Analysis of a 100 kW Wind Turbine System

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Abstract

As the global effort to reduce reliance on fossil fuels accelerates, the development of renewable energy technologies has become increasingly critical. Wind energy continues to be a major contributor to the renewable energy sector and is expected to account for 35% of global energy production by 2050. However, enhancing efficiency and reducing the cost of wind energy remains a challenge, especially in lower-wind regions. This paper will explore the application and bio-inspired turbine designs, machine learning techniques, and optimization methods to improve wind turbine efficiency and performance. A comparative analysis between conventional and bio-inspired turbines demonstrates up to 33% improvement in computational fluid dynamics (CFD) and blade element momentum theory (BEMT) simulations. Additionally, AI has shown remarkable potential in wind speed prediction, design optimization, fault detection, and maintenance planning, enhancing the viability of wind energy applications. The transition to renewable energy also improves energy security by reducing dependence on fossil fuels, but it also introduces new challenges, such as large required investments in infrastructure. This study will highlight innovative approaches to improving wind turbine design, maximizing wind energy production, and strengthening energy security.

Introduction

Importance of Renewable Energy

The transition to renewable energy is essential to address the growing global demand for energy while reducing greenhouse gas emissions and mitigating climate change. According to the International Energy Agency (IEA), wind energy is poised to play a pivotal role in the global energy mix, contributing an estimated 35% of total energy production by 2050 [2]. The transition away from fossil fuels, driven by geopolitical, economic, and environmental considerations, is accelerating the adoption of renewable technologies. Wind energy offers an abundant and sustainable energy source that can help reduce our carbon footprint.

Lowering the Cost of Renewable Energy

Despite the promise of wind energy, challenges remain in maximizing efficiency and minimizing costs, particularly in regions with low wind speeds. Technological advancements, including bio-inspired turbine designs and machine learning-based optimization, have the potential to address these challenges. Studies have shown that bio-inspired designs, such as blades modeled after humpback whale tubercles, significantly enhance lift and reduce drag, resulting in increased power output in low-wind conditions [4]. By leveraging biomimetic principles, wind turbines can achieve higher performance and adaptability, making wind energy more viable in many locations.

Current Efforts and Optimization Techniques

Recent research has focused on developing innovative methodologies to optimize wind turbine performance using numerical and experimental approaches, including Blade Element Momentum Theory (BEMT) and Computational Fluid Dynamics (CFD). CFD simulations allow for the detailed analysis of airflow and turbulence around turbine blades, while BEMT models calculate aerodynamic performance by analyzing blade segments under varying wind conditions [6]. These methods have validated the higher performance of bio-inspired turbine designs, demonstrating up to a 33% improvement in power coefficients (Cp) and thrust coefficients (Ct) compared to conventional turbines [3].

Application of Artificial Intelligence in Wind Energy

Artificial intelligence, particularly artificial neural networks (ANNs), is playing a transformative role in enhancing wind energy systems. ANNs have been employed across various applications, including wind speed prediction, design optimization, fault detection, and maintenance planning [9]. Wind speed prediction, a critical aspect of wind energy management, benefits from ANN models that can process vast amounts of meteorological data and provide more accurate forecasts. This improves grid stability and energy dispatch. Similarly, ANNs can be used to optimize turbine design by analyzing aerodynamic variables and predicting optimal performance parameters, reducing computational time, and enhancing reliability [4]. Moreover, fault detection systems utilizing ANNs can identify potential failures, enabling predictive maintenance and minimizing downtime [8].

Energy Security and the Green Transition

The transition to renewable energy has profound implications for global energy security. By reducing dependence on fossil fuels and diversifying the energy supply, renewable energy enhances energy security. However, the shift also introduces new challenges, such as the inconsistency of solar and wind power and the need for infrastructure investments in energy storage and grid management [5]. Addressing these challenges requires a combination of policy interventions, technological advancements, and strategic investments to ensure a smooth and secure energy transition. A well-thought-out approach to infrastructure development and diversification of energy sources will be critical to maintaining energy security in a world that is going to become more dependent on renewable energy sources.

Methodology

Our design is for a 100kW fixed-speed turbine. The turbine collected wind speeds from the years 2004 to 2006 from the National Renewable Energy Laboratory (NREL) in 10-minute increments [1]. With the only main parameters for our design being a fixed 2.2 degree pitch angle and a tip speed of 100 RPM, the rotor diameter and the gear ratio were free to be changed to improve the production of energy of the wind turbine [1]. The goal of this design was to maximize production of the wind turbine, and in order to do so, the following methodology was used:

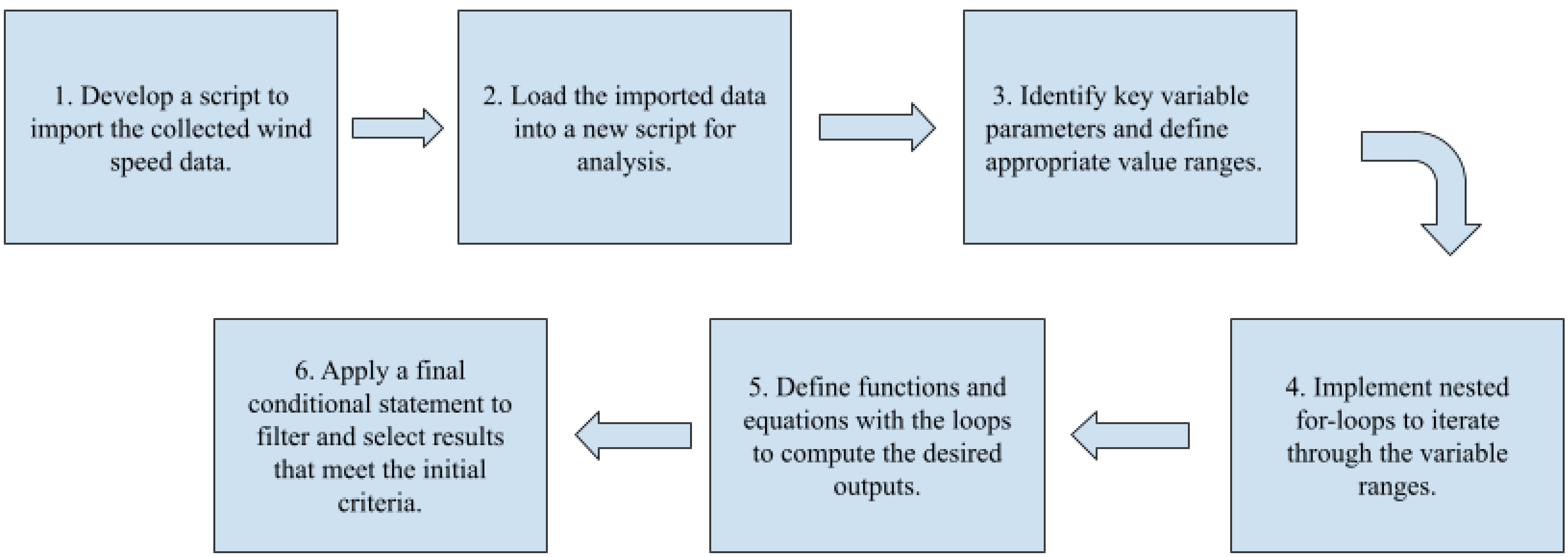


Figure 1: Decision-Making Flowchart for Programming

In coordination with the flowchart above, the design process for this project started with developing a script to import the wind speed data from the NREL wind data file. Once this was completed, a function call was utilized to transport the imported data to a new script. This new script was very similar to the 100 kW system model, with this time the variables of interest being the rotor diameter and gear ratio. Understanding that these two inputs would be manipulated to produce the highest power, a range was decided for both the rotor diameter and the gear ratio. Once this range was created, for loops, with the proper functions and equations, were utilized to iterate through the different combinations of parameters. Finally, as shown in the flowchart, a final conditional statement was used to compare the results and determine the best possible design to maximize power. This process followed the design technique shown in the flowchart above, allowing us to reach and calculate our desired output.

Results

For each year (2004 to 2006), there were 52,559 wind data points collected. These data points are shown in graphs in Figures 2 - 4. After the data points were collected, the maximum power production was calculated as 309.79 kWh. This was calculated with a gear ratio of 20, and the rotor diameter was 22 m. The gear ratio and rotor diameter were determined by using the script described in the methodology section of this report.

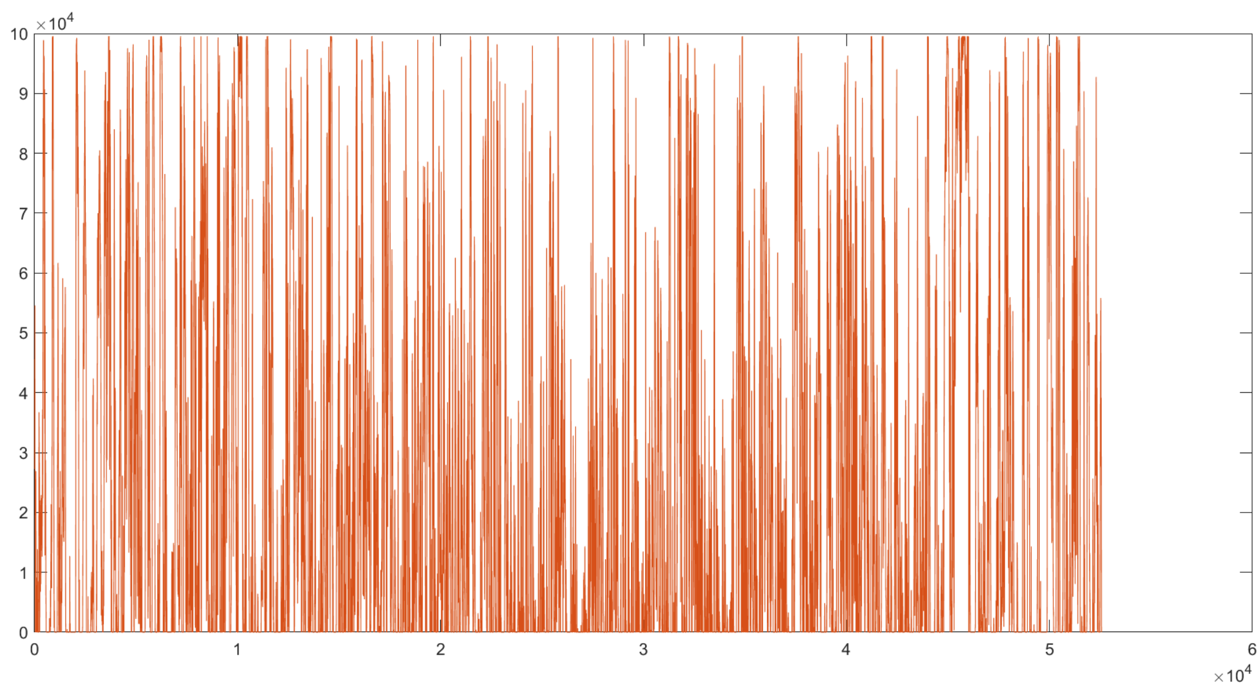


Figure 2: NREL Data from 2004

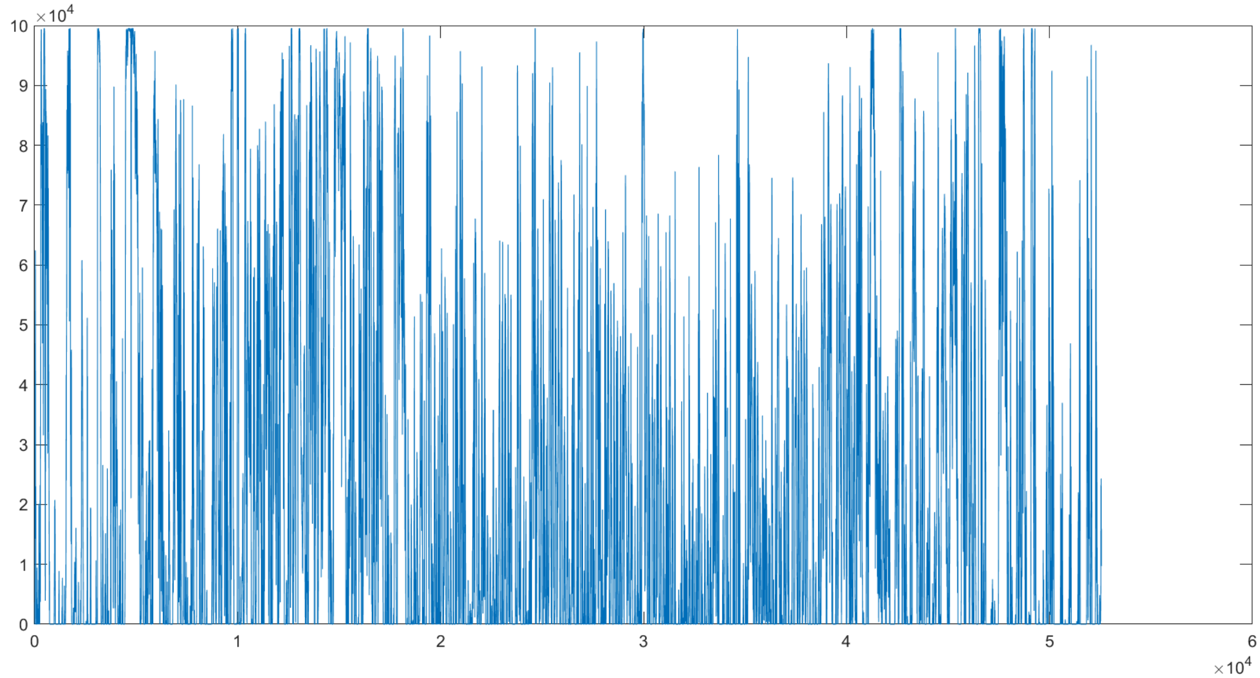


Figure 3: NREL Data from 2005

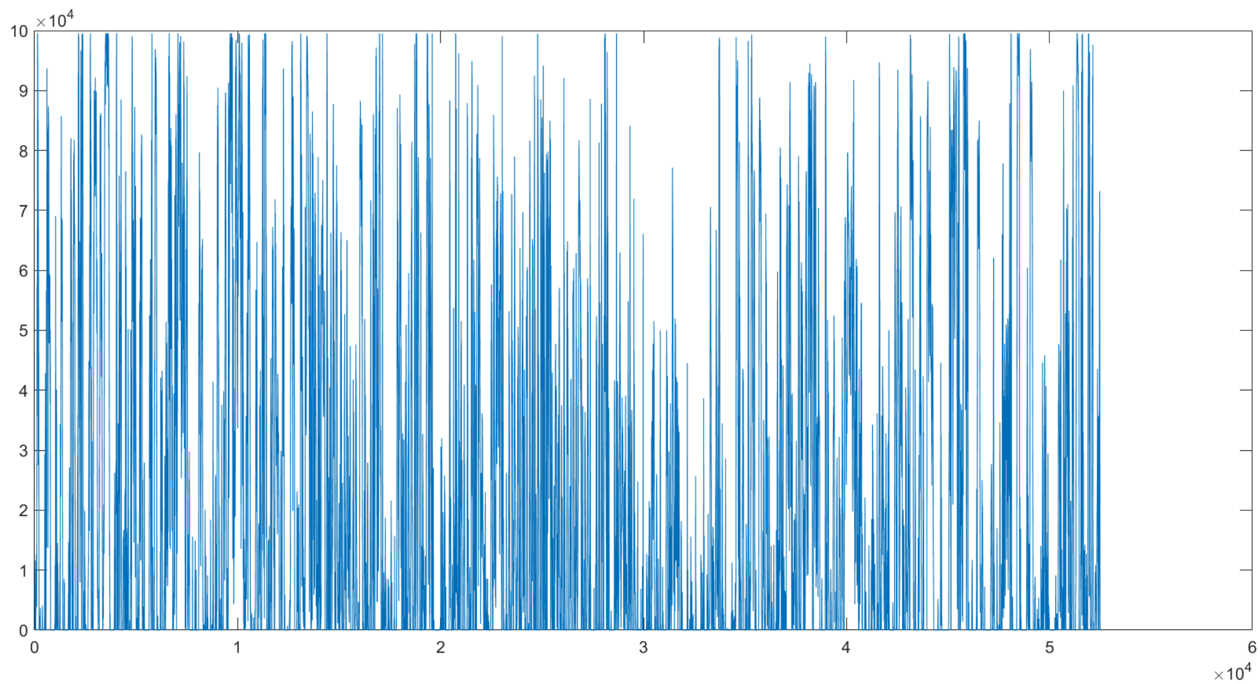


Figure 4: NREL Data from 2006

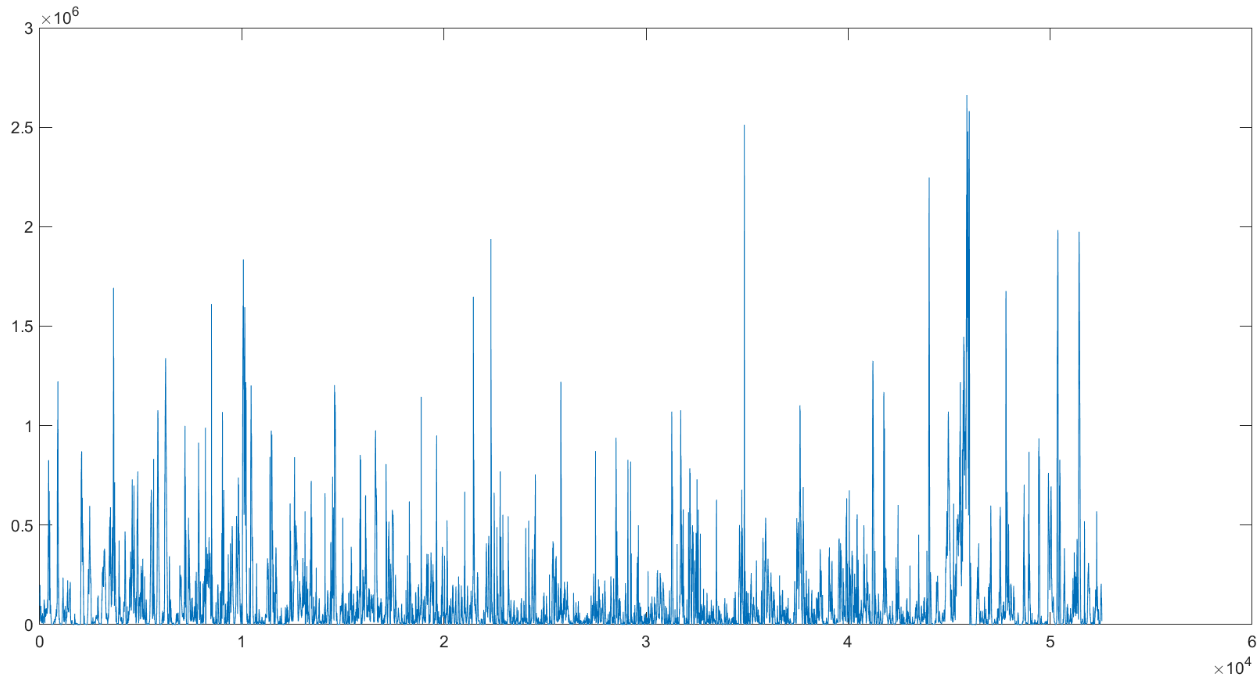
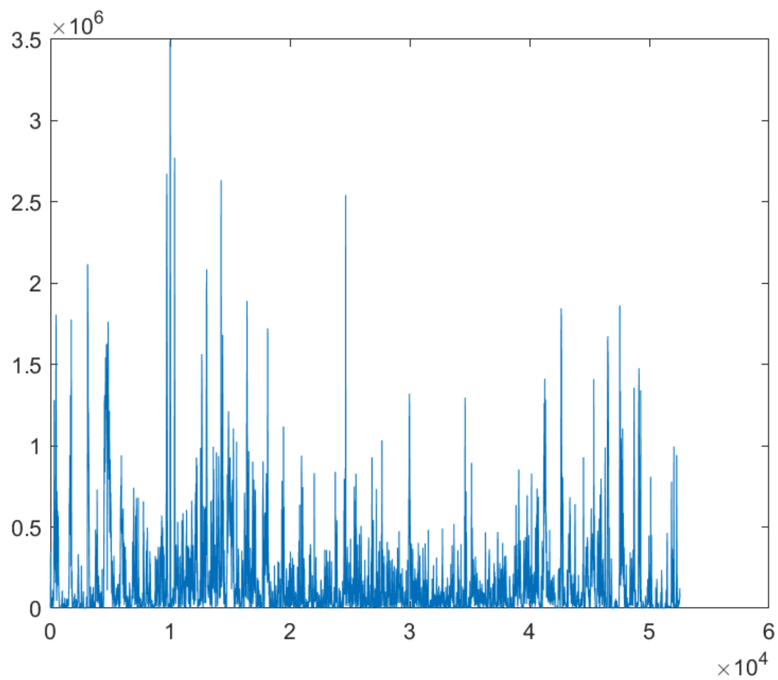


Figure 5: Wind Energy Available in 2004



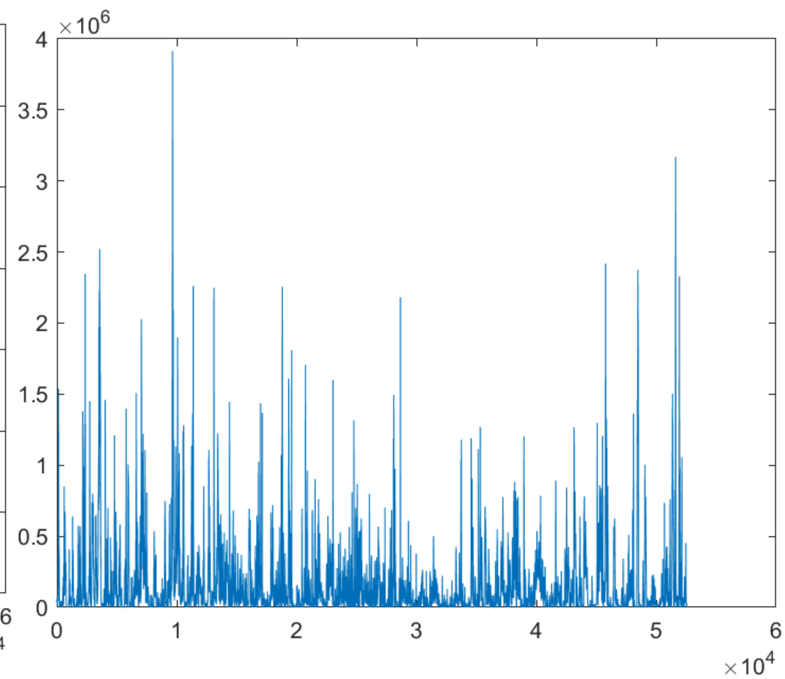


Figure 6: Wind Energy Available in 2005

Figure 7: Wind Energy Available in 2006

With the maximum power produced, the available wind energy is shown in Figures 5 - 7. The power available is calculated using Equation 1.

$$P = \frac{1}{2} * 1.27 * (\frac{\pi}{4 * D^2}) * V_w \quad (1)$$

Where:

P is power,

1.27 is the density of air,

D is the rotor diameter, and

V_w is the imported data collected from NREL.

This formula gives us an estimate of how much energy a wind turbine can potentially capture from the wind. P stands for power, that's the final number we're trying to find. It tells us how much energy is available to be turned into electricity. The 1.27 is a constant that represents the density of air, measured in kilograms per cubic meter. Air density matters because heavier air carries more energy. (This number can change slightly depending on altitude and temperature, but 1.27 kg/m^3 is a common average used for sea level conditions.) The D^2 part refers to the square of the rotor diameter, the length of the blades on the turbine. The diameter is squared because we're interested in the area the blades sweep through as they spin, and that area grows with the square of the diameter. Think of it like this: doubling the blade length doesn't just double the area, it quadruples it. That area (multiplied by 4 here, as a simplification based on geometry and empirical adjustments) tells us how much wind is being intercepted by the turbine. V_w is the wind speed at the location of the turbine. This comes from actual wind data collected by the National Renewable Energy Laboratory (NREL). Wind speed is crucial because the energy in wind increases quickly with speed. The faster wind means a lot more potential power.

So, putting it all together, this equation estimates how much power a wind turbine can pull from the wind, based on the air's density, the size of the rotor, and how fast the wind is blowing.

Even though the maximum power was that high, Table 1 shows the energy produced in Region 2 and Region 3 for each three years. Figures 8 - 10 show the power curves of the data collected from 2004 to 2006, but they also show the regions where the power production is located. To put this into perspective, the average home in the United States uses about 899 kWh per month [9]. Region 2 is where the wind speed is above the cut-off speed but below the rated speed (the rated speed is at 11.2 m/s for all three years). While Region 3 is all the wind speeds at and or above the rated wind speed. Also in the "power must be maintained above 90% of full power when operating in Region 3" [1].

Table 1: The Energy Produced in Region 2 & Region 3

	2004	2005	2006
Region 2	323.31 GJ	352.77 GJ	339.34 GJ
Region 3	387.61 GJ	357.17 GJ	340.569 GJ

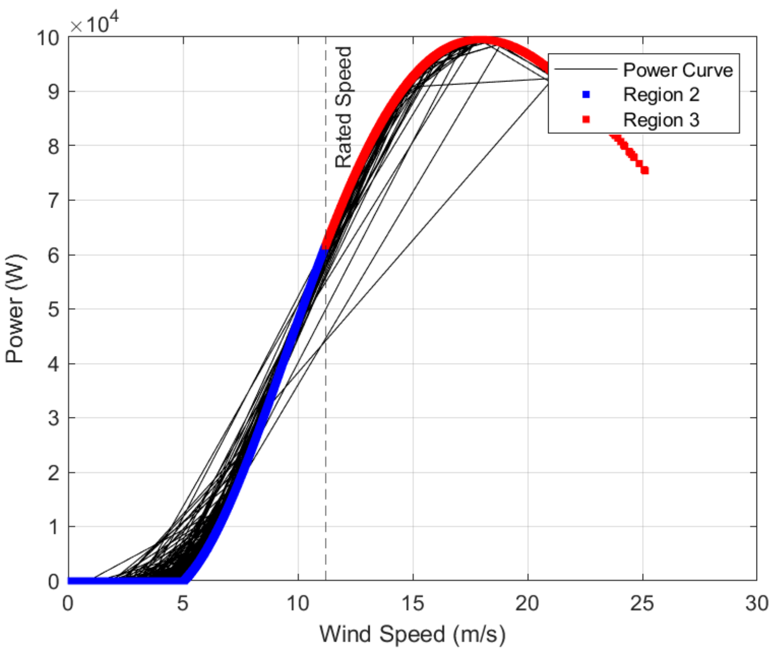


Figure 8: Showing Power Produced in Regions 2 & 3 for 2004

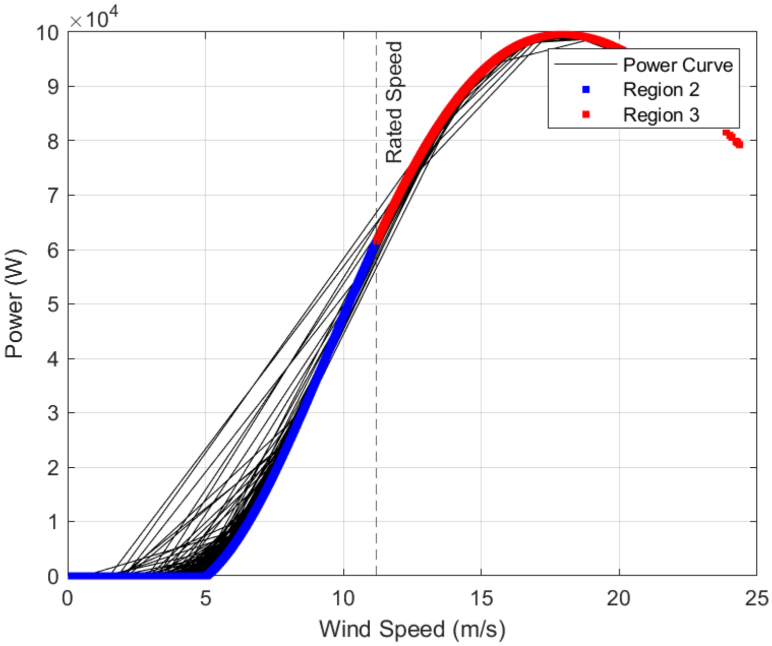


Figure 9: Showing Power Produced is Regions 2 & 3 for 2005

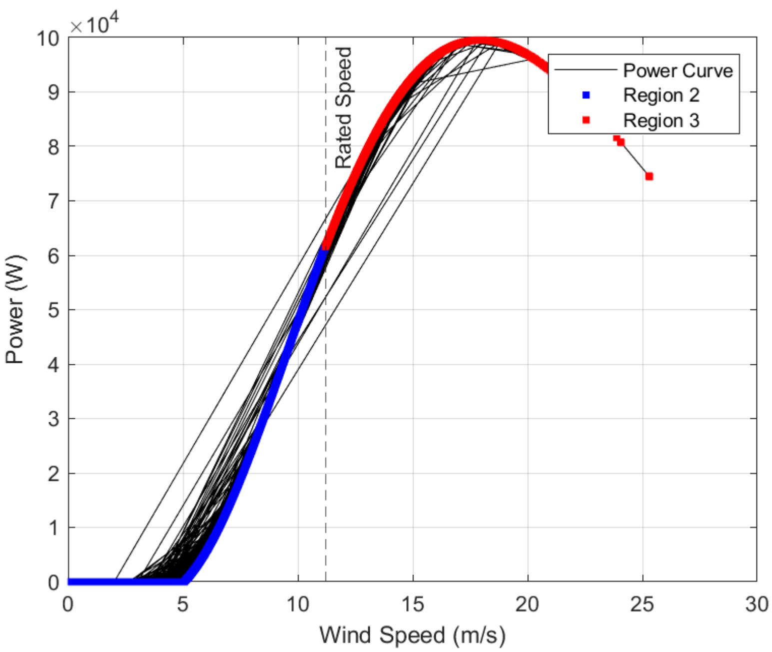


Figure 10: Showing Power Produced in Regions 2 & 3 for 2006

Figures 8 through 10 show how wind turbines performed between 2004 and 2006, specifically how their power output changed with wind speed. The curves are divided into different regions based on how fast the wind is blowing. In what's called Region 2, the wind is strong enough to start generating power but hasn’t yet reached the turbine’s rated speed (which is 11.2 m/s). In this range, power output climbs quickly as wind speed picks up. Then there's Region 3, which includes wind speeds at or above that rated level. Here, the turbine hits its stride and generates close to its maximum output, usually around 90% or more of full capacity. You can see this in the graphs where the lines level off into a flat section, showing that the turbine has reached its performance ceiling.

Table 1 goes a step further by showing how much energy was produced annually in each of these regions. Early on, Region 3 was responsible for more of the energy output, but by 2006, both regions were contributing almost equally. That shift might be due to changes in wind patterns or adjustments in how the turbines were managed. For context, the energy generated in each region was enough to power dozens of typical U.S. homes every month, so these differences matter. Taken together, the figures and the table offer a solid snapshot of how wind speed affects both the moment-to-moment performance and the total energy output over time.

Conclusion

In summary, the optimization of wind energy systems through bio-inspired designs, AI-based predictive models, and advanced simulation techniques holds great potential for improving the efficiency, reliability, and cost-effectiveness of renewable energy. As the world transitions to cleaner energy, continued innovation and investment in these technologies will be essential to achieving a sustainable and secure energy future.

References

[1] J. F. Hall and D. Chen, "Dynamic Optimization of Drivetrain Gear Ratio to Maximize Wind Turbine Power Generation-Part 1: System Model and Control Framework," Journal of Dynamic Systems, Measurement and Control, vol. 135, 2012 2012.

[2] J. F. Hall and D. Chen, "Dynamic Optimization of Drivetrain Gear Ratio to Maximize Wind Turbine Power Generation-Part 2: Control Optimization," Journal of Dynamic Systems, Measurement and Control, vol. 135, 2012 2012.

[3] J. F. Hall, D. Palejiya, M. L. Shaltout, and D. Chen, "An Integrated Control and Design Framework for Optimizing Energy Capture and Component Life for a Wind Turbine Variable Ratio Gearbox," Journal of Solar Energy Engineering, vol. 137, no. 2, Apr. 2015, Art. no. 021022. https://doi.org/10.1115/1.4029812.

[4] H. K. Nejadkhaki, A. Sohrabi, T. P. Purandare, F. Battaglia, and J. F. Hall, "A Variable Twist Blade for Horizontal Axis Wind Turbines: Modeling and Analysis," Energy Conversion and Management, vol. 248, Nov. 2021, Art. no. 114771.

[5] D. Stratton, D. Martino, F. M. Pasquali, K. Lewis, and J. F. Hall, "A Design Framework for Optimizing the Mechanical Performance, Cost, and Environmental Impact of a Wind Turbine Tower," Journal of Solar Energy Engineering, vol. 138, no. 4, Aug. 2016, Art. no. 041008.

[6] H. K. Nejadkhaki and J. F. Hall, "Modeling and Design Method for an Adaptive Wind Turbine Blade with Out-of-Plane Twist," Journal of Solar Energy Engineering, vol. 140, no. 5, Oct. 2018, Art. no. 051010.

[7] H. K. Nejadkhaki, S. Chaudhari, and J. F. Hall, "A Design Methodology for Selecting Ratios for a Variable Ratio Gearbox Used in a Wind Turbine with Active Blades," Renewable Energy, vol. 118, Apr. 2018, pp. 1041-1051.

[8] H. K. Nejadkhaki, A. Lall, and J. F. Hall, "A Methodology to Synthesize Gearbox and Control Design for Increased Power Production and Blade Root Stress Mitigation in a Small Wind Turbine," Journal of Mechanical Design, vol. 139, no. 8, Aug. 2017, Art. no. 081404.

[9] U.S. Energy Information Administration, "How much electricity does an American home use?", EIA. Available: https://www.eia.gov/tools/faqs/faq.php?id=97&t=3.