations. PSO is an evolutionary optimization technique. Each used solution set (or particle) represents a specific set of GR and D values. The particles move through the search space by adjusting their positions based on their own performance and that of their neighbors; this leads them to gradually converging toward an optimal solution.

For each particle the power curve *P(V)* is computed using the above equations across a range of wind speeds from 0.1 m/s to 30 m/s. The total energy produced by a given turbine design is calculated by integrating this curve:

$$E = \int_{V_{\min}}^{V_{\max}} P(V)\, dV$$

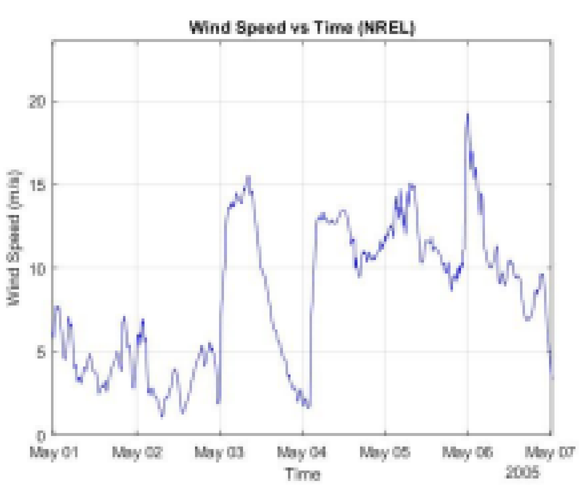
(4)

To limit the design parameter to more real world turbine applications, two constraints are applied during optimization: The blade tip speed must remain below 100 m/s to ensure the design is structurally and aerodynamically feasible. The turbine’s power output must not exceed 100 kW at any point on the power curve.

Any candidate design that violates these constraints is automatically penalized by assigning it zero energy output. The PSO algorithm uses this function to guide the swarm toward high performance designs that are physically feasible for the turbine constraints. In the updated model, a cost estimate is incorporated into the objective function to improve economic feasibility. The estimated system cost is based on simplified expressions for blade cost (scaling with $1500 times rotor diameter squared), gearbox cost (scaling with $2000 times gear ratio to the 1.2 power), and a fixed base cost of $100,000. Instead of maximizing energy alone, the algorithm minimizes the ratio of cost to energy produced (i.e., $/MJ), thereby selecting designs that offer the best energy return per dollar spent. This dual-objective formula ensures that both performance and affordability are optimized simultaneously.

The search space for the PSO is bound by rotor diameters from 10 to 30 meters and gear ratios from 1 to 28. A swarm size of 50 particles is used and the algorithm is allowed to run for 100 iterations or until convergence. The optimal design found through this process maximizes energy capture per dollar spent, while still adhering to the turbine rating and tip speed constraints

To support this methodology, real measured wind speed data from the National Renewable Energy Laboratory (NREL) is used. The dataset includes three full years (2004–2006) of 10-minute interval wind speed measurements. This data serves as the input to the power model to assess the turbine's long term performance. Figures 2 and 3 illustrate the behavior of the wind data: short-term variability over one week and long-term trends over three years, respectively.



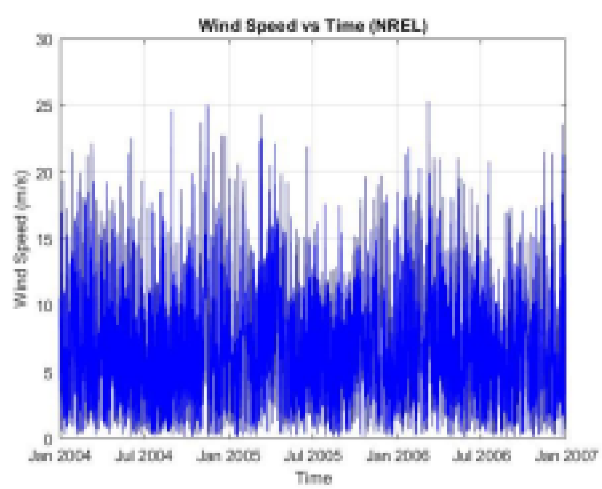
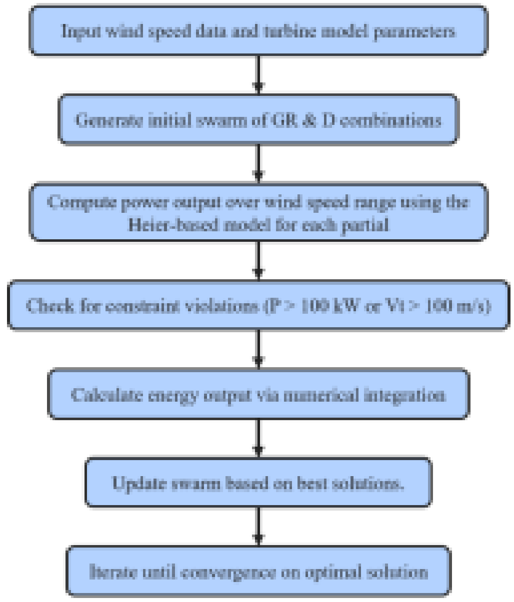


Figure 2: NRE Wind Data (May 1-7, 2005) Figure 3: NRE Wind Data (2004-2006)

The methodology used is summarized in a process flowchart (Figure 4) which outlines each step from data loading and turbine modeling to constrain enforcement and optimization. This provides a generic, flexible framework that can be applied to any wind site that local wind data has been measured for. This enables designers to tailor wind turbine configurations to specific operating environments. By integrating economic modeling with physical constraints, the methodology supports more realistic, cost-effective wind turbine design under site-specific wind conditions.

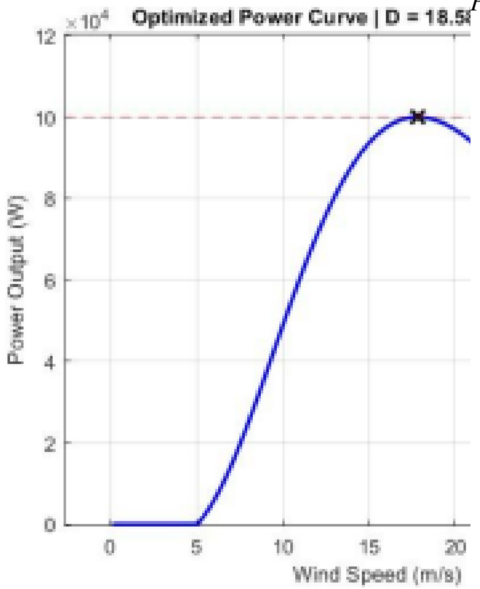
Methodology Flowchart



4. RESULTS

The optimization process yielded a wind turbine design with a rotor diameter of 18.58 meters and a gear ratio of 22.0. This GR and D combo was identified by the particle swarm optimization (PSO) algorithm as the most cost-effective design, maximizing total energy output per dollar spent while satisfying all physical design constraints. The power output curve for the optimized turbine is shown in Figure 5. The curve shows the expected bell-shaped response with power increasing rapidly at moderate wind speeds, peaking at the 100-kW rated limit, and then declining due to aerodynamic limitations at higher speeds. The rated wind speed for this design is approximately 17.8 m/s; this is the wind speed the turbine achieves its maximum allowable output.

Figure 5: Power curve optimized by GR and D



The energy output of the turbine as a function of design parameters is visualized in the PSO search space graph shown in Figure 6. This plot maps the total energy output for combinations of rotor diameter and gear ratio. The feasible design region is bound by the tip speed constraint which results in the triangular shape of the graph. One important insight is the yellow band across the upper right region of the design space reveals that there is not one perfect design point but rather a range of near optimal solutions. This follows findings in recent renewable energy research where practical design constraints lead to clusters of viable solutions rather than a single global optimum (Wang et al., 2022). An overlay of cost contours on the same design space reveals that while the highest energy solutions tend to occur at higher gear ratios and larger diameters, the most cost-effective configurations lie slightly to the left of the energy ridge. This emphasizes the importance of including cost in design selection, especially for commercial feasibility. This allows engineers to be flexible when making decisions; they can prioritize other design factors like weight or mechanical limitations when selecting the final configuration within this optimal window. Similar multi-solution contours have been observed in other energy system design problems as well (Ghasemi et al., 2020); this highlights the advantage of using evolutionary algorithms to expose windows of optimal solutions.

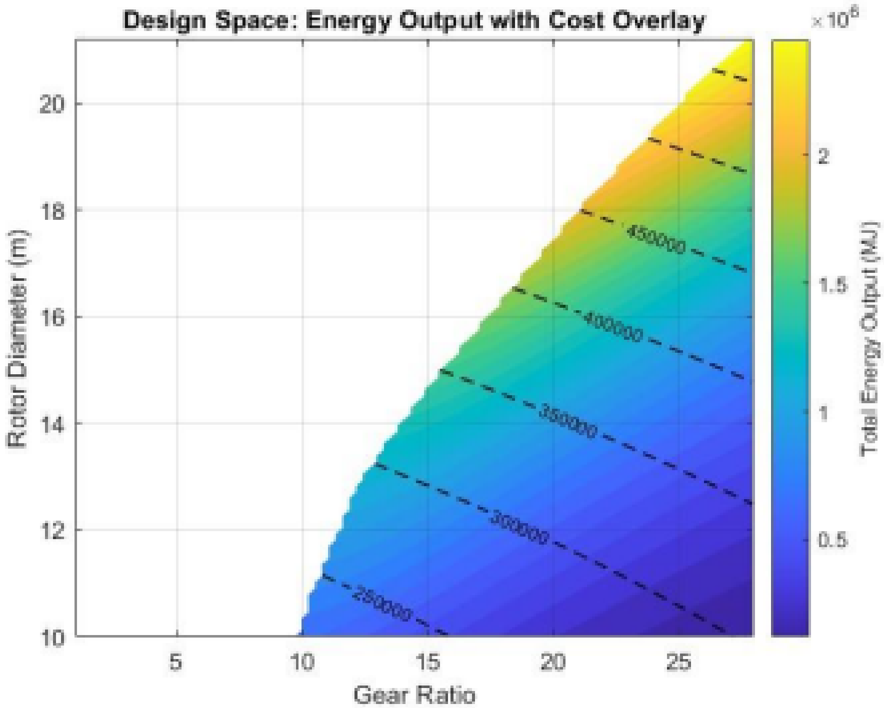


Figure 6: PSO design space: Energy output (MJ) as a function of GR & D

To evaluate the real-world performance of the selected design parameters, a power output simulation was conducted using the full NREL wind speed dataset. Figure 7 shows the turbine's power output over a one-week period (May 1–7, 2005). Output varies significantly during this time with low generation during calm conditions and several intervals of high wind producing output at the 100 kW rating. This graph shows the turbine's ability to respond to real wind fluctuations while staying within rated limits. Over the entire three-year period, the total energy output of the turbine was approximately 2.14 million megajoules. The corresponding estimated system cost was $470,231, yielding a cost-to-energy ratio that significantly improves upon prior energy-only optimization approaches

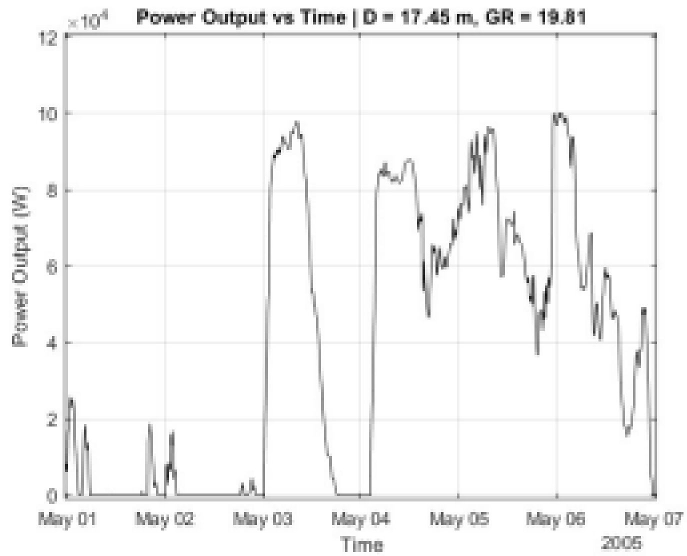


Figure 7: Power output (May 1–7, 2005)

A broader view of the turbine's power output vs time is shown in Figure 8 which plots the power output across the full three-year wind dataset. The plot reveals the seasonal variability and intermittent nature of wind power generation. Despite the variability, the turbine consistently reaches a near peak output during periods of strong wind.

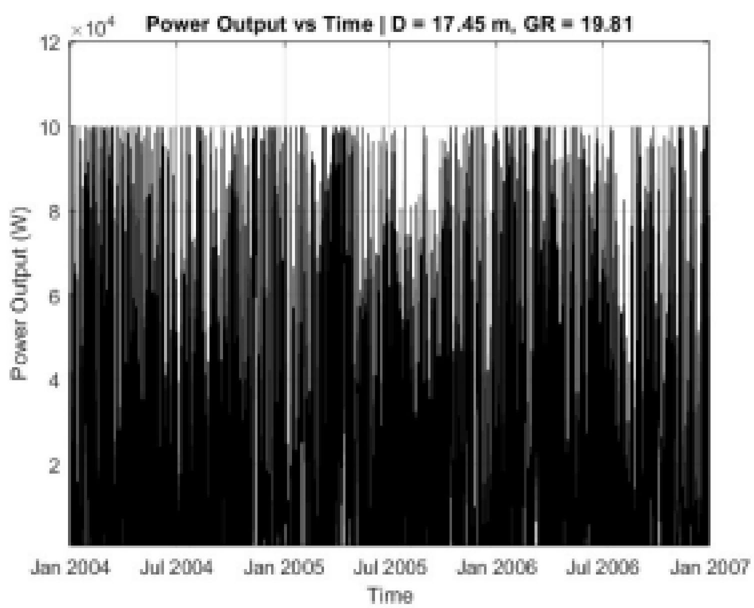


Figure 8: Power output (2004 – 2007)

Overall, the results validate the effectiveness of the modeling and optimization strategy. The optimized turbine design maximizes energy output per dollar spent, without exceeding power or speed constraints and the PSO framework provides a flexible set of solutions rather than a single fixed answer. This flexibility offers real value to engineers seeking site specific wind turbine configurations that balance performance with practical design considerations.

5. Conclusion

This study developed and applied a computational optimization framework used for designing a 100-kW rated wind turbine. This framework combines the Heier aerodynamic model with particle swarm optimization (PSO) and identified the optimal rotor diameter and gear ratio combination for maximizing energy output per dollar spent under realistic wind conditions. The final selected solution had a rotor diameter of 18.58 meters and a gear ratio of 22.0; this design met all operational constraints and delivered 2.14 million MJ of energy with an estimated system cost of $470,231 across the three-year wind dataset.

A valuable outcome of the optimization process is the insight gained from the PSO design space. Rather than producing a single solution, the optimization revealed a region of near-optimal designs, shown as a yellow band, where many GR and D combinations yield similarly high energy output. This flexibility allows designers to make trade-offs in the design process based on structural, economic, or logistical constraints without sacrificing overall performance.

The method is broadly applicable and can be reused for other wind datasets or geographic locations. This framework integrates both performance and cost modeling, making it a practical tool for tailoring turbine configurations to specific site and budget constraints. Future work could incorporate more detailed cost breakdowns, maintenance modeling, or the inclusion of variable speed control for further refinement.

6. References

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