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# Operational performance of a 8-MW scale grid integrated Wind Energy conversion system

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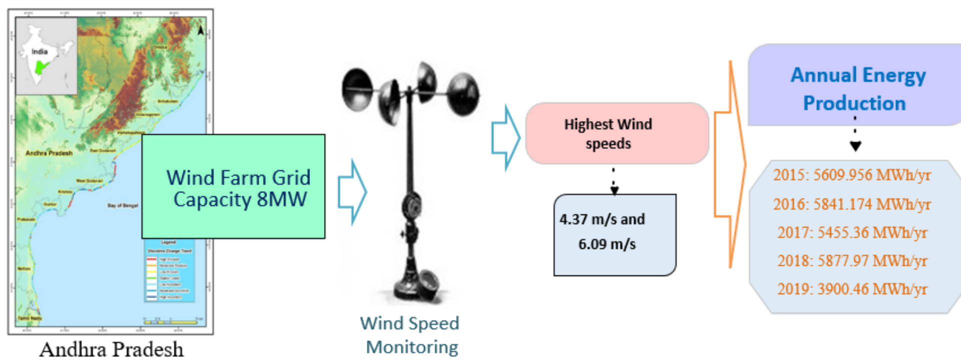
## ABSTRACT




In this article, the operational performance of an 8 MW grid-connected cluster wind farm in Andhra Pradesh, India, is evaluated over a five-year period. At various heights above sea level, the wind farm's yearly average wind speeds were monitored. The highest recorded wind speeds were 4.37 m/s and 6.09 m/s. With capacity factors ranging from 24.6% to 44.9% between 2015 and 2019, the wind farm's reported annual energy production was found to be 5609.956, 5841.174, 5455.36, 5877.97, and 3900.46 MWh/yr. About 21.68% of the total wind farm was available. Analysis of the mean bias error (MBE) and normalized mean bias error (NMBE), which is the normalized version of the MBE, indicated significant trends between 2015 and 2019 in this study. The case study suggests building the right turbines nearby the research region to enhance the performance of wind farms.

*Keywords: Wind Data Analysis, Resource Estimation, Cluster Wind Farm; Performance indicators; Power Curve; Annual Energy output.*

## INTRODUCTION

One of the most essential resources is wind, which arises from the sun, and it also plays a vital part in wind energy generation.[1] The wind's energy generation is influenced by factors like wind speed, direction, air density, temperature, pressure, humidity, and turbine parameters like blade length, rotor diameter, and hub height, all influenced by the sun's lopsided atmosphere warmth.[2] The wind energy generation theory highlights wind's crucial role in energy development, with wind turbines converting kinetic energy into mechanical energy for specialized operations like grain crushing and water pumping.[3]

Wind turbines convert wind energy into electricity using propeller-like blades around a rotor, suitable for various applications including energy harnessing and personal use. Horizontal turbines are preferred under steady wind streams, producing superior wind energy.[4] Small wind turbines are frequently selected for local applications. They are often erected in isolated, rural, and off-grid places where there is no connection to the national grid and have a capacity of less than 0.1 MW.[5] Wind turbine energy production is influenced by wind speed, rotor diameter, and hub height. The rotor spins an electric generator, driven by the driveshaft. Modern wind turbines are a renewable, sustainable, profitable, and pollution-free source of global wind power technology.[6]

Wind speed, density, and the area swept by the rotor's diameter all have an impact on how much energy a turbine can harvest from the wind.[7] Because of the increased use of electrical energy around the world, the load on the power system increases.[8] India is the fourth-largest greenhouse gas producer, accounting for 6.96% of emissions, after China (25.26%), the United States (14.4%), and the European Union (11.6%. Renewable energy sources like solar, wind, and urban trash minimize greenhouse gas emissions. The main greenhouse gas emissions include water vapor, carbon dioxide, methane, ozone, nitrogen oxide, and chlorofluorocarbons.[9]

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Due to the scarcity of natural fuels like coal and oil, which are derived from dead animals or plants in the earth that developed millions of years ago, these green energy alternatives are contending with the world's electricity-generating sectors.[10] Wind power has evolved into an unlimited, low-cost, green energy source over the last decade.[11] The wind energy system block diagram is shown in figure 1.

India has 42.6 GW of installed generation capacity as of March 31, 2023, with thermal energy accounting for the majority (211.8 GW coal + lignite & 24.8 GW gas, 6.78 GW nuclear, and 4.7 GW hydro), as well as modest hydro, wind, bio-power, and solar energy.[12] The WAsP (Wind Atlas Analysis and Application Program) Climate Analyst tool was employed to generate wind climatology estimates for nine stations. Utilizing 10-minute average wind speeds at 10 meters above ground level, the tool produced wind rose and Weibull distribution function representations. Subsequently, the WAsP Map Editor tool incorporated coordinates and topographic data to create surface roughness and contour maps for the stations.[29]

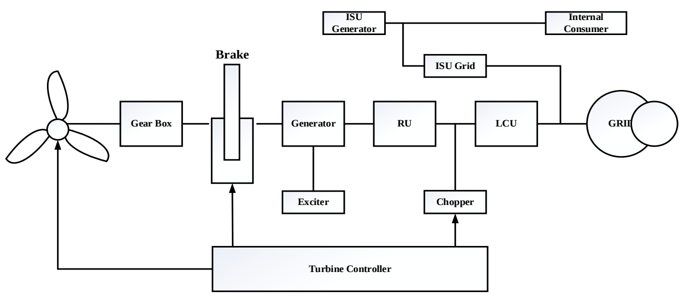


**Figure 1:** General Components of Wind Turbine

India's wind generation capacity has reached 42 GW, making it the world's fourth-largest installed wind power capacity. The growth is primarily in the southern, western, and northern regions. Andhra Pradesh, with a total installed capacity of 8.1 GW, has the highest wind power densities. To meet the state's growing energy demand, it is crucial to encourage wind power generation, attract private capital, and invest in manufacturing facilities to create jobs.[13] The installed capacity of wind farms by the end of 2022 in Andhra Pradesh is 8.5GW (https://www.nrel.gov/docs/fy18osti/70948.pdf) [14].

This article examines the performance of 8-MW grid-connected wind power plants, focusing on Cluster wind farms I, II, and III. The study highlights the significant load, employment, and environmental benefits of these cluster-based energy sources. The goals of the present study are

- To comprehend the wind data analysis, resource estimation, energy outputs, and performance indicators.
- To analyse the operation of a cluster wind farm installed in Ramagiri Mandal, Anantapur District, Andhra Pradesh, India.
- Estimation of the error matrices of the studied wind farm.

In the present study, wind data analysis, resource estimation, and performance indicators are identified which are useful for feasibility analysis of the studied wind farm. The values attained from this study will create awareness of the wind potential of such a system being used to regulate the problem of energy shortage.[15] and increase the usage of wind renewable energy sources in the several parts of wind feasible locations in the world. The developing countries can be a universal leader in using these renewable sources.

## LITERATURE REVIEW

In 2021 Astolf et al.[16] employed multivariate Support Vector Regression on SCADA data from two Italian wind farms with 15 turbines. Innovative models, incorporating minimum, maximum, and standard deviation of variables, achieved one-third improvement in error metrics. Results showed competitive performance, with a 2.5% mean absolute percentage error in one test case, and enhanced interpretability of wind turbine performance.

In 2021 Pandit et al.[17] addressed the challenges of offshore wind turbine maintenance by proposing a SCADA data-based Gaussian process fault detection algorithm. Operational variables, pitch angle, and rotor speed were integrated, enhancing early failure detection. Comparative studies revealed rotor speed significantly improved model accuracy. Validation against existing methods demonstrated the algorithm's effectiveness in detecting yaw misalignment failures with no false positives, reducing downtime and improving power production. The study utilized historical SCADA 10-min data from pitch-regulated turbines for training and validation, emphasizing the algorithm's practical applicability.

In 2021 Bilgili et al.[18] examined the aerodynamic rotor performance of a 3.3 MW modern onshore wind turbine using one year of measurement data. Analyzing wind speeds and directions, the study calculated key turbine parameters, including power coefficient, thrust force, and tip-speed ratio. Results contributed valuable insights for assessing economic and technical feasibility, supporting advancements in wind energy and turbine technology.

In 2021 Gao et al.[19] examined a 2.5 MW utility-scale wind turbine's performance and structural responses during a 51-hour natural icing event at the Eolos Wind Energy Research Field Station, systematically. The analysis revealed significant reductions in rotor speed and pitch angle due to ice accretion, leading to notable power losses. The 51-hour icing event resulted in approximately 25 MWh of energy loss, with the post-icing phase contributing 17%. These findings offer valuable insights for developing advanced control strategies to enhance the efficiency and safety of wind turbines operating in natural icing conditions.

In 2021 Chen et al.[20] introduced a method employing long short-term memory (LSTM) and auto-encoder (AE) neural networks for sequential wind turbine condition monitoring data. The approach constructed a performance assessment model and utilized an adaptive threshold estimation method, incorporating support vector regression. Mutual information theory was applied to identify critical condition monitoring parameters. The method's effectiveness was validated through a real-world wind turbine condition monitoring case study.

In 2022 Kumar et al.[21] quantitatively assessed the operational efficiencies of 14 Indian wind power plants from 2016 to 2020 using a two-stage data envelopment analysis Tobit model. Results revealed that 14% of these plants operated at the most productive scale. Tobit regression indicated a negative impact of wind turbine age on production efficiency, while site elevation positively influenced operational efficiency. The study's findings offer insights for stakeholders and policymakers to optimize strategies for ongoing wind power plants in India.

In 2022 Kumar et al.[22] utilized HOMER Pro modeling and optimization to propose cost-effective HRES configurations for a community building in Vaddeswaram, Andhra Pradesh. Two optimized systems were proposed, one with solar panels and wind turbines (HRES-1) and another with solar panels, wind turbines, and a bio-generator (HRES-2. The approach considered variations in component costs to analyze the impact on net present cost and cost of energy, offering valuable insights for system optimization and component significance.

In 2023 Shukla et al.[23] assessed the effectiveness of eight novel probability distribution models in analyzing wind speed distribution over 39 years across six stations in Kerala, India with diverse topographies. Utilizing regression-based test statistics (AIC and BIC), A-D test statistics, and histogram analysis, the Weighted Pranav distribution demonstrated optimal fit for low and middle-altitude stations, while the Shukla distribution excelled in A-D test statistics. Geometric features also played a significant role in confirming overall model fitness. The study recommended Weighted Pranav, Shukla, Ram Awadh, and Prakaamy distributions for representing wind speed variations in locations with diverse topographic features based on low-altitude measurements.

In 2021 Yadav et al.[24] compared numerical methods for wind energy analysis, including Method of Moments (MoM), Energy Pattern Factor Method (EPFM), Maximum Likelihood Method (MLM), Energy Density Method (EDM), Energy Pattern Factor Method of Sathyajith (EPFMS), Rayleigh's distribution (Rayl), and Novel Energy Pattern Factor Method (NEPFM. NEPFM performed best for wind energy density in Visakhapatnam, Amaravati, and Tirupati, while MLM excelled for Rajamahendravaram. Rayleigh's distribution was optimal for probability density in Visakhapatnam, Rajamahendravaram, and Amaravati, while EPFM was best for Tirupati. Rayleigh's distribution proved statistically superior for cumulative density in Visakhapatnam and Amaravati, and NEPFM for Rajamahendravaram and Tirupati.

In 2023 Kaliappan et al.[25] reported that the Wind power, while feasible, requires effective Maximum Power Point Tracking (MPPT) to ensure optimal turbine output. This study evaluated MPPT algorithms, focusing on Perturb and Observe (P&O) and Particle Swarm Optimization (PSO. The research aimed to develop and assess optimization methods, considering factors like initial investment, responsiveness, and energy production capacity. A comprehensive comparative analysis was conducted using the MATLAB Simulink tool.

## DESCRIPTION OF THE STUDIED WIND SYSTEM

The studied wind farm is located at a longitude of 77° 30' 41.82" E and a latitude of 14° 19' 42.20" N in the Rayalaseema Region of Ramagiri Mandal, Anantapur district, Andhra Pradesh, India. The wind farm under investigation is located between Ramagiri and Muthuvakuntla, and the elevation is 535 meters above sea level. The studied wind turbine energy system has the specifications is listed in the below table 1 and the total wind speed of each mill in each clusters are shown in table 2.

**Table 1:** Details of Installed Wind Turbines at the Study location

| Specification of installed wind turbine | Make or type | Swept Area ($m^2$) | Number of blades | Hub Height(m) | Quantity (no.) | Total Power Output (MW) |
|---|---|---|---|---|---|---|
| NW25.5/ 0.25 MW | Ned Wind | 511 | 3 | 30 | 4 | 1 |
| NW40/ 0.5 MW | Ned Wind | 1306 | 2 | 39 to 65m/80m | 14 | 7 |

**Table 2**: Total wind mills in each cluster

| Clusters | Total Power Generation | No. of Turbine | Number of Wind Turbine |
|---|---|---|---|
| I | 3MW | 500 | 5 |
| | | 250 | 2 |
| II | 3MW | 500 | 5 |
| | | 250 | 2 |
| III | 2MW | 500 | 4 |

During 1995, Commissioned 3 MW Cluster wind farm I as Pilot plant for Multiparty Venture Company Windia Power Ltd. During 1996, Commissioned second 3 MW Cluster wind farm II at Ramgiri, Anantpur District, Andhra Pradesh, and during 1998 commissioned other 2 MW Cluster wind farm III at Tallimadugulla, located in the Anantapur district of Andhra Pradesh. The wind farm view and geographical map are shown in Figure 2 and Figure 3 respectively. The specifications of installed wind turbines are listed in table 3.

**Figure 2:** Installed wind turbines at the studied location

**Figure 3:** Geographical map of wind farm Located at Ramagiri Mandal, Anantapur District, Andhra Pradesh (ref: Google maps (14.302417464002092, 77.51032415242346))

**Table 3**: Installed Wind Turbine Specifications

| | |
|---|---|
| Wind turbine Rotor Diameter | 25.5m/40m |
| Wind Turbine Hub Height | 30m/80m |
| Implementation of the Wind Farm | Grid-Connected |
| Operative range of the wind speed | 5 to 25m/s |
| The range of wind speed to obtain the design capacity | 15 to 25 m/s |
| Extreme wind speed turbine design | 52m/s |
| Wind Turbine Tip-Speed Ratio | 7 |
| Rotational speed of wind turbine | 40.6RPM |
| Rated Output Power | 0.25 MW/0.5 MW |
| Number of blades of the wind turbine | 2/3 |
| Angle of twist | 9.88° |
| Regulation of power | Stall |
| Axis Tilt Angle | 5° |
| Type of the system in transmission | Parallel, Three Stage |
| Rotor Coupling in transmission | Direct |
| Coupling of Generator in transmission | Flexible coupling with an intermediate shaft |
| Generators Used in Electrical system | Induction motor with a single speed, 3-ϕ 380/660V, four-pole, Nominal Speed 1520 rpm |
| Connection of grid integrated electrical network | Automatic direct coupling, inrush current is minimized by using thyristors |
| Rotor's weight | 4550kg |
| Nacelle's weight | 11000kg |
| Tower's weight | 16850kg for 29m height |

## FRAMEWORK AND METHODOLOGY

This case study involves the analysis of an 8 MW grid-connected wind energy system. The study aims to compare calculated values with actual measured energy output data. The steps taken are as follows:

1. **Step I:** Analysing Meteorological and Site Potential
   - Observe maximum and average wind speeds at 50m above sea level at the study location.
2. **Step II:** Monthly Energy Generation Analysis
   - Observe energy generated by Cluster wind farms I, II, and III monthly for 2015 and 2019.
3. **Step III:** Meteorological Analysis and Resource Assessment
   - Statistical analysis is used for methodologies Assessments.
4. **Step IV:** Energy Output Determination
   - Determine energy outputs for 2015 to 2019 using average wind speed and turbine specifications.
5. **Step V:** Performance Indicators Calculation
   - Calculate performance indicators such as Average Energy Generated, Max and Min Monthly Energy Generated, Capacity Factor, Specific Energy Production.
6. **Step VI:** Real-time Data Comparison
   - Compare real-time collected data with estimated/calculated values.
7. **Step VII:** Normalized Mean Bias Error Calculation
   - Calculate Normalized Mean Bias Error and Normalized Mean Bias Error.
8. **Step VIII:** Mean Bias Error Comparison
   - Compare Mean Bias Error and Normalized Mean Bias Error over the Five-year study period.

## POWER AVAILABLE IN THE WIND:

The concept of fluid mechanics involved in the wind flow pattern going through the power-producing rotor or wind turbine, the aerodynamic effect and efficiency of the generator/rotor combination, must be considered when determining a wind turbine's actual power production capability. The latest available HAWT is known to harvest a maximum of 45 percent of the existing wind power.[27]

$$P_{avail} = \frac{1}{2}\rho A U^3 \qquad (1)$$

It's worth noting that the density of wind power is proportionate to the density of air. The air density is 1.225kg/m3 under typical conditions (sea level, 150°C); A is the rotor's swept area (m2); the wind velocity (m/s) is denoted by the letter U.

## POWER COEFFICIENT

The ratio of a wind turbine's real electric power output to the total wind power flowing through the turbine blades at a given wind speed. The wind turbine power coefficient is commonly used to describe the performance of the installed wind turbine.

$$C_p = \frac{Rotor\ power}{Power\ available\ in\ the\ wind} = \frac{P}{\frac{1}{2}\rho A U^3} \qquad (2)$$

## MEAN BIAS ERROR

The mean bias is the average difference between the estimated and actual power throughout the entire dataset. The accuracy of a forecast or prediction in comparison to actual observations is measured statistically using the Mean Bias Error (MBE).[28] The MBE can be used to evaluate the performance of a wind speed or wind power prediction model in relation to windmills or wind energy forecasts.

$$Mean\ Bias\ Error = \frac{Calculated\ value_i - Measured\ Value_i}{Measured\ Value_i} * 100 \qquad (3)$$

$$where\ i = months\ in\ a\ year\ ie..,from\ 1\ to\ 12$$

## NORMALIZED MEAN BIAS ERROR

The Normalized Mean Bias Error (NMBE) is a statistic that is used to evaluate the precision of predictions or forecasts in a number of different domains, including the forecasting of wind energy production from wind turbines or windmills. NMBE calculates the systematic bias in the forecasts in relation to the measured or observed values, normalized to the observed values. The formula used to calculate it is as follows, and it is commonly given as a percentage:

$$Normalized\ Mean\ Bias\ Error = \frac{Calculated\ value_i - Measured\ Value_i}{Mean\ Measured\ Value_i^{12}} * 100 \qquad (4)$$

$$where\ i = months\ in\ a\ year\ ie..,from\ 1\ to\ 12$$

The selected error indices, including Weibull, Rayleigh, Mean Bias Error, and Normalized Mean Bias Error, were chosen for their superior performance in capturing the accuracy and reliability of the model in wind energy studies. Weibull and Rayleigh distributions are well-suited for modeling wind speeds, and Mean Bias Error along with Normalized Mean Bias Error provide robust metrics that account for both systematic and proportional errors, offering a comprehensive assessment of the model's predictive capability. These indices collectively outperform others by providing a more accurate and nuanced evaluation of the model's performance in capturing wind characteristics.

## RESULTS AND DISCUSSION

### AVERAGE AND MAXIMUM WIND SPEEDS

Since wind speed varies during the day, wind energy generation does not remain consistent throughout the day. It is a result of the fact that the effective wind speeds of wind turbines typically range from 3 to 25 m/s. The output power of wind turbines will be zero if the wind speed is not within this range. The observed average and maximum wind speed at the Ramagiri location is shown in the figure 4 below.

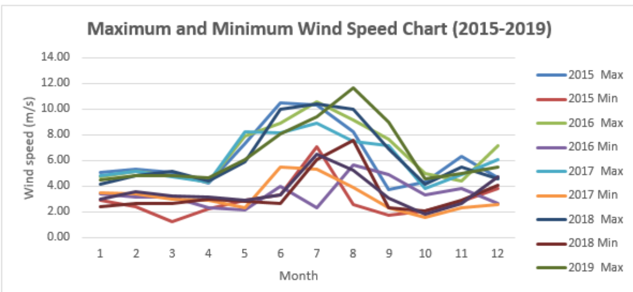


**Figure 4:** Minimum and Maximum wind speeds monitored for Five years.

Figure 4 provides details on climatic conditions and wind patterns by displaying the average wind speeds in the Ramagiri region from 2015 to 2019. The data reveals considerable variations in wind speeds over time, with August 2019 recording the highest wind speed. These variations may be caused by weather-related elements such seasonal shifts or atmospheric pressure systems.

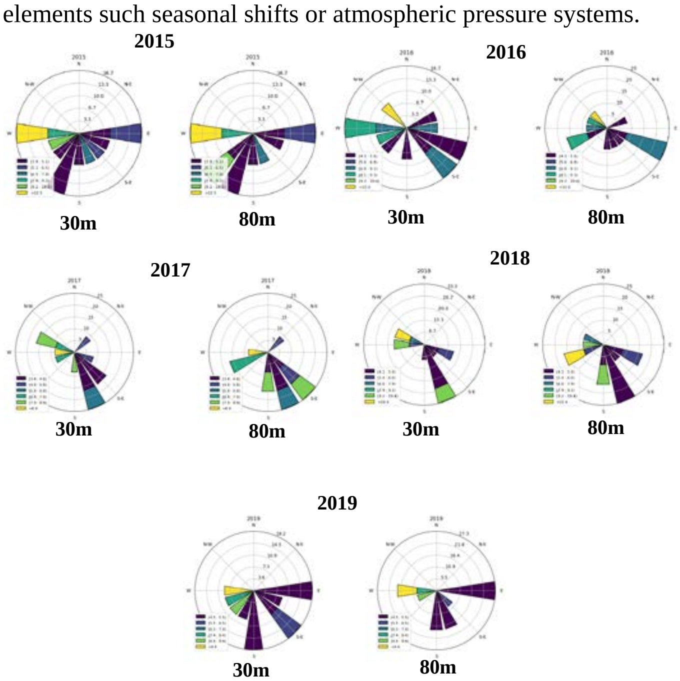


**Figure 5:** Variation of the direction of the wind (in degrees) and Speed of the wind (m/s) at 30m & 80m

On the other hand, March 2015 witnessed the lowest wind speeds ever recorded, presumably as a result of peculiar weather patterns or climatic characteristics in Ramagiri. This information emphasizes how weather-related elements have a big influence on the local climate and wind patterns. The wind direction in each years has been represented in rose diagram and shown in figure 5.

**5.2. Mathematical Analysis**

Power = $\frac{1}{2}\rho A V^3 C_p$

Where,

ρ = Density of air (1.293 kg/m3),

A = Swept Area of the Turbine,

V= Velocity of the wind,

$C_p$= Maximum Power coefficient (0.593).

The velocity and operational hour of three cluster for 2015 has been shown in table 4 and 5.

**Table 4**: Velocity for each cluster wind farm

| Month-Year | Cluster I-0.25 MW | Cluster I-0.5 MW | Cluster II - 0.25MW | Cluster II -0.5 MW | Cluster III-0.5 MW |
|---|---|---|---|---|---|
| Jan-15 | 4.635 | 5.808 | 4.335 | 5.608 | 5.908 |
| Feb-15 | 4.969 | 6.226 | 4.999 | 6.099 | 6.126 |
| Mar-15 | 4.835 | 6.458 | 4.835 | 6.358 | 6.358 |
| Apr-15 | 3.977 | 4.984 | 4.597 | 4.984 | 4.784 |
| May-15 | 5.397 | 6.762 | 5.497 | 6.562 | 6.562 |
| Jun-15 | 8.487 | 9.734 | 8.328 | 10.934 | 9.694 |
| Jul-15 | 9.481 | 11.731 | 9.109 | 11.189 | 9.831 |
| Aug-15 | 7.593 | 10.315 | 7.493 | 9.715 | 11.915 |
| Sep-15 | 9.784 | 12.960 | 9.684 | 12.660 | 10.860 |
| Oct-15 | 3.794 | 4.754 | 3.894 | 4.454 | 4.854 |
| Nov-15 | 4.816 | 6.034 | 4.716 | 6.563 | 6.134 |
| Dec-15 | 4.587 | 5.747 | 4.787 | 5.647 | 5.847 |

**Table 5**: Operational hour of turbines in each month

| Month-Year | Cluster-I | Cluster-II | Cluster-III |
|---|---|---|---|
| Jan-15 | 3.35 | 3.865 | 2.094 |
| Feb-15 | 53.023 | 21.161 | 71.231 |
| Mar-15 | 32.144 | 25.094 | 35.542 |
| Apr-15 | 7.543 | 8.430 | 2.730 |
| May-15 | 49.305 | 61.335 | 42.202 |
| Jun-15 | 94.272 | 78.051 | 81.211 |
| Jul-15 | 110.716 | 135.242 | 153.137 |
| Aug-15 | 133.086 | 155.028 | 70.123 |
| Sep-15 | 30.045 | 39.003 | 46.140 |
| Oct-15 | 1.644 | 3.678 | 0 |
| Nov-15 | 26.767 | 25.212 | 37.994 |
| Dec-15 | 12.364 | 10.223 | 27.580 |

### CALCULATION FOR JANUARY 2015

**Cluster I:**

**0.25 MW:**

P = $\frac{1}{2}\rho A V^3 C_p$

P = 0.5 *1.293*510.446*4.6353*0.593

P = 0.019485979 MW

There are two 0.25 MW turbine available in Cluster I
Therefore, total power generated from 0.25 MW turbines are

= 2* 19485.979
= 0.038971959 MW (5.1)

**0.5 MW:**

$$P = \frac{1}{2}\rho A V^3 C_p$$

P = 0.5 *1.293* 1962.5*5.8083*0.593
P = 0.147405168 MW

There are five 0.5 MW turbine available in Cluster I
Therefore, total power generated from 0.5 MW turbines are

= 5*147405.168
= 0.737025841 MW (5.2)

Total power generation at Cluster I:
Adding (5.1) & (5.2)

Total power = 38971.959 + 737025.841
= 0.884431009 MW

Power generation in Wh =Total power* Total hour turbine operated in a month
= 884431.009*3.35
= 2962843.882 Wh
= 2.962 MWh

Similarly, the cluster 2 and cluster 3 has been calculated and the power generations are 2.687 MWh and 1.29MWh.

Total power has been generated in January 2015 is

Total Power in Jan-15 = Power at cluster I + Power at cluster II + Power at cluster III
= 2.962 +2.687 +1.29
= 6.939 MWh

Similarly, we have calculated the Mathematical approach for Feb 15 to Dec 2019. The result has been tabulated and been shown in Table.6 to Table.10

**Table 6**: Theoretical calculated power generation from Jan-15 to Dec-15

| | **Cluster Wind farm I** | **Cluster Wind farm II** | **Cluster Wind farm III** | **Theoretical analysis** |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 15 | 2.962 | 2.687 | 1.29 | 6.939 |
| Feb' 15 | 50.677 | 18.954 | 49.139 | 118.7709 |
| Mar' 15 | 33.846 | 25.284 | 27.080 | 86.2116 |
| Apr' 15 | 3.433 | 4.031 | 0.659 | 8.123728 |
| May' 15 | 60.025 | 68.825 | 35.727 | 164.5781 |
| Jun' 15 | 348.688 | 401.264 | 222.121 | 972.074 |
| Jul' 15 | 704.712 | 751.496 | 437.506 | 1893.715 |
| Aug' 15 | 571.926 | 560.188 | 356.369 | 1488.484 |
| Sep' 15 | 256.706 | 311.613 | 177.359 | 745.6804 |
| Oct' 15 | 0.425 | 1.066 | 0 | 1.492479 |
| Nov' 15 | 22.631 | 27.616 | 25.709 | 75.95763 |
| Dec' 15 | 9.025 | 7.206 | 16.250 | 32.48323 |
| Total MWh Generated/year | 2064.422 | 2179.629 | 1349.16 | 5593.227 |

**Table 7**: Theoretical calculated power generation from Jan-16 to Dec-16

| | **Cluster Wind farm I** | **Cluster Wind farm II** | **Cluster Wind farm III** | **Theoretical analysis** |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 16 | 5.148 | 14.916 | 18 | 38.065 |
| Feb' 16 | 0.938 | 4.481 | 3.460 | 8.880 |
| Mar' 16 | 10.07 | 12.440 | 28.671 | 51.182 |
| Apr' 16 | 7.172 | 18.141 | 17.469 | 42.782 |
| May' 16 | 0 | 216.318 | 134.404 | 350.722 |
| Jun' 16 | 208.936 | 442.097 | 271.571 | 922.605 |
| Jul' 16 | 514.202 | 575.460 | 331.704 | 1421.368 |
| Aug' 16 | 587.436 | 605.365 | 371.642 | 1564.445 |
| Sep' 16 | 438.971 | 437.391 | 277.572 | 1153.935 |
| Oct' 16 | 53.543 | 66.488 | 44.757 | 164.790 |
| Nov' 16 | 18.848 | 23.104 | 17.370 | 59.324 |
| Dec' 16 | 18.288 | 11.957 | 23.473 | 53.7193 |
| Total MWh Generated/year | 1863.558 | 2428.164 | 1540.099 | 5831.821 |

**Table 8**: Theoretical calculated power generation from Jan-17 to Dec-17

| | **Cluster Wind farm I** | **Cluster Wind farm II** | **Cluster Wind farm III** | **Theoretical analysis** |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 17 | 61.15871 | 52.14821 | 44.85561 | 158.1625 |
| Feb' 17 | 50.18877 | 44.93326 | 36.46922 | 131.5913 |
| Mar' 17 | 7.701106 | 13.87205 | 6.377536 | 27.95069 |
| Apr' 17 | 22.36008 | 41.50034 | 25.59696 | 89.45738 |
| May' 17 | 184.3786 | 212.606 | 133.4057 | 530.3903 |
| Jun' 17 | 549.3003 | 581.9589 | 327.4193 | 1458.679 |
| Jul' 17 | 731.0708 | 706.7541 | 322.9441 | 1760.769 |
| Aug' 17 | 332.5929 | 398.9075 | 214.6516 | 946.152 |
| Sep' 17 | 91.6533 | 105.2112 | 54.98148 | 251.846 |
| Oct' 17 | 0.588394 | 1.250091 | 1.499044 | 3.337529 |
| Nov' 17 | 7.904227 | 11.57714 | 6.112405 | 25.59377 |
| Dec' 17 | 13.36456 | 12.07413 | 14.68731 | 40.126 |
| Total MWh Generated/year | 2052.262 | 2182.793 | 1189 | 5424.055 |

**Table 9**: Theoretical calculated power generation from Jan-Dec-18

| | **Cluster Wind farm I** | **Cluster Wind farm II** | **Cluster Wind farm III** | **Theoretical analysis** |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 18 | 3.175598 | 5.637645 | 9.16405 | 17.97729 |
| Feb' 18 | 18.97277 | 18.72219 | 22.88265 | 60.57761 |
| Mar' 18 | 11.77162 | 15.1932 | 14.03058 | 40.9954 |
| Apr' 18 | 1.16831 | 6.602326 | 1.023878 | 8.794514 |

| | | | | |
|---|---|---|---|---|
| May' 18 | 7.864867 | 20.32263 | 6.900296 | 35.08779 |
| Jun' 18 | 387.5515 | 503.4123 | 262.9276 | 1153.891 |
| Jul' 18 | 729.2707 | 720.4333 | 433.9561 | 1883.66 |
| Aug' 18 | 792.0676 | 904.1904 | 482.9661 | 2179.224 |
| Sep' 18 | 112.9972 | 152.8067 | 76.97407 | 342.778 |
| Oct' 18 | 17.64148 | 25.00181 | 13.99108 | 56.63437 |
| Nov' 18 | 18.78356 | 20.58158 | 17.90061 | 57.26575 |
| Dec' 18 | 6.039753 | 5.366278 | 4.051671 | 15.4577 |
| Total MWh Generated/year | 2107.305 | 2398.27 | 1346.769 | 5852.344 |

**Table 10**: Theoretical calculated power generation from Jan-19 to Dec-19

| | Cluster Wind farm I | Cluster Wind farm II | Theoretical analysis |
|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 19 | 2.174532 | 1.24631655 | 3.420848 |
| Feb' 19 | 2.053207 | 6.084613147 | 8.13782 |
| Mar' 19 | 0 | 0.786952278 | 0.786952 |
| Apr' 19 | 0 | 4.038253247 | 4.038253 |
| May' 19 | 73.28377 | 56.3428644 | 129.6266 |
| Jun' 19 | 258.2313 | 289.3895952 | 547.6209 |
| Jul' 19 | 585.1907 | 622.3276289 | 1207.518 |
| Aug' 19 | 663.2109 | 672.1611201 | 1335.372 |
| Sep' 19 | 307.5197 | 310.2231169 | 617.7428 |
| Oct' 19 | 0.792772 | 0.971051062 | 1.763823 |
| Nov' 19 | 10.6211 | 4.549311712 | 15.17041 |
| Dec' 19 | 10.33842 | 6.38758664 | 16.72601 |
| Total MWh Generated/year | 1903.078 | 1968.121 | 3871.199 |

## OPERATIONAL PERFORMANCE OF CLUSTER WIND FARM AT STUDIED LOCATION

A cluster is a group of wind farms located in different topographical areas that form a partnership and work toward a collective purpose, such as promoting modernization, entrepreneurship, knowledge transfer, improved commercial relationships, and more effective government intervention. Tables 11 to 15 exhibits the measured or real-time monitored annual energy output data for three phases of the wind project, namely Cluster Wind farm I, II, and III, and figure 6 shows the comparison of estimated and real-time energy outputs.

**Table 11**: Total Energy Generation in MWh of Cluster Wind farm I, II & III monitored from January 2015 to December 2015.

| | Cluster Wind farm I | Cluster Windfarm II | Cluster Wind farm III | Real-time monitored data |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 15 | 2.6 | 2.688 | 1.3 | 6.588 |
| Feb' 15 | 50.7 | 19.100 | 49.3 | 119.1 |
| Mar' 15 | 34.0 | 25.380 | 27.5 | 86.88 |
| Apr' 15 | 3.7 | 4.248 | 0.9 | 8.848 |
| May' 15 | 60.4 | 69.204 | 35.9 | 165.504 |
| Jun' 15 | 349.7 | 401.532 | 222.7 | 973.932 |
| Jul' 15 | 709.3 | 752.844 | 437.9 | 1900.044 |
| Aug' 15 | 572.3 | 560.292 | 357.0 | 1489.592 |
| Sep' 15 | 257.1 | 311.640 | 177.9 | 746.64 |
| Oct' 15 | 0.7 | 1.308 | 0.0 | 2.008 |
| Nov' 15 | 23.3 | 27.852 | 26.4 | 77.552 |
| Dec' 15 | 9.3 | 7.368 | 16.6 | 33.268 |
| Total MWh Generated/year | 2073.1 | 2183.456 | 1353.4 | 5609.956 |

**Table 12**: Total Energy Generation in MWh of Cluster Wind farm I, II & III monitored from January 2016 to December 2016.

| | Cluster Wind farm I | Cluster Wind farm II | Cluster Wind farm III | Real-time monitored data |
|---|---|---|---|---|
| **Month/ year** | **Generation (MWh)** | **Generation (MWh)** | **Generation (MWh)** | **Total Generation (MWh)** |
| Jan' 16 | 5.20 | 15.204 | 18.10 | 38.504 |
| Feb' 16 | 1.60 | 4.500 | 3.70 | 9.8 |
| Mar' 16 | 10.50 | 12.60 | 29.10 | 52.2 |
| Apr' 16 | 7.40 | 18.400 | 17.60 | 43.4 |
| May' 16 | 0.00 | 216.600 | 135.00 | 351.6 |
| Jun' 16 | 209.01 | 442.300 | 272.00 | 923.31 |
| Jul' 16 | 514.22 | 575.700 | 332.50 | 1422.4 |
| Aug' 16 | 587.49 | 606.500 | 371.90 | 1565.8 |
| Sep' 16 | 439.38 | 437.400 | 277.60 | 1154.3 |
| Oct' 16 | 53.80 | 66.700 | 44.80 | 165.3 |
| Nov' 16 | 18.93 | 23.500 | 17.40 | 59.83 |
| Dec' 16 | 18.44 | 12.200 | 23.90 | 54.54 |
| Total MWh Generated/year | 1865.97 | 2431.604 | 1543.6 | 5841.174 |

**Table 13**: Total Energy Generation in MWh of Cluster Wind farm I, II & III monitored from January 2017 to December 2017.

| | Cluster Wind farm I | Cluster Windfarm II | Cluster Wind farm III | Real-time monitored data |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 17 | 61.890 | 52.700 | 45.200 | 159.79 |
| Feb'17 | 50.600 | 45.200 | 36.900 | 132.7 |
| Mar' 17 | 7.800 | 13.900 | 6.400 | 28.1 |
| Apr' 17 | 22.520 | 41.800 | 25.600 | 89.92 |
| May' 17 | 185.200 | 213.200 | 133.500 | 531.9 |
| Jun' 17 | 551.060 | 584.100 | 328.400 | 1463.56 |
| Jul' 17 | 734.700 | 710.400 | 324.500 | 1769.6 |
| Aug' 17 | 333.530 | 401.800 | 215.400 | 950.73 |
| Sep' 17 | 93.050 | 107.200 | 56.500 | 256.75 |
| Oct' 17 | 0.890 | 1.800 | 1.700 | 4.39 |
| Nov' 17 | 8.440 | 12.000 | 6.200 | 26.64 |
| Dec' 17 | 13.980 | 12.600 | 14.700 | 41.28 |
| Total MWh Generated/year | 2063.66 | 2196.7 | 1195 | 5455.36 |

**Table 14**: Total Energy Generation in MWh of Cluster Wind farm I, II & III monitored from January 2018 to December 2018.

| | Cluster Wind farm I | Cluster Windfarm II | Cluster Wind farm III | Real-time monitored data |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 18 | 3.520 | 5.900 | 9.300 | 18.72 |
| Feb'18 | 19.600 | 19.400 | 23.100 | 62.1 |
| Mar' 18 | 11.920 | 15.200 | 14.400 | 41.52 |

| | | | | |
|---|---|---|---|---|
| Apr' 18 | 1.430 | 6.800 | 1.300 | 9.53 |
| May' 18 | 8.550 | 21.500 | 7.100 | 37.15 |
| Jun' 18 | 389.600 | 504.200 | 264.300 | 1158.1 |
| Jul' 18 | 732.250 | 722.300 | 434.600 | 1889.15 |
| Aug' 18 | 795.460 | 904.600 | 483.100 | 2183.16 |
| Sep' 18 | 113.770 | 155.100 | 77.600 | 346.47 |
| Oct' 18 | 17.960 | 25.200 | 14.400 | 57.56 |
| Nov' 18 | 19.490 | 20.700 | 18.000 | 58.19 |
| Dec' 18 | 6.220 | 5.800 | 4.300 | 16.32 |
| Total MWh Generated/year | 2119.77 | 2406.7 | 1351.5 | 5877.97 |

**Table 15**: Total Energy Generation in MWh of Cluster Wind farm I, II & III monitored from January 2019 to December 2019.

| | **Cluster Wind farm I** | **Cluster Wind farm II** | **Real-time monitored data** |
|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 19 | 2.240 | 1.400 | 3.64 |
| Feb'19 | 2.100 | 6.500 | 8.6 |
| Mar' 19 | 0.230 | 1.100 | 1.33 |
| Apr' 19 | 0.200 | 4.700 | 4.9 |
| May' 19 | 73.910 | 57.200 | 131.11 |
| Jun' 19 | 258.690 | 291.700 | 550.39 |
| Jul' 19 | 585.220 | 622.900 | 1208.12 |
| Aug' 19 | 663.480 | 674.500 | 1337.98 |
| Sep' 19 | 307.550 | 311.900 | 619.45 |
| Oct' 19 | 0.810 | 1.000 | 1.81 |
| Nov' 19 | 10.990 | 4.600 | 15.59 |
| Dec' 19 | 10.840 | 6.700 | 17.54 |
| Total MWh Generated/year | 1916.26 | 1984.2 | 3900.46 |

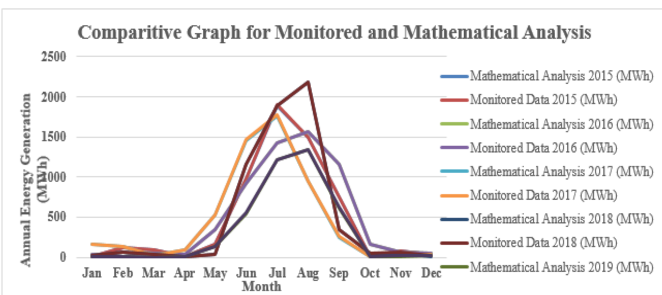


**Figure 6:** Comparison of Estimated and real time annual energy generation

## KEY PERFORMANCE INDICATORS OF STUDIED WIND FARM

Key performance indicators (KPIs) are tools for measuring a wind farm's progress toward its objectives. Despite the fact that wind energy is now a mature technology, there is a lack of well-defined best practises for evaluating a wind farm's performance during the operation and maintenance phase; asset management techniques and tools, such as KPIs, are not yet well-established [26].

This study provides a review of the primary existing indicators utilised in the operation and maintenance of wind farms, as such data is not currently available in the literature. Finally, a list of appropriate key performance indicators to help stakeholders have a better understanding of an operational asset and make sophisticated decisions. It is found that in-depth research into certain KPIs and the difficulties surrounding their implementation is likely required. The most identified KPI's of the study location are listed below in table 16 and the calculated values has been mentioned in table 17

**Table 16:** Performance Indicators of Studied Wind Farm (from monitored Analysis)

| **Performance Indicators of Studied Wind Farm** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|
| Total Energy Generated | 5609.95MWh | 5841.17 MWh | 5455.360 MWh | 5877.97 MWh | 3900.46 MWh |
| Maximum Energy Generated during the year | 1900.04 MWh (July) | 1565.89 MWh (August) | 1769.6 MWh (July) | 2183.16 MWh (August) | 1337.98 MWh (August) |
| Minimum Energy Generated during the year | 2.01 MWh October | 9.50 MWh February | 4.39MWh (October) | 9.53 MWh (April) | 1.33MWh (March) |
| Average Energy Generated during the period | 467.49 MWh | 449.32 MWh | 454.613 MWh | 489.83 MWh | 600.07 MWh |
| Capacity factor | 24.6% | 28.7% | 25.69% | 22.44% | 44.85% |

**Table 17:** Performance Indicators of Studied Wind Farm (from Mathematical Analysis)

| **Performance Indicators of Studied Wind Farm** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|
| Total Energy Generated | 5593.227 | 5831.821 | 5424.055 | 5852.344 | 3871.199 |
| Maximum Energy Generated during the year | 1893.715 (July) MWh | 1564.445 (August) MWh | 1760.769 (July) MWh | 2179.224 (August) MWh | 1207.518 (July) MWh |
| Minimum Energy Generated during the year | 1.492479 (October) MWh | 8.880 (Feb) MWh | 3.337529 (October) MWh | 8.794514 (April) MWh | 0.786952 (March) MWh |
| Average Energy Generated during the period | 466.2092 MWh | 485.9848 MWh | 452.0046 MWh | 487.6953 MWh | 323.9937 MWh |
| Capacity factor | 24.61% | 31.06% | 25.67% | 22.37% | 26.83% |

## ANALYSIS OF WIND DATA AND RESOURCE ASSESSMENT

## WIND ANALYSIS THROUGH STATISTICAL METHODS:

Statistical analysis of wind data has been used to assess the wind energy potential and energy production of a wind turbine erected in the Ramagiri area. The commonly used Probability distributions are Weibull (shown in figure 7), Rayleigh (shown in figure 8) distributions respectively.

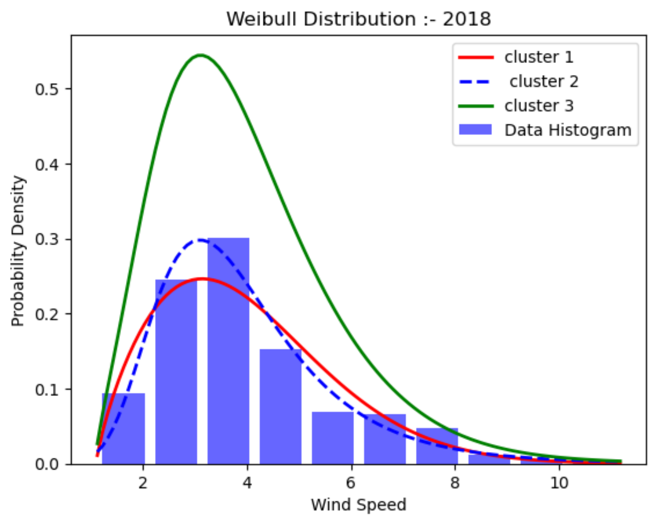


**Figure 7:** Weibull probability density function at various mean wind speeds

Reliability engineering and survival analysis both heavily rely on the Weibull distribution to calculate how long it will be before an incident happens. Its settings determine the graph's shape. The Weibull distribution over three different clusters is shown graphically in Figure 7. A noteworthy finding from the data is that cluster 3 has a significantly greater probability density than clusters 1 and 2, as well as cluster 4. This stark difference in probability density emphasizes the distinctive qualities and statistical importance of cluster 3 within the Weibull distribution. When the form parameter is less than 1, however, the distribution shows a dropping failure rate, indicating a more effective model.

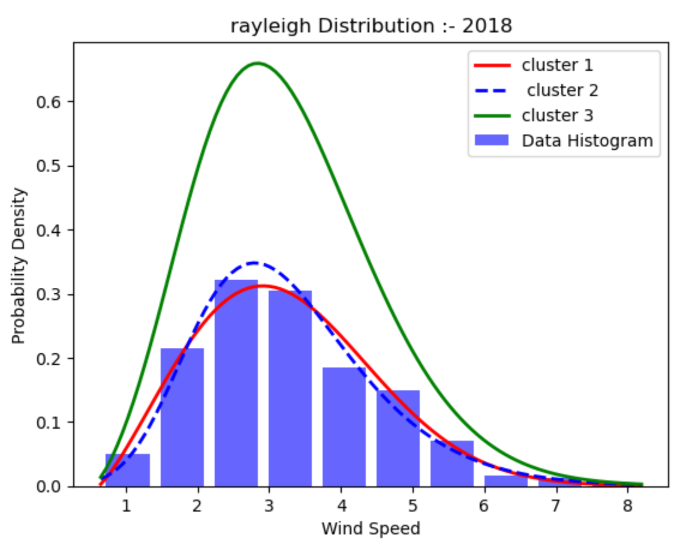


**Figure 8:** Rayleigh Probability Density Function

An essential probability distribution utilized in the analysis of wind farm reliability is the Rayleigh distribution. It frequently takes the form of a bell-shaped curve and depicts the probability density function of wind speeds or power output. One parameter, frequently related to the average wind speed or power output, describes this distribution. When compared to extreme levels, it suggests a lower likelihood of coming across moderate wind speeds or power output values. For wind farm performance to be optimized and to guarantee that turbines can endure the full range of wind conditions, an understanding of the Rayleigh distribution is crucial. Making informed judgments about the location of turbines, the timing of maintenance, and overall reliability is made easier thanks to this analysis.

## ERROR MATRICES

Table 18 summarizes the results obtained from the proposed study. It presents not only the overall accuracy, but also the wind speed and direction, as both parameters are critical in real application.

**Table 18**: %MBE and %NMBE of the Year 2015 and 2019

| S. NO | Month | 2015 | | 2016 | | 2017 | | 2018 | | 2019 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | %MBE | %NMBE | %MBE | %NMBE | %MBE | %NMBE | %MBE | %NMBE | %MBE | %NMBE |
| 1 | Jan | 2.764 | 0.958 | -0.694 | -0.017 | -1.018 | -1.0237 | -3.96747 | -4.04776 | -6.02066 | -6.20753 |
| 2 | Feb | -0.738 | -4.624 | -0.097 | -0.001 | -0.835 | -0.839 | -2.45151 | -2.48194 | -5.37419 | -5.52258 |
| 3 | Mar | -0.738 | -3.373 | -0.901 | -0.025 | -0.531 | -0.5327 | -1.26349 | -1.27152 | -40.8307 | -51.3047 |
| 4 | Apr | -0.544 | -0.253 | -0.796 | -0.022 | -0.514 | -0.5158 | -7.71759 | -8.02735 | -17.5867 | -19.2822 |
| 5 | May | -0.853 | -7.431 | -0.942 | -0.211 | -0.283 | -0.2842 | -5.55104 | -5.7095 | -1.13142 | -1.13785 |
| 6 | June | -0.152 | -7.809 | -0.617 | -0.364 | -0.333 | -0.3340 | -0.36344 | -0.3641 | -0.50312 | -0.50438 |
| 7 | July | -0.169 | -16.912 | -0.598 | -0.543 | -0.499 | -0.5002 | -0.29061 | -0.29103 | -0.04983 | -0.04984 |
| 8 | Aug | -0.491 | -38.531 | -0.569 | -0.569 | -0.481 | -0.4826 | -0.18029 | -0.18045 | -0.19492 | -0.19511 |
| 9 | Sep | -0.759 | -29.823 | -0.608 | -0.448 | -1.910 | -1.9284 | -1.0656 | -1.07131 | -0.2756 | -0.27598 |
| 10 | Oct | 19.34 | 2.044 | -0.645 | -0.068 | -23.97 | -27.239 | -1.60811 | -1.62115 | -2.55122 | -2.58418 |
| 11 | Nov | 0.476 | 1.944 | -0.271 | -0.010 | -3.927 | -4.0059 | -1.58833 | -1.60105 | -2.6914 | -2.72812 |
| 12 | Dec | 0.600 | 1.050 | -0.216 | -0.008 | -2.795 | -2.8351 | -5.2837 | -5.42708 | -4.64076 | -4.75101 |

## PREDICTIVE ANALYSIS FOR 8 MW TURBINE:

A thorough examination of the power production from horizontal axis wind turbines (HAWTs) in Ramagiri Mandal, Anantapur District, Andhra Pradesh, was presented in the part before. Wind speed, efficiency, and climatic variables were among the data gathered from the location. Following that, the data was applied to a projection of the turbines' power output. The calculations included information on wind speeds, turbine characteristics, and conversion efficiencies to produce a thorough knowledge of the expected power output. In order to conduct a thorough evaluation of accuracy and dependability, the computed power generation numbers were compared with empirical values from 2015 to 2019. The study helped detect temporal trends in power generation and gave important insights into the effectiveness and efficiency of HAWTs in the Ramagiri Mandal area. The findings not only aid in understanding wind turbine performance but also offer useful information for future wind energy project optimization. The Ramagiri Mandal and beyond can support renewable energy activities thanks to this study, which is a cornerstone for sustainable energy planning and decision-making.

It is clear from the analysis and validation that mathematical computations have the capacity to produce results that are comparable to those of real-time data. As a result, the projection of turbine power generation is covered in this section. We specifically intend to forecast the power generation of a 8MWh turbine in the Ramagiri Mandal wind farm after it has been replaced with a 0.5 MW turbine. We may determine the degree of the differences by contrasting the current power generation with the projected outcomes from this predictive study. The parameters for 8MW turbine with cluster wind speed and operating hours has been shown in Table 19 to Table 22

The predictive analysis has been done as follows:

**Table 19**: Total windmills in each cluster

| CLUSTERS | TOTAL POWER GENERATION | TURBINE RATING | NUMBER OF WIND TURBINE |
|---|---|---|---|
| **I** | 5.5 MW | 1 MW | 5 |
| | | 0.25 MW | 2 |
| **II** | 5.5 MW | 1 MW | 5 |
| | | 0.25 MW | 2 |
| **III** | 4 MW | 1MW | 4 |

**Table 20**: Velocity for each cluster wind farm

| Month-Year | Cluster I-0.25 MW | Cluster I-1MW | Cluster II -0.25 MW | Cluster II - 1MW | Cluster III-1MW |
|---|---|---|---|---|---|
| Jan-18 | 4.08 | 5.11 | 4.37 | 5.63 | 5.43 |
| Feb-18 | 4.66 | 5.84 | 4.76 | 6.19 | 6.19 |
| Mar-18 | 4.55 | 5.70 | 4.33 | 5.50 | 5.20 |
| Apr-18 | 4.21 | 5.28 | 3.58 | 4.94 | 4.84 |
| May-18 | 4.51 | 5.65 | 5.51 | 7.35 | 7.25 |
| Jun-18 | 8.46 | 10.60 | 7.46 | 9.67 | 9.37 |
| Jul-18 | 10.24 | 12.83 | 8.40 | 10.47 | 10.37 |
| Aug-18 | 10.12 | 12.68 | 8.11 | 10.39 | 10.59 |
| Sep-18 | 4.69 | 5.88 | 6.96 | 8.57 | 8.47 |
| Oct-18 | 3.94 | 4.93 | 4.42 | 5.39 | 5.49 |
| Nov-18 | 4.78 | 5.99 | 4.37 | 5.45 | 5.25 |
| Dec-18 | 4.41 | 5.53 | 4.58 | 5.52 | 5.52 |

**Table 21**: Operational hour of turbines in each month

| Month-Year | Cluster-I | Cluster-II | Cluster-III |
|---|---|---|---|
| Jan-18 | 6.650716 | 8.372291 | 19.28187 |
| Feb-18 | 24.79343 | 20.72407 | 32.30396 |
| Mar-18 | 16.20168 | 23.0103 | 33.86888 |
| Apr-18 | 2.44798 | 14.41916 | 3.809046 |
| May-18 | 11.95824 | 13.75314 | 6.173648 |
| Jun-18 | 82.43344 | 141.2206 | 106.5533 |
| Jul-18 | 87.35543 | 158.4094 | 129.1914 |
| Aug-18 | 98.41973 | 204.0924 | 135.0374 |
| Sep-18 | 140.9574 | 61.91548 | 42.34153 |
| Oct-18 | 37.66804 | 40.31708 | 28.81836 |
| Nov-18 | 22.82741 | 32.18411 | 41.22763 |
| Dec-18 | 9.268591 | 8.646588 | 8.490323 |

**Table 22**: Windmill specifications(predictive)

| Specification of installed wind turbine | Make or type | Swept Area ($m^2$) | Number of blades | Hub Height(m) | Quantity (no.) | Total Power Output(MW) |
|---|---|---|---|---|---|---|
| NW25.5/ 0.25 MW | NedWind | 511 | 3 | 30 | 4 | 1MW |
| NW40/1 MW | NedWind | 1450 | 3 | 39 to 65m/80 m | 14 | 14MW |

## POWER GENERATION IN 2018

**Table 23**: Theoretical calculated power generation from Jan-18 to Dec-18

| | Cluster Wind farm I | Cluster Wind farm II | Cluster Wind farm III | Theoretical analysis |
|---|---|---|---|---|
| **Month/ year** | **Generation in MWh** | **Generation in MWh** | **Generation in MWh** | **Total Generation in MWh** |
| Jan' 18 | 3.17944 | 5.81503 | 9.25602 | 18.25049 |
| Feb' 18 | 19.5748 | 18.9378 | 22.6773 | 61.18988 |
| Mar' 18 | 11.583 | 14.8254 | 14.382 | 40.79039 |
| Apr' 18 | 1.31493 | 6.70733 | 1.26054 | 9.282799 |
| May' 18 | 8.05773 | 21.0428 | 6.77884 | 35.87937 |
| Jun' 18 | 386.641 | 503.017 | 263.41 | 1153.068 |
| Jul' 18 | 729.631 | 722.01 | 433.936 | 1885.577 |
| Aug' 18 | 795.411 | 901.372 | 480.63 | 2177.413 |
| Sep' 18 | 113.21 | 154.267 | 77.0152 | 344.4913 |
| Oct' 18 | 17.8481 | 24.8573 | 14.3494 | 57.05474 |
| Nov' 18 | 19.2023 | 20.2679 | 17.6967 | 57.16688 |
| Dec' 18 | 6.04296 | 5.55571 | 4.11397 | 15.71264 |
| Total MWh Generated/year | 2111.696 | 2398.676 | 1345.505 | 5855.877 |

The data in Table 23 for 2018 indicates a total power generation of 5855.877 MWh, but the wind farm actually produced slightly less at 5852.44 MWh. This suggests that using a larger unit, like 8MW, may offer a more accurate representation. This highlights the importance of precise units in assessing power output, with potential implications for decision-making and optimization in energy production and resource utilization. Careful consideration of measurement units is crucial for accurate assessments in power generation.

## CONCLUSION

The study evaluated the 8-MW scale Wind Energy Conversion System (WECS) in Ramagiri Mandal, Anantapur District, India, using theoretical projections and real-time monitoring data. The system's efficiency aligned with theoretical projections, demonstrating alignment with actual performance. The Rayleigh and Weibull were found to be the best statistical methods for evaluating a region's wind energy potential. The research also analysed wind power generation from 2015 to 2019, using real-time data from a wind farm. The study found that installing a 0.5 MW turbine yielded a substantial total power output of 5852.344 MWh, while replacing it with a more potent 1 MW turbine resulted in a slightly increased total power generation of 5855.877 MWh. The findings provide valuable insights into turbine selection strategies for optimizing power output. Future work could expand the analysis by exploring additional probability distribution functions for wind power density in coastal Andhra Pradesh. This includes evaluating larger turbines' impact on power generation and employing advanced modeling for more accurate predictions, guiding optimized wind farm configurations.


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## DECLARATION OF INTEREST STATEMENT:

The authors declare that they have no known competing financial interests such as those defined above or personal relationships that might be perceived to influence the results and discussions reported in this paper.

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