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Feasibility Study and Simulation of Wind Energy Integration at PDEU Campus

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Abstract

This study presents a comprehensive assessment of wind energy potential at the Pandit Deendayal Energy University (PDEU) campus by integrating wind resource analysis, turbine performance evaluation, and hybrid system simulation. Historical wind speed data at 10 m height were extrapolated to 20 m hub height using power law and logarithmic profiles to account for surface roughness. Estimated wind power densities ranged from 51.6 W/m² (2020) to 65.9 W/m² (2021), with seasonal peaks during summer and monsoon. The Archimedes AWM 1500D turbine, suitable for moderate wind regimes with a cut-in speed of 3 m/s and rated power of 1 kW, was selected. Applying the turbine's power curve to site-specific wind frequency distributions yielded annual average outputs of 32.6-41.2 W, translating to capacity factors of 5-6%. While insufficient to meet full demand, the turbine can provide supplementary power to campus energy needs.

Keywords

Renewable energy integration, Small-scale wind turbines, Wind power density, Sustainable campus energy

Introduction

In recent decades, advancements in aerodynamics, materials science, and digital technology have significantly improved the efficiency and reliability of wind turbines. The introduction of offshore wind farms, smart grid integration, and artificial intelligence-driven optimization has further enhanced the global wind energy sector. Today, wind power is a critical component of renewable energy strategies, contributing to national and international goals for reducing carbon emissions and achieving energy sustainability.

Recent advances in wind turbine power curve (WTPC) modeling have progressed from basic polynomial approximations to sophisticated data-driven methods. Teyabeen, Akkari, and Jwaid (2017) found that power-coefficient-based models outperformed polynomial and general models in terms of prediction accuracy. Pelletier, Masson, and Tahan (2016) demonstrated the effectiveness of artificial neural networks (ANNs) in minimizing modeling errors. Shokrzadeh, Jafari Jozani, and Bibeau (2014) explored spline regressions offering improved flexibility over traditional methods. Astolfi, Castellani, Lombardi, and Terzi (2021) proposed multivariate support

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vector regression incorporating operational parameters for enhanced accuracy. Gottschall and Peinke (2008) introduced dynamic frameworks decomposing turbine response into deterministic and stochastic components. Bandi and Apt (2016) emphasized post-installation calibration for site-specific conditions. Manobel, Sehnke, Lazzús, Salfate, Felder, and Montecinos (2018) achieved 25% improvement combining Gaussian process filtering with ANN techniques. These studies demonstrate the evolution toward data-driven approaches incorporating operational and environmental variables for enhanced modeling accuracy.

The transition to renewable energy sources addresses critical environmental and economic challenges posed by fossil fuel dependence and climate change. PDEU, as a leading energy-sector institution, can model sustainable practices through renewable energy integration. This research evaluates the technical and economic feasibility of campus-level wind energy deployment, providing insights into whether small-scale turbines can effectively supplement energy needs and reduce electricity costs. The study leverages advancements in wind turbine technology and data analytics to establish a practical framework for wind energy assessment applicable to similar institutional settings.

Methodology

Site Selection and Data Collection

The study is conducted at Pandit Deendayal Energy University (PDEU) campus, located in Gandhinagar, India (23.2156°N, 72.6369°E). The site is selected based on open spaces, accessibility, and wind energy potential. Site characterization included topographical analysis (latitude, longitude, elevation) and evaluation of obstacles (buildings, trees) that influence wind flow and turbulence patterns. Historical wind data for the period 2020–2024 were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset at monthly temporal resolution and 10-meter reference height. ERA5 provides satellite-derived reanalysis estimates at 0.25° × 0.25° spatial resolution, combining observational data with numerical weather prediction models. While higher temporal resolution data would capture short-term wind variability, monthly averages provide a reliable basis for long-term resource assessment and annual energy yield estimation, which are the primary objectives of this feasibility study. Geographic Information System (GIS) tools are employed to assess terrain elevation, land use, and obstacles affecting wind flow.

Wind Resource Assessment

Since wind speed measurements are commonly recorded at a standard reference height of 10 meters, it is essential to adjust these values to the hub height of the wind turbine for accurate energy potential assessment. In this study, wind speeds at 20 meters above ground level were estimated using two widely accepted methods: The Power Law and the Logarithmic Wind Profile. The Power Law is a simple empirical model given by Eq. (1), where V_1 is the known wind speed at height H_1 (10 m), V_2 is the estimated wind speed at height H_2 (20 m), and α is the wind shear exponent, typically ranging from 0.10 to 0.20 depending on surface roughness. In this case, a value of 0.14 was used, assuming moderately open terrain.

$$V_2 = V_1 * \left(\frac{H_2}{H_1}\right)^{\alpha} \tag{1}$$

The Logarithmic Profile, based on boundary layer theory, as shown in Eq. (2), where Z_0 is the surface roughness length, assumed to be 0.03 m for open flat terrain. Both methods were applied to adjust the 10-meter wind speed data to 20 meters, ensuring more accurate input values for wind power density and subsequent energy calculations.

$$V_2 = V_1 * \left(\frac{ln(H_2/Z_0)}{ln(H_1/Z_0)}\right) \tag{2}$$

Additionally, Wind Power Density is calculated on monthly basis to evaluate how wind energy potential fluctuates over time. This information is vital for assessing the feasibility and expected performance of wind turbines. The Wind Power Density is given by Eq. (3), where ρ is the air density (typically taken as $1.225\ kg/m^3$ at sea level and standard conditions) and V is the wind speed in meters per second.

$$WPD = \frac{1}{2} * \rho * V^3 \tag{3}$$

The capacity factor is a key performance indicator used to evaluate the efficiency and productivity of a wind turbine over a specific period. It is defined as the ratio of the actual energy output of the turbine to the maximum possible energy it could generate if it operated at its rated capacity continuously. Mathematically, it is expressed as shown in Eq. (4).

$$Capacity\ Factor = \frac{Actual\ Energy\ Output}{Rated\ Power} \tag{4}$$

System Performance Simulation

To assess grid integration potential, HOMER Pro software was used to simulate system performance incorporating the selected turbine, converter, and campus load profile. The simulation enabled evaluation of annual energy generation patterns, grid dependency, and system capacity factor under site-specific wind conditions.

Results and Discussion

The wind speed at 20 meters was calculated from the measured values at 10 meters using both the Power Law and Logarithmic formulas across different years. These methods are commonly used for vertical wind speed extrapolation, with each based on distinct atmospheric assumptions. Upon analyzing the results year by year, both methods showed similar trends in wind speed variation, but the logarithmic values demonstrated slightly smoother and more stable transitions over time. The logarithmic method yielded consistent results with lower fluctuations because it is derived from boundary layer theory and explicitly accounts for surface roughness effects through the roughness length parameter (Z_0). In contrast, the empirical power law uses a fixed exponent (α) that cannot adapt to varying terrain conditions, leading to greater sensitivity to local variations. This theoretical foundation makes the logarithmic profile more physically representative of actual wind shear behavior in the atmospheric surface layer, particularly for the moderately open terrain at PDEU. The calculated wind speed value using both methods is summarized in Table 1.

Table 1. Wind speed at 20m using power law & logarithmic

Year	Power Law	Logarithmic
2020	3.64	3.70
2021	3.91	3.97
2022	3.85	3.92
2023	3.77	3.82
2024	3.79	3.85

To understand the variation in wind availability throughout the year, the monthly wind speed analysis was performed (Figure 1) to identify seasonal trends and high/low-wind periods, providing insights for operational planning and maintenance scheduling.

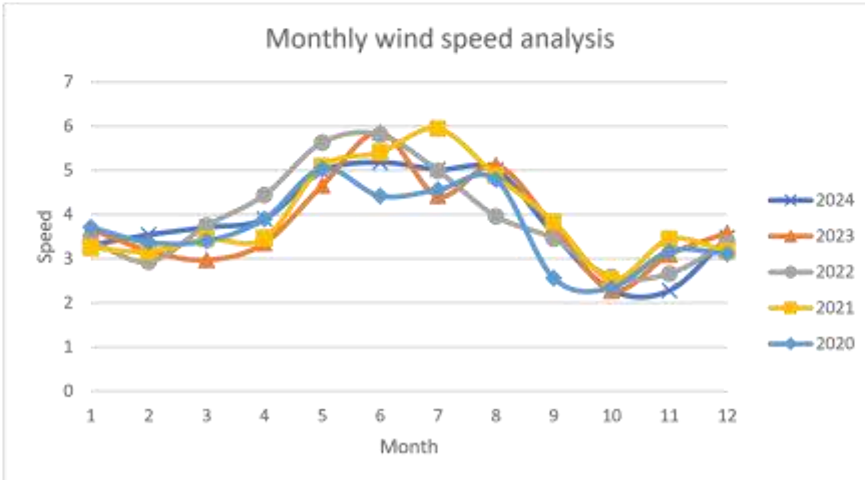

Figure 1. Monthly average wind speed (m/s) at 20m height

The monthly wind power density (WPD) analysis reveals significant temporal variation in energy potential (Figure 2). Higher WPD values during summer-monsoon months correspond to stronger, more consistent winds, directly influencing monthly energy output estimates.

The observed seasonal wind speed peaks during summer and monsoon months (May-August) can be attributed to regional meteorological drivers specific to Gujarat. During summer, intense solar heating creates strong thermal gradients that drive convective winds and sea-breeze circulation from the nearby Gulf of Khambhat. The southwest monsoon (June–September) brings moisture-laden winds from the Arabian Sea, resulting in sustained higher wind speeds. Conversely, the post-monsoon and winter seasons exhibit significantly lower wind speeds (2.28–3.51 m/s) due to stable atmospheric conditions and reduced pressure gradients. These seasonal patterns directly influence the turbine's operational profile, with 60–70% of annual energy generation concentrated in the high-wind summer-monsoon period.

The Archimedes AWM1500D was selected for its suitability to moderate wind conditions, featuring a 3.0 m/s cut-in speed and 1 kW rated capacity. The turbine's power curve (Eq. 5) was applied to wind speed frequency distributions to calculate expected power output, providing realistic energy estimates. Capacity factors were calculated using annual energy output from the turbine's power curve and site-specific wind data, supporting long-term planning decisions (Table 2). The monthly averaging approach provides conservative long-term energy estimates suitable for preliminary feasibility assessment. However, this temporal resolution does not capture short-term wind variability and turbine intermittency, which would require sub-daily (hourly or finer) measurements for detailed load-matching analysis.

$$Power\ Output = 9.7401 - 20.5574 * x + 5.4497 * x^2 + 0.0751 * x^3 \tag{5}$$

The calculated capacity factors of 5–6% are significantly lower than typical small wind turbine benchmarks. Industry standards suggest that micro-turbines (< 10 kW) in viable wind sites typically achieve capacity factors of 15–25%, while utility-scale turbines exceed 30–40%. The low performance at PDEU reflects marginal wind conditions where average speeds (3.7–3.97 m/s) barely exceed the turbine's cut-in threshold (3.0 m/s), resulting in frequent operation in the low-efficiency region of the power curve. This indicates that the site is sub-optimal for standalone wind generation and would require either significantly taller hub heights (40–60 m) to access stronger winds aloft, or integration within a hybrid solar-wind system to ensure consistent energy supply.

To evaluate practical implementation feasibility, HOMER Pro software was employed to simulate a wind-grid hybrid configuration incorporating the Archimedes AWM-1500D turbine specifications, monthly wind resource data, and estimated campus electrical demand. The simulation analyzed annual energy generation potential and grid dependency ratio. Results indicated that while the turbine can generate supplementary power, the performance limitations (5-6% capacity factor) result in limited annual energy contribution relative to total campus demand. The analysis suggests that wind energy at this location would function as a minor supplementary source, requiring continuous grid backup to ensure reliable power supply.

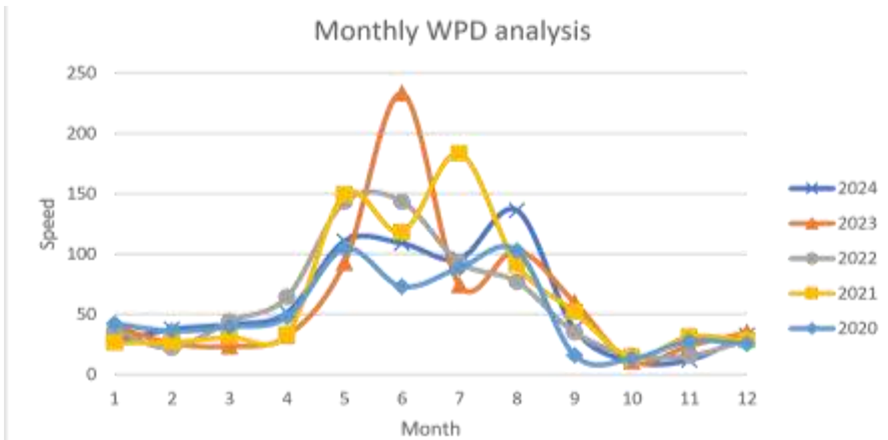

Figure 2. Monthly average wind power density (W/m^2) at 20m height

Table 2. Yearly average power calculations using power curve and capacity factor

Year	Average Power	Capacity Factor
2020	32.61	0.05
2021	41.17	0.06
2022	39.24	0.05
2023	39.33	0.06
2024	37.94	0.05

Conclusion

The study effectively evaluated the feasibility of harnessing wind energy at the selected site. By using both the power law and logarithmic wind profile equations, the project accurately estimated the wind speed at turbine hub height. This enabled the calculation of wind power density, which served as a key indicator of the site's wind energy potential. The results obtained indicate that while the wind speeds at the site are moderate, there is sufficient potential for small to medium-scale wind energy generation. Additionally, the study highlighted the importance of accurate wind data, proper system sizing, and site-specific analysis in the successful implementation of renewable energy systems. Future work should incorporate high-resolution (hourly or sub-hourly) wind data and real-time campus demand profiles to analyze power generation under varying scenarios including peak demand periods with low wind conditions, enabling more accurate assessment of wind-grid integration strategies. Overall, this project contributes valuable insights toward renewable energy planning and sustainability initiatives at PDEU.

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