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ORIGINAL RESEARCH PAPER

Wind speed and direction on predicting wind energy availability for a sustainable ecosystem

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ABSTRACT

BACKGROUND AND OBJECTIVES: Overusing renewable resources for various purposes is making it necessary to use fewer non-renewable ones to generate energy. Finding alternative renewable energy sources is essential for energy production. This study concentrated on using wind direction and speed to produce wind energy among renewable energy sources. Data on wind direction and speed were statistically analyzed to determine the current distribution pattern, which is then used to project the amount of wind energy that will be available in the future.

METHODS: This study concentrated on choosing wind direction and speed to minimize the potential for current electricity generation from wind turbines, using data collected between 1981 and 2023. The wind speed and direction distribution pattern was assessed through the Weibull distribution, beta distribution, and three-parameter Weibull distribution. The Anderson-Darling test and the Kolmogorov-Smirnov test were employed in this study to determine the goodness-of-fit of a specific distribution. The forecasting analysis was expanded from 2024 to 2050 based on the three-parameter Weibull distribution and Anderson-Darling test results for future sustainable wind energy production.

FINDINGS: The average wind speed was found to be 6.51 meters per second, with a standard deviation of 0.280 meters per second between 1981 and 2023. The wind direction varied between a minimum of 3.56 and a maximum of 356.44 degrees for the same duration. The study discovered that the three-parameter Weibull distribution caused less error in the wind speed data distribution pattern than both the Weibull distribution and beta distribution, based on the results of the Anderson-Darling and Kolmogorov-Smirnov tests. From both the tests on Weibull distribution, beta distribution, and three-parameter Weibull distribution, this study found that the Anderson-Darling test was the most appropriate for forecasting the wind speed corresponding to the wind direction for the periods between 2024 and 2050 to produce sustainable wind energy from the wind turbine.

CONCLUSION: The outcomes of this study demonstrate that there is a good likelihood that the parameter Weibull distribution and Anderson-Darling test will be used in other nations to aid in the complementary integration of wind energy. This research has the potential to significantly reduce the amount of environmentally hazardous energy sources used to meet societal requirements. This study offers a trustworthy technique for assessing wind direction and speed, which helps design sustainable wind power plants, construct engineering curricula, and estimate clean, environmentally friendly energy sources.

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52	10	6

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INTRODUCTION

The term "non-renewable" refers to energy sources that are difficult to refill on a human timescale and whose use negatively affects the environment. For millennia, the main energy sources have been fossil fuels, such as coal, oil, and natural gas. They are limited resources developed over millions of years from organic materials (Zhang 2020). One of the most common and ancient fossil fuels, coal, is employed widely in industrial processes and power production. When it burns, toxins and greenhouse gases are released, which contaminate the air and water (Sajid *et al.,* 2022). Renewable energy sources are becoming increasingly important in the global shift towards sustainable energy systems (Sivakumar 2020). These sources are sustainable and environmentally benign substitutes for fossil fuels since they come from natural processes that are constantly replenished (Al Mashkoor 2022). Solar energy is produced by the sun's rays and can be captured by concentrated solar power (CSP) systems or photovoltaic (PV) panels. It is widely accessible, plentiful, and has a large amount of potential for producing power (Jacobson and Delucchi 2011). Using wind turbines, the kinetic energy of moving air is captured to create wind energy. Its established technology and quickly dropping costs make it increasingly competitive with traditional energy sources (Erdiwansyah *et al.,* 2022). Hydropower produces electricity by harnessing the energy of flowing water. It offers a dependable and adaptable power supply and is the world's largest renewable electricity source (Zhao *et al*., 2022). Organic materials, including wood, agricultural wastes, organic waste, and domestic and industrial wastewater, are the source of biomass energy (Sivakumar 2021). It provides a flexible renewable energy source that can be used for transportation fuels, electricity generation, and heating (van Leeuwen *et al.,* 2021). Compared to fossil fuels, wind energy has fewer adverse effects on the environment because it does not release greenhouse gases or air pollutants when in use (Jaber 2013). In many areas, wind energy is more cost-effective than fossil fuels, particularly when taking long-term price stability and externalities like health and environmental costs into account (Wang *et al.,* 2023). Forecasting wind energy production is based on the following: i) meteorological parameters, which affect wind turbine performance and are considered in forecasting models; ii) terrain characteristics, which affect local wind patterns and are taken into account in forecasting models; and iii) seasonal variations, diurnal cycles, and other temporal patterns in wind speed and direction are analyzed to account for recurring trends in energy production (Valsaraj *et al.,* 2022). The range of wind energy production was found to be determined by wind speed patterns on the multi-criteria framework for designing a stand-alone and grid-connected photovoltaic, wind, and battery clean energy system considering reliability and economic assessment (Lin *et al.,* 2021). Solaun *et al*. (2002) analyzed the effect of wind speed variability on wind energy generation in Spain. Sørensen *et al*. (2021) investigated the influence of wind speed on energy yield in offshore wind farms located in the North Sea. Li *et al*. (2020) evaluated the effect of wind speed variation on wind turbine performance in both onshore and offshore wind farms. Sorknaes *et al*. (2019) quantified the impact of wind speed variability on energy production in wind farms in Denmark. Previous research could evaluate the effect of wind direction on wind energy generation. The impact of wind direction variations on wind farm performance in the United States was examined by Dallas *et al*. (2024). The impact of wind direction on energy yield in offshore wind farms situated in the North Sea was investigated by Gaumond *et al*. (2014). The impact of wind direction variation on wind turbine performance in onshore and offshore wind farms was compared by Jeon *et al*. (2015). Using Danish wind farms as a case study. Dallas *et al*. (2024) measured the effect of wind direction variations on energy output. Hulio and Jiang *et al*. (2018) applied statistical models to estimate the impact on income fluctuation, presented data results about financial risks and economic performance, and used wind speed and energy generation data from numerous wind farms in the state. Oyedepo *et al*. (2012) gathered data from several state sites, performed statistical techniques, and presented their findings regarding the feasibility of various locales for wind energy development. Srinivas *et al*. (2022) examined the performance of wind farms and the wind speed data gathered from weather stations throughout the state. Similar to studies conducted in India, some recent studies provided valuable insights into the comparison of the effect of wind speed on energy generation in Tamil Nadu, offering literature reviews (Srinivas *et al*., 2022), case studies (Oyedepo

et al., 2012), comparative analyses and statistical data results (Srinivas *et al*., 2022) to support wind energy research and development in the region. Tamil Nadu is a viable region for wind energy development because of Kanyakumari's unique geographic location, wind patterns, government assistance, and technology breakthroughs. Wind turbines in Kanyakumari are positioned to take advantage of the major wind directions, which are primarily from the southwest during the monsoon and from the northeast during other seasons. In light of this, when choosing the ideal process parameters, it is essential to determine the technical, seasonal, and environmental variables that can be controlled to produce wind energy from wind turbines. As a result, the forecasting techniques utilized in this study to obtain the data were the main focus, and they might also be applied to forecast wind energy production in the future (Baranitharan *et al.,* 2021). This study concentrated on choosing the crucial variables, such as wind direction and speed, to minimize the potential for electricity generation from wind turbines using data collected between 1981 and 2023. The forecasting analysis was expanded based on three distributions, viz., Weibull distribution (WD), beta distribution (BD), and three-parameter Weibull distribution (3P WD). It tested the wind speed and wind direction data using Anderson-Darling (AD), and Kolmogorov-Smirnov (KS) before (1981-2023) and after (2024-2050) prediction of wind energy for sustainable energy management. The study aims to know the exact probability distribution, which has often been used to simulate data in various fields, including but not limited to environmental, financial, health, and trustworthiness studies for sustainable environmental management, to choose the exact policy making. Optimizing turbine functioning and maximizing energy production, as well as state-of-the-art wind speed and direction monitoring for wind energy production, combine sophisticated sensor technology with data analytics and computational modeling. This study was conducted at Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, in 2023.

MATERIALS AND METHODS

Informed decision-making and policy development in the renewable energy sector will be made easier with the help of a thorough overview of the state and prospects of renewable energy sources in India, Tamil Nadu, and Kanyakumari District, as well as statistical data analysis on these issues.

Current status of non-renewable energy sources in India

As of 2022, non-renewable energy sources make up roughly 75.7 percent (%) of India's total energy mix. This covers primary power, coal, oil, biomass, and natural gas. With a 46% share in 2022, coal will be the most popular energy source in the nation, followed by oil (24%), biomass (21%), natural gas (5%), and primary electricity (4%). Presently, India is the third-largest crude oil importer in the world, with 232 Metric tonnes (Mt), which contributes 9.6% of imports in 2022, the highest. By 2030, the nation hopes to raise the proportion of non-fossil fuel-based energy resources to almost 50% of installed electrical power capacity. A total of 176.49 Gigawatt (GW) of renewable energy capacity has been installed in the nation as of June 30, 2023; of that, 88.81 GW were under implementation, 51.43 GW were under implementation, and 51.43 GW were under tender (Pachar 2020).

Current status of renewable energy sources in India

The current status of renewable energy production in all States of India is presented in Fig. 1. In recent years, India's solar energy capacity has grown significantly. The Ministry of New and Renewable Energy (2020) estimates that as of December 2020, India had about 38.8 GW of installed solar power. In terms of solar capacity installed, Rajasthan is first, followed by Gujarat, Tamil Nadu, and Karnataka.

A substantial portion of India's renewable energy sources come from wind energy. India had about 38.6 GW of installed wind power capacity as of December 2020. The biggest wind power capacity installations in India are found in states like Tamil Nadu, Gujarat, Maharashtra, Karnataka, and Rajasthan. Biomass energy is still a significant renewable energy source in India, especially for rural areas. An estimated 10.2 GW of biomass power capacity was installed in India as of December 2020. Biomass power production is spread throughout several states, with notable biomass power capacities found in Maharashtra, Uttar Pradesh, and Andhra Pradesh. India had an installed hydroelectric capacity of about 46.9 GW as of December 2020 (Majid 2020). Due to investments in conventional and renewable energy sources, India's

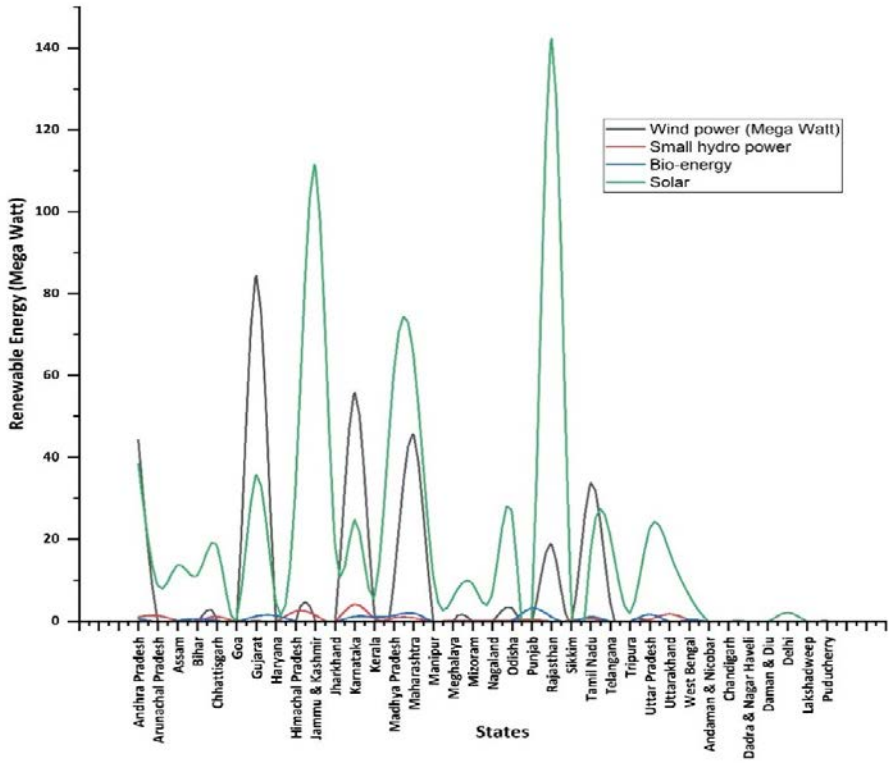


Fig. 1: Current status of renewable energy production in all States of India (Ministry of New and Renewable Energy, 2020)

total installed capacity has increased significantly over the years (Bhardwaj 2013).

Benefits of wind energy

The benefits of sustainable wind energy over other renewable energy sources include its availability, low environmental impact, economic advantages, affordability, and ability to diversify an energy portfolio. Unlike other renewable energy sources, such as fossil fuels, wind energy is an endless resource that does not destroy natural resources. Since sustainable wind power generation produces no greenhouse gases, it is a greener energy source that lessens greenhouse gas emissions, smog, acid rain, and air pollution. Because wind energy does not require fuel, its cheap operational costs shield consumers from changes in the price of coal and natural gas (Murty *et al*., 2020).

Wind energy potential status in Tamil Nadu

Tamil Nadu has been among the top states in India in terms of installed wind energy capacity. In India's history, Tamil Nadu has been at the forefront of wind energy development. It has a large installed wind power capacity, which makes a major contribution to the state's electricity production. The state boasts a varied portfolio of wind farms dispersed among plains, hilly terrain, and coastal areas. These regions have steady, powerful winds, which is advantageous for producing wind energy. Research has revealed the state's significant potential for additional wind power capacity expansion, suggesting plenty of room for future development. Through a number of laws, grants, and programs, the Tamil Nadu government has promoted the growth of wind energy (Natarajan *et al*., 2021).

Wind energy potential status in Kanyakumari

Kanyakumari District in Tamil Nadu has drawn investments in wind energy projects because of its coastal position and ideal wind conditions. The Kanyakumari District's high topography and coastline are home to wind farms. These wind farms are groups of wind turbines that have been

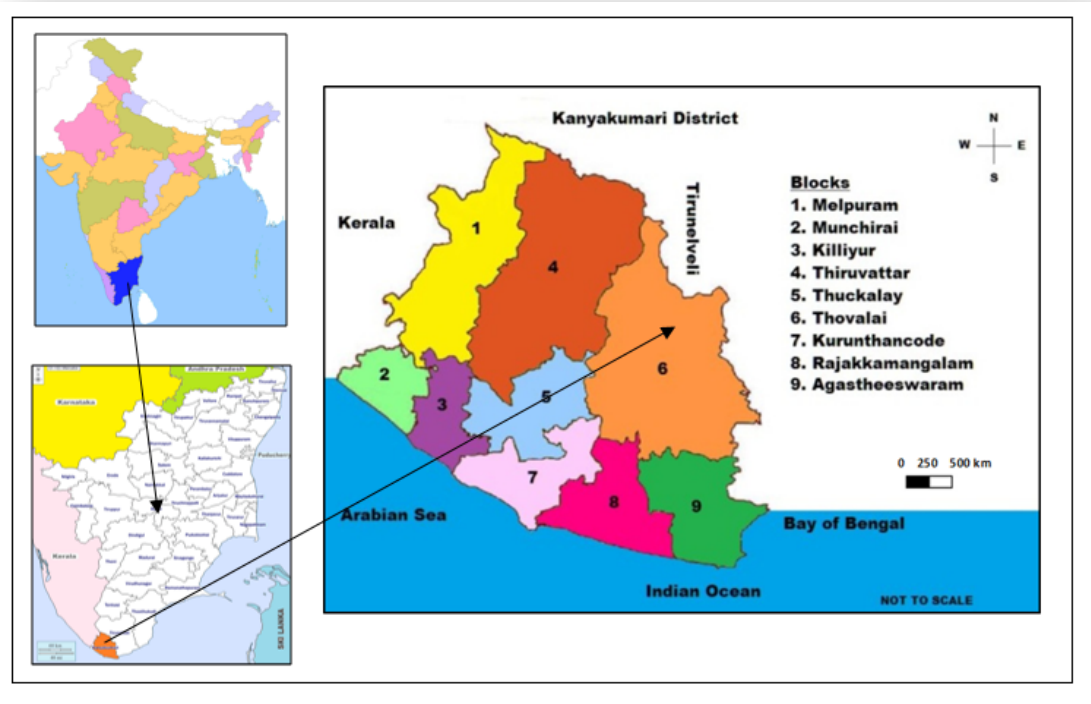


Fig. 2: Geographical location of the study area – Kanyakumari District, India

placed to use the wind energy potential in the area. Kanyakumari District's wind farms increase the state's total wind energy production. Research has been done to evaluate Kanyakumari District's wind energy potential, demonstrating the area's wind power projects' viability and feasibility. Although wind energy development in Kanyakumari has some potential for producing clean energy and economic growth, it also faces obstacles such as a lack of available land, environmental issues, and problems with grid connectivity (Prakash and Dhal 2021). The convergence point of the Bay of Bengal, the Indian Ocean, and the Arabian Sea, Kanyakumari possesses a crucial maritime location with latitudes of 8.0883° North (N) and longitudes of 77.5385° East (E) (Fig. 2).

Kanyakumari District enjoys a tropical climate with elevated temperatures and humidity all year round. Temperatures are often constant because of the proximity to the equator. Kanyakumari District's normal annual temperature ranges from mild to hot, with average highs of 30 to 35 degrees centigrade (°C) and average lows of 20 to 25 °C. Significant wind patterns are experienced in the area, particularly near the shore, which supports the viability of wind energy production. The area's climate is characterized by predominant elements such as sea breezes and southwest monsoon winds (Raj *et al.,* 2017). Given its location at the southernmost extremity of the Indian subcontinent, long beach, and pleasant climate, Kanyakumari District is an intriguing case study for renewable energy research. Kanyakumari is the perfect place to generate solar electricity because it receives plenty of sunlight year-round (Kaur *et al*., 2021). Due to the region's high level of agricultural activity, biomass resources are available for energy production processes such as biogas generation (Chandrasekaran and Swamy 2002). The area is suited for wind energy generation since, in contrast to other energies, it has strong and reliable coastal winds, especially during the monsoon season (Prakash and Dhal 2021). The Indian government's Ministry of New and Renewable Energy identified three offshore locations with possibly profitable wind energy extraction: Kanyakumari, Rameshwaram, and

Jakhau. The identified área has a wind speed of 8 metres per second (m/s) and an average yearly power potential of 200 watts per square metre (W/m^2).

Statistical analysis

Various statistical distributions are generally used, namely beta, chi-squared, exponential, gamma, generalized extreme value, Pareto, Gumbel, Laplace, Normal, Uniform, Weibull, and others. Still, this study used Weibull, Beta, and three-parameter Weibull distribution to analyze the wind speed and direction for sustainable wind energy generation. Anderson-Darling and Kolmogorov-Smirnov tests were the two separate tests employed in this study to determine the goodness-of-fit. Both tests determine if a sample is representative of a specific distribution (Baranitharan *et al.,* 2022). Additional statistical characteristics computed in this study include the median, coefficient of variation (CV), skewness (SKW), kurtosis (KRS), upper and lower quartiles (LQ and UP), mean, minimum, maximum, and standard deviation (SD).

Weibull distribution

A continuous probability distribution called the Weibull distribution is frequently used to simulate how long technical equipment will last or how long a system will last before failing. It is distinguished by its scale parameter, which establishes the location along the x-axis, and its shape parameter, which establishes the shape of the distribution curve. The Weibull distribution's probability density function (PDF) is provided using Eq. 1 (Teimourian *et al.,* 2022):

$$f(x;\lambda,k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(x/\lambda\right)^{k}} \quad (1)$$

Where the random variable is x, the scaling parameter is λ, and the shape parameter is k. Depending on k, this distribution can take on many forms. The Weibull distribution, for instance, collapses to the exponential distribution when k = 1, and it shows an increasing failure rate when k > 1 and a decreasing failure rate when k < 1.

Beta distribution

A continuous probability distribution defined on the interval [0, 1] is called the Beta distribution. Random variables that indicate proportions or probabilities are frequently modeled using this technique. The beta distribution's PDF can be found using Eq. 2 (Soni and Bhattacharjee 2024):

$$f(x;\propto,\beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \quad (2)$$

Where the variable of randomness is x, shape parameters are α and β, where α, β > 0. As a normalization constant, the beta function (α, β) ensures that the total probability integrates to 1 over the interval [0, 1].

Three-parameter Weibull distribution

A continuous probability distribution called the three-parameter Weibull distribution is used to simulate how long it will take for an event to happen. Extreme value theory, survival analysis, and reliability engineering are three areas in which it is most helpful. Eq. 3 (Albani *et al.,* 2024) represents the three-parameter Weibull distribution's PDF:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x-\gamma}{\alpha}\right)^{\beta}} \quad (3)$$

Where, the location parameter is gamma (γ), the scale parameter is beta (β), and the shape parameter is alpha (α). For $x > \gamma$, The scale parameter is $\alpha > 0$, while the shape parameter is $\beta > 0$.

Anderson–Darling test

To determine if a data collection is representative of a given distribution, apply the Anderson-Darling Test. Eq. 4 represents the yields of the AD statistic (Al-Muhain *et al.,* 2019):

$$AD = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)\left[lnf(x_i) + ln\left(1-f\left(x_{n-i+1}\right)\right)\right] \quad (4)$$

Where , i is the i^{th} sample after the data is sorted in ascending order, n is the sample size, and $f(x)$ is the cumulative distribution function for the given distribution. It is common to encounter this statistic, A^2. The statistical hypothesis testing characteristics in this study, such as wind direction and speed, were measured using the AD statistical analysis to ascertain whether a given sample is representative of a certain distribution, such as the normal distribution. It is predicated on the discrepancies between the

expected and actual cumulative distribution functions (CDFs) for the given distribution.

Kolmogorov-Smirnov test

Kolmogorov-Smirnov test statistic is computed using Eq. 5 (Al-Muhain *et al.,* 2019):

$$KS = \max\left(\left|f_1(x) - f_2(x)\right|\right) \quad (5)$$

In which, $f_1(x)$ represents the first sample's empirical cumulative distribution function (ECDF), $f_2(x)$ represents the second sample's ECDF, and for all x Values, max indicates calculating the maximum absolute difference between the two ECDFs. The maximum vertical distance between the two cumulative distribution functions is calculated using Eq. 5.

Formulation of hypotheses

The following are some systematic hypotheses that could be developed to investigate how wind direction and speed affect the ability to predict wind energy availability for a sustainable ecosystem: (i) *Hypothesis 1:* Higher wind speeds result in more energy production; (ii) *Hypothesis 2:* The direction of the wind has a major impact on how efficiently wind turbines operate, with turbines facing the wind showing higher rates of energy capture than those facing the other way; (iii) *Hypothesis 3:* Variations in wind direction induce turbulence, which impacts wind turbine performance and causes variations in energy output; (iv) *Hypothesis 4:* Through the examination of past wind data collected over a long time, patterns in wind speed and direction can be found that can be utilized to forecast future energy availability and guide the planning of sustainable ecosystems; and (v) *Hypothesis 5:* The predictability and dependability of wind energy generation are impacted by wind speed and direction variability, which calls for the development of sophisticated forecasting tools to enhance resource allocation and energy scheduling. Through the methodical application of data analysis, computational modeling, and empirical observation, researchers can test these hypotheses and improve our understanding of the intricate relationships between wind characteristics and energy production. This will help optimize the use of wind energy to develop sustainable ecosystems.

RESULTS AND DISCUSSIONS

The primary emphasis of this study was the current state of wind direction and speed in a Kanyakumai for sustainable wind energy generation. Analyzing the wind direction and speed over the previous four to five decades is necessary to boost wind energy. This study was expanded to analyze wind speed and direction data from 1981 to 2023 using a variety of distribution functions that ranked the data on a scale of one to ten. The AD and KS tests were used to determine the goodness of fit for wind speed and direction data from 1981 to 2023. Forecasting the wind direction and speed for sustainable wind energy production might be done using the distribution and test results.

Effect of wind speed

This study focused on the effect of wind speed on wind energy generation concerning seasonal and overall wind speed variations. Global climate change greatly influences the marine ecosystem, including rising temperatures, shifting ocean currents, shifting precipitation patterns, melting ice caps and glaciers, and increasing ocean acidity, all of which have serious repercussions (Rao 2019). While an adequate estimate may be generated with a minimum of 10 years, more than 50 years is often thought essential to forecast long-term wind conditions at a given place (Azad *et al.,* 2014). Data from 43 years (1981–2023), containing a range of data on wind speed, were applied in this research. Tables 1-2 present the average seasonal and overall wind speed (m/s) variations between 1981 and 2023. The overall average wind speed between 1981 and 2023 is shown in Fig. 3.

It can be observed from Table 1 that the average wind speed over the summer was 5.3 m/s, while the

Table 1: Seasonal average wind speed (m/s) variations between 1981 and 2023

Period	Mean	SD	Min	Max	LQ	Median	UQ	CV (%)	SKW	KRS
Winter	6.63	1.04	3.87	8.55	5.99	6.84	7.33	15.77	-0.48	0.06
Summer	5.30	1.36	3.13	8.09	4.18	4.92	6.48	25.80	0.50	-1.00
Monsoon	7.90	0.62	6.15	9.52	7.55	7.96	8.28	7.86	-0.31	-0.001
Post-monsoon	6.03	1.30	3.41	8.85	4.94	5.95	7.12	21.63	0.14	-0.80

Table 2: Overall average wind speed (m/s) variations between 1981 and 2023

Period	Mean	SD	Min	Max	LQ	Median	UQ	CV (%)	SKW	KRS
Total	6.51	0.28	5.81	7.03	6.37	6.55	6.7	4.41	-0.50	-0.02

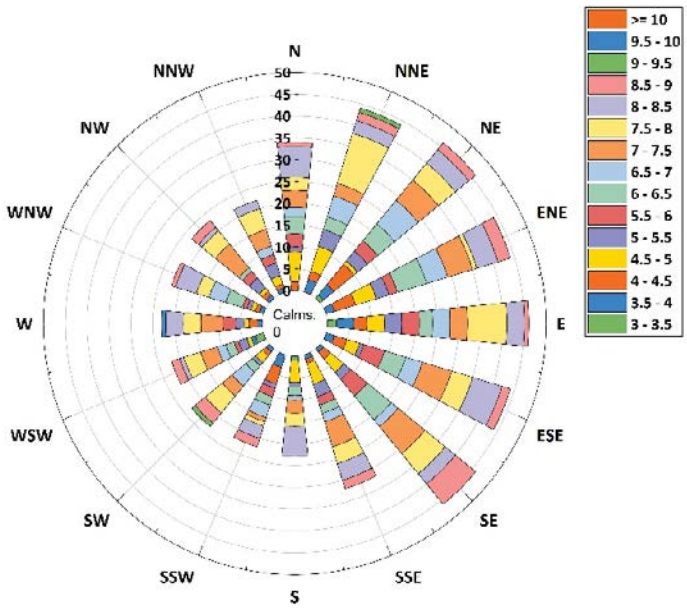


Fig. 3: Overall average wind speed between 1981 and 2023

monsoon season's mean wind speed was 7.9 m/s. The CV indicates how variable the wind speed is at this location, ranging from 7.86% in monsoon to 25.80% in summer. All seasons had an SKW ranging from -0.48 in winter to 0.50 in summer. The range of peaks in the distribution of wind speed is reflected by the coefficient of kurtosis, which ranged from -001 in monsoon to 0.06 in winter and indicated various levels of weakness. From Table 2, it could be observed wind speed was 6.51 m/s on average, with a standard deviation of 0.280 m/s. The estimated values for skewness and kurtosis were -0.50 and -0.02, respectively, while the CV was found to be 4.41%. These findings imply that the wind speed data had a very high degree of fluctuation. It is essential to comprehend how wind speed affects energy production in Kanyakumari, Tamil Nadu, to maximize energy yield and optimize wind farm performance. Kassem *et al.* (2018) assessed the generation of renewable power in metropolitan areas using solar radiation and wind speed, and the mean wind speed was found to be 2.505 m/s based on data gathered between 2000 and 2016 in the Girne urban region. The mean wind speed of 6.51 m/s was discovered in this study using data collected from 1981 to 2023. The geology and geography of the research area account for the higher values found in this study compared to the previous study (Kassem *et al.,* 2018). According to Chacko *et al*. (2002), seasonal weather patterns and the geography of the area have an impact on the temporal and geographical variability of wind speed in Kanyakumari and found that wind speeds are positively correlated with enhanced energy production (Prakash and Dhal 2021). Srinivas *et al*. (2022) evaluated patterns of variability, gathered wind speed data from meteorological stations in Kanyakumari, performed statistical analysis, and presented the data results pertaining to energy generation and turbine efficiency. Oyedepo *et al*. (2012) analyzed wind speed data gathered from meteorological stations within the area, assessed the operational efficiency of wind farms, and provided statistical data on energy generation patterns and capacity factors unique to Kanyakumari. This study also demonstrated that wind speed might be utilized to assess a wind turbine's efficiency in producing

Table 3: Seasonal average wind direction variations for the periods between 1981 and 2023

Period	Mean	SD	Min	Max	LQ	Median	UQ	CV (%)	SKW	KRS
Winter	*50.89*	*15.67*	8.25	184.75	44.88	50.69	56.81	0.30	4.87	43.73
Summer	217.07	79.82	202.23	264.62	16.16	354.81	350.31	0.36	-1.17	-0.03
Monsoon	271.17	6.01	253.62	283.25	267.09	272.08	276.05	0.02	-0.40	-0.12
Post-monsoon	199.62	116.70	3.56	356.44	43.86	263.25	271.98	0.58	-0.64	-1.33

Table 4: Overall average wind direction variations for the periods between 1981 and 2023

Period	Mean	SD	Min	Max	LQ	Median	UQ	CV (%)	SKW	KRS
Total	190.84	105.50	3.56	356.44	56.25	261.38	271.23	0.55	-0.55	-1.53

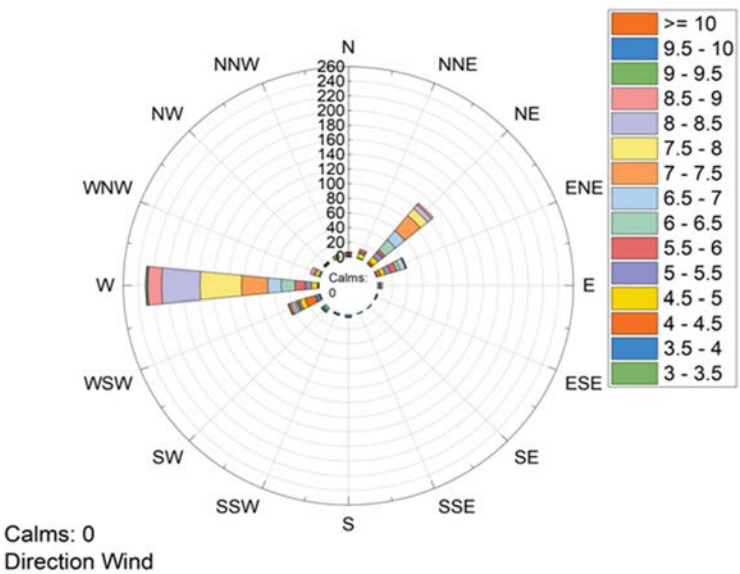


Fig. 4: Overall average wind direction for the periods between 1981 and 2023

energy. The findings of this study provided guidance for the construction of wind energy projects and infrastructure and emphasized the significance of wind speed variability analysis in wind energy planning and optimization strategies. These initiatives and policies for renewable energy were based on wind energy forecasts in Kanyakumari.

Effect of wind direction

Data from 43 years (1981–2023), containing a range of data on wind direction, were used to analyze the present condition of wind energy production in Kanyakumari. Tables 3 and 4 present the average seasonal and overall wind direction variations between 1981 and 2023. The overall average wind direction for the periods between 1981 and 2023 is shown in Fig. 4.

Table 3 shows that the average value is comparatively low, 50.89, with an average deviation from the mean of 15.67 throughout the winter. The large range observed over this era, from 8.25 to 184.75, suggests a high degree of observational variability. CV of only 0.30 indicates a moderate degree of variability to the mean. With SKW of 4.87, which is noticeably positive, the distribution is right-skewed and may have been impacted by outliers. A very peaked distribution is suggested by the KRS value of 43.73, which also raises the possibility of an exception or irregularities. By comparison, the Summer season shows significantly higher mean values, with an average of 217.07 and

Table 5: The season-wise and overall wind speed average value between 1981 and 2023 for WD, BD, and 3P WD

Distribution	Estimated Parameters	Entire Period	Winter	Summer	Monsoon	Post-monsoon
3P WD	□	0.737	6.862	1.691	5.126	2.555
	□	1.868	6.470	2.525	3.000	3.448
	□	4.759	0.591	3.050	5.142	2.981
BD	□□	3.922	23.877	0.948	113.610	1.873
	□□	2.262	6.847	1.167	22.817	2.061
	a	5.501	-4.319	3.130	-8.313	3.287
	b	7.092	9.778	8.096	11.157	9.087
WD	□	26.449	7.248	4.593	15.506	5.410
	□	6.626	7.058	5.783	8.160	6.504

Table 6: AD and KS test results on WD, BD and 3P WD for the overall and season-wise average wind speed value observed in the periods between 1981 and 2023

Period	Distribution	KS	AD
Entire Period	3P WD	0.064	0.201
	BD	0.093	0.311
	WD	0.069	0.239
Winter	3P WD	0.040	0.183
	BD	0.042	0.222
	WD	0.045	0.236
Summer	3P WD	0.080	1.278
	BD	0.112	1.870
	WD	0.147	4.590
Monsoon	3P WD	0.043	0.275
	BD	0.040	0.286
	WD	0.038	0.482
Post-Monsoon	3P WD	0.068	0.381
	BD	0.055	0.229
	WD	0.076	0.799

a higher standard deviation of 79.82. With a range of 202.23 to 264.62, it is likewise quite broad.

Table 4 shows a significant standard deviation of 105.50 and a mean value of 190.84 for all eras, and the results show significant variability. From a minimum of 3.56 to a maximum of 356.44, the range illustrates the diverse range of occurrences that are included in the analysis. Energy output levels are influenced by seasonal fluctuations in wind direction, and greater wind speeds and energy yield are recorded during the southwest monsoon months (Prakash and Dhal 2021). According to a different study, the wake effects of the wind turbines in Kanyakumari may cause downstream turbines to produce less energy, especially in specific wind direction configurations and turbine designs (Politis *et al*., 2012).

Statistical analysis

Out of the two parameters, wind speed and wind direction, a more thorough statistical analysis was provided for the wind speed parameter. Since the wind direction alone determines how much the wind changes in speed, the investigation of wind speed alone was included in this study. Finding the distribution pattern of wind speed requires the wind speed data gathered from the periods between 1981 and 2023 in a particular study region. This study concentrated on three distributions, namely WD, BD, and 3P WD. The wind speed data was then tested using AD and KS for goodness of fit. The constants α, β and g in 3P WD, α_1 and α_2, a and b in BD and α, and β in WD were estimated for season-wise and overall average wind speed during the periods between 1981 and 2023 and are presented in Table 5. Table 5 shows that the values of each estimated parameter, corresponding to WD, BD and 3P WD, were used for obtaining WD, BD and 3P WD pattern.

The AD and KS test results on WD, BD and 3P WD for the overall and season-wise average wind speed values observed between 1981 and 2023 are presented in Table 6. Table 6 shows that the error prediction was minimal for 3P WD in overall periods,

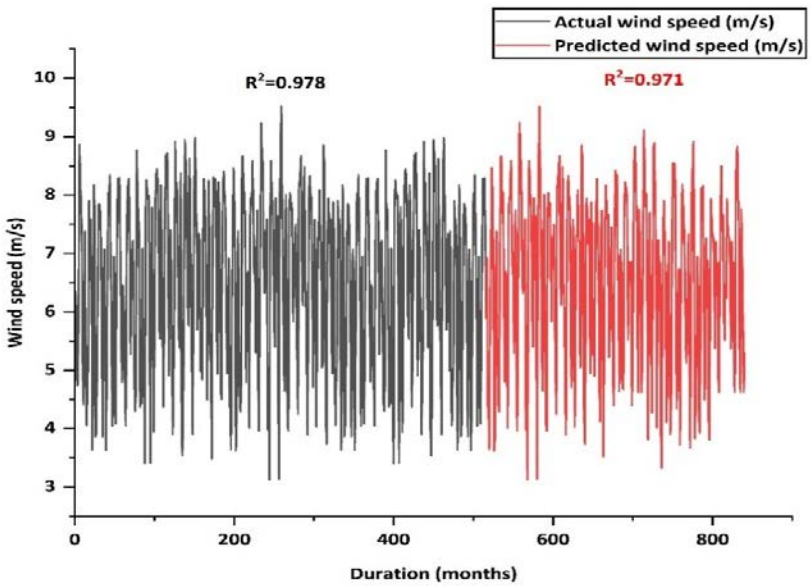


Fig. 5: Observed and predicted average wind speeds from 1981 to 2023 (actual) and 2024 to 2050 (predicted)

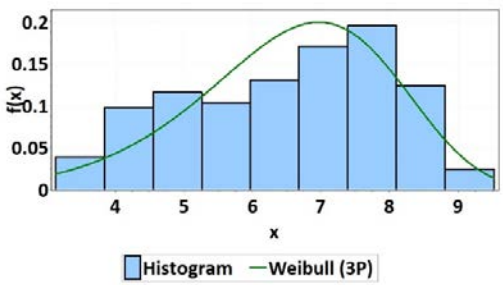


Fig. 6a: PDF of 3P WD pattern for wind speed during the periods between 1981 and 2023

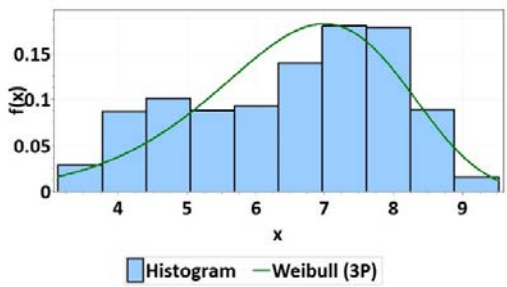


Fig. 6b: PDF of 3P WD pattern for wind speed during the periods between 2024 and 2050

3P WD in winter, 3P WD in summer, WD in monsoon, and BD in post-monsoon periods observed from the KS test. Similarly, the least error was observed for 3P WD in overall periods, 3P WD in winter, 3P WP in summer, 3P WD for monsoon, and BD for post-monsoon periods observed from the AD test (Table 6).

Forecasting the wind energy

The efficiency, profitability, and sustainability of wind energy generation depend on precise wind speed and direction predictions. From site selection and resource evaluation to turbine optimization and grid interconnection, it facilitates sound choices across the entire wind farm development and operation process (Naderipoura *et al.,* 2022). The study discovered that the 3P WD caused less error in the wind speed data distribution pattern than both WD and BD based on the results of the AD and KS tests. This study only utilized 3P WD to forecast wind speed data beyond 2024–2050. From both AD and KS tests on the WD, BD, and 3P WD (Table 6), this study found that the 3P WD distribution was the best and the AD test was the most appropriate for forecasting the wind speed corresponding to the wind direction for the periods between 2024 and 2050 to produce sustainable wind energy from the wind turbine. The observed and predicted average wind speed for the periods from 1981 to 2023 and from 2024 to 2050 are presented in Fig. 5. From Fig. 5, it can be noted that

the actual wind speed from 1981 to 2023 produced R^2 value of 0.978, and the predicted wind speed from 2024 to 2050 produced R^2 value of 0.971. There was little difference between the observed and predicted wind speeds during the respective periods using the 3P WD pattern and AD testing. The PDF for the 3P WD pattern of the wind speed between the years 1981 and 2023 is shown in Fig. 6a. The corresponding PDF for the 3P WD pattern of the wind speed between the years 2024 and 2050 is shown in Fig. 6b. As similar to overall average wind speed for the periods between 1981 and 2023 (Fig. 3), the overall average wind speed for the periods between 1981 and 2050 is shown in Fig. 7.

Similarly, the observed and predicted wind direction between 1981 and 2023 and between 2024 and 2050 is presented in Fig. 8. The actual wind direction during the periods between 1981 and 2023 produced

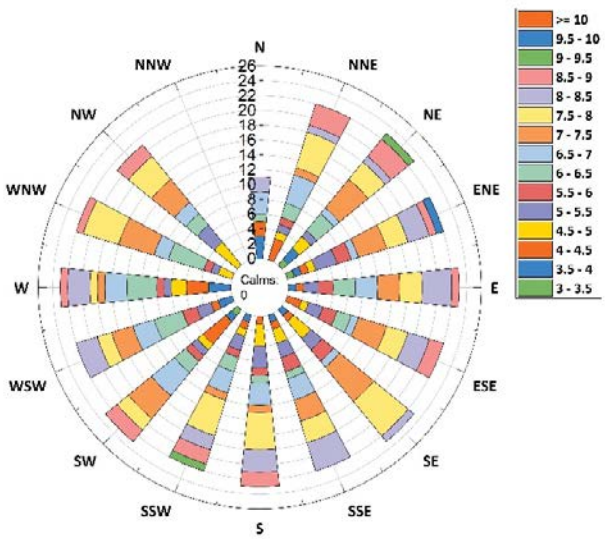


Fig. 7: Overall average wind speed between 1981 and 2050

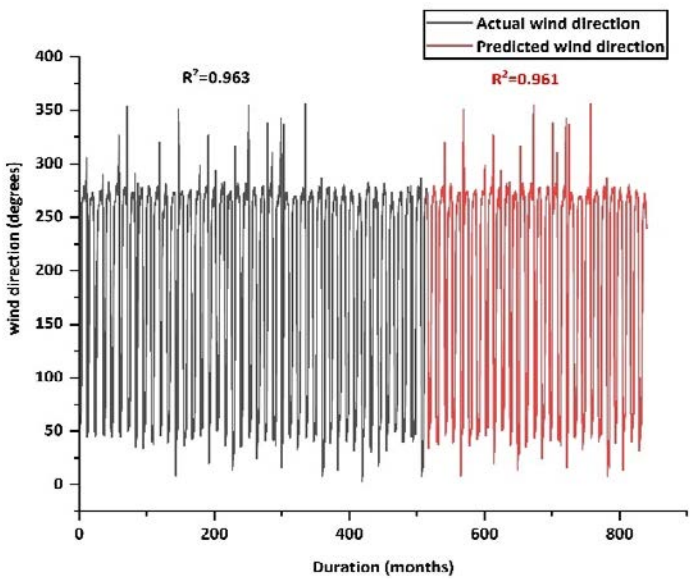


Fig. 8: Observed and predicted wind direction between 1981 and 2023 and 2024 and 2050

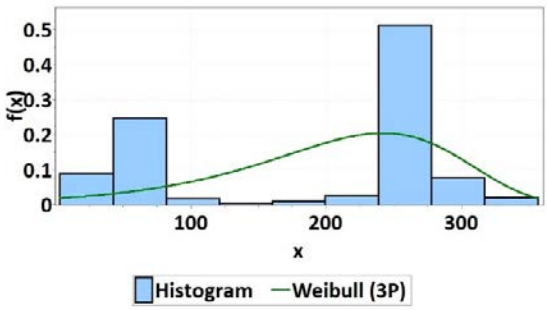


Fig. 9a: PDF of 3P WD pattern for wind direction between 1981 and 2023

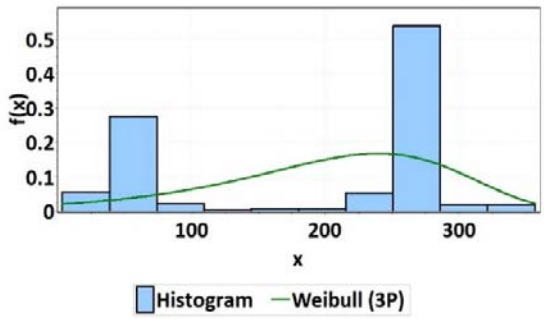


Fig. 9b: PDF of 3P WD pattern for wind direction between 2024 and 2050

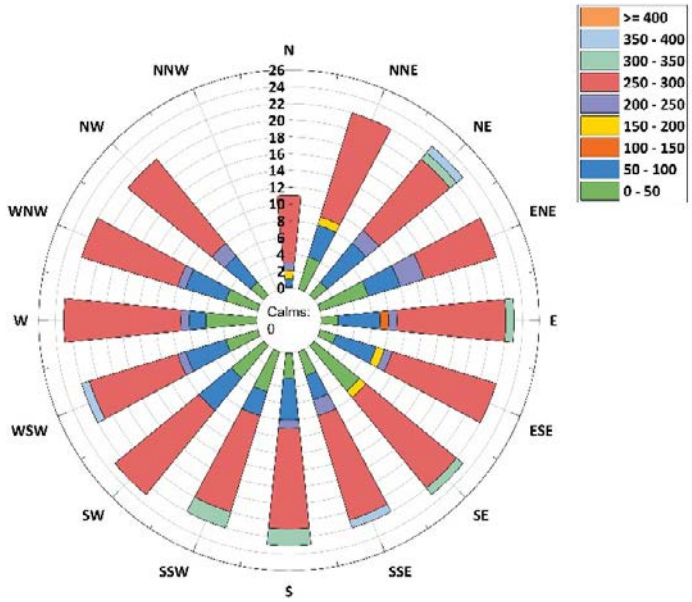


Fig. 10: Overall average wind direction for the periods between 1981 and 2050

R^2 value of 0.963, and the predicted wind direction for the periods between 2024 and 2050 produced R^2 value of 0.961. From Fig. 8, it may be found that there was no such variation in the distribution of wind direction between the actual and predicted values using the 3P WD pattern and AD testing. The PDF for the 3P WD pattern of the wind direction between the periods between 1981 and 2023 is shown in Fig. 9a. The corresponding PDF for the 3P WD pattern of the wind direction between the periods between 1981 and 2023 is shown in Fig. 9b. As similar to the overall average wind direction between 1981 and 2023 (Fig. 4), the overall average wind direction for the periods between 1981 and 2050 is shown in Fig. 10.

This study determined the R^2 value of 0.975, which was between the R^2 values of 0.971 to 0.978 (Fig. 5), using the wind speed data from 1981 to 2050 (containing both observed and forecasted wind speed data), the distribution pattern of observed and predicted wind speed data (Figs. 6a and 6b) and the overall average wind speed (Fig. 7).

This study demonstrated a high degree of fit with an R-squared value of 0.962, falling within the range of 0.961 to 0.963 (Fig. 8). This was determined by comparing observed and anticipated wind direction data from 1981 to 2050, along with the wind direction distribution patterns for both observed and predicted values (Figs. 9a and 9b), as well as the overall average wind direction (Fig. 10). This study concluded that wind energy projects in the Kanyakumari District were

successful in forecasting wind speed and direction utilizing 3P WD and AD tests.

Comparison of the study

The results were matched with those of other studies to evaluate and confirm the impact of wind direction and speed data utilized in this study for future wind energy production. Solaun and Cerdá (2020) found that variations in wind speed had a notable effect on energy production. Specifically, low wind speed periods resulted in reduced output from wind turbines. Gul *et al.* (2018) investigated the risk assessment for wind turbine construction and operation. The fuzzy analytical hierarchy process, a popular multicriteria decision-making technique, was utilized by Gul *et al.* (2018) to determine the functionality of wind turbines during their construction and operation phases. In contrast, the wind speed data in this study was assessed for goodness of fit using AD and KS after the three distributions, namely WD, BD, and 3P WD, were employed. The study conducted by Cavazzi and Dutton (2019) demonstrated a robust relationship between wind speed and energy production. Specifically, higher wind speeds are associated with higher energy yields from offshore wind turbines. According to Ren *et al.* (2018), offshore wind farms demonstrated more steady performance because of greater and more consistent wind speeds, even if wind speed fluctuation affected energy production in both types of installations. Variations in wind speed impacted energy output, and using advanced control techniques and grid integration measures, the impact was lessened, and the overall energy yield increased (Boutsika and Santoso 2018). The framework for a stand-alone and grid-connected hybrid photovoltaic/wind/battery renewable energy system was designed by Naderipoura *et al.,* (2021) with reliability, cost, and emission índices. The results showed that the hybrid system's reliability was improved, and the reliability constraint was within an acceptable range (Naderipoura *et al.,* 2021). Seasonal weather patterns, topography, and local topography all impact the temporal and spatial variability of wind speeds in Tamil Nadu (Raj *et al.*, 2017). Wind farms that experience higher wind speeds tend to produce more energy, which raises capacity factors and energy yield (Navas *et al.,* 2020). Sanchez Gomez and Lundquist (2020) analysed the impact of wind direction variability, and the results indicated that changes in wind direction significantly affected energy production, with turbines facing into the prevailing wind direction generating higher output compared to those facing away. Cavazzi and Dutton (2016) revealed that wind direction variations significantly impacted energy production, with turbines positioned to capture prevailing wind directions, achieving higher yields. Li *et al.* (2020) showed that changes in wind direction impacted energy production differently in onshore and offshore installations, with offshore turbines being less affected by direction changes due to their exposure to more consistent winds. Boutsika and Santoso (2017) demonstrated that changes in wind direction affected energy output, with turbines positioned to capture prevailing wind directions exhibiting higher yields. All the previous studies and this study concluded that the wind turbine position in the direction of the wind produced a high yield. Research on the effect of wind direction on energy production in Tamil Nadu highlights its importance in optimizing wind farm performance and maximizing energy yield. Natarajan *et al.*,(2021) assessed the wind energy potential using GIS and concluded that Tamil Nadu's diverse geography influenced the wind patterns, with coastal areas experiencing predominantly onshore winds and inland regions affected by terrain-induced wind variations. Natarajan *et al.,* (2021) analysed wind energy generation and wind speed, and the results indicated that proper turbine orientation aligned with prevailing wind directions enhances energy capture efficiency and maximizes power generation. Seasonal changes in wind direction influenced by monsoonal patterns affected energy production levels (Shukla *et al.,* 2023). This study presented a more comprehensive statistical analysis of the wind speed parameter of wind direction and wind speed. Since the amount of wind change in speed depends only on its direction. The wind direction depends on several elements, including air stability, terrain, and turbine characteristics, to effectively simulate real-world conditions. The direction of the wind can influence the wind speed in the chosen study region, which in turn affects the amount of wind energy produced there. The distribution patterns and correlations between wind conditions and energy output are provided by the historical wind speed and direction data from weather stations or remote

sensing devices installed at the wind farm site, which are correlated with energy production records. Researchers can quantify the sensitivity of energy production to various wind characteristics and gain insights into how wind direction and speed influence wind energy availability by methodically varying input parameters, particularly wind speed, based on the direction of wind and monitoring changes in wind energy output. The researchers can also develop more precise predictive models for sustainable ecosystem planning. The quantity of kinetic energy in the wind that can be transformed into mechanical energy by wind turbines is directly influenced by wind speed. In general, more energy is produced at higher wind speeds. Nonetheless, the direction of the wind also has a big impact on how well energy is captured. Since turbines are oriented to face the wind, the angle of attack and, consequently, the amount of energy extracted depends on the direction of the wind with respect to the turbine's orientation. Accurately estimating the potential for wind resources at a certain location requires understanding wind patterns, including direction and speed. Different places may have different wind regimes because of topography, regional geography, and typical weather patterns. The best places for wind energy projects may be found, and energy yield can be maximized by developers evaluating historical wind data and considering wind direction and speed.

Limitations of the study

The assessment of wind energy potential and the optimization of wind energy production depend on wind speed and direction data. But employing wind speed and wind direction has some disadvantages in wind energy production: (i) significant spatial and temporal variability in wind speed and direction makes it difficult to predict and model wind resource availability over various time scales; and (ii) wind speed and direction data may not accurately capture the effects of complex terrain features like hills, valleys, and urban areas on local wind patterns. Evaluating wind energy potential and improving energy production can benefit from the wind speed and wind direction data forecasts conducted in this work.

Recommendations of the study

The execution of wind energy projects can significantly benefit from the analysis of wind velocity data. The following suggestions are derived from the examination of wind velocity data:

1. Choose the best location and find areas with steady, intense wind speeds. Generally speaking, places that have typical wind speeds of at least 6-7 m/s at hub height are appropriate for wind energy projects.
2. Select models of wind turbines that are most appropriate for the site's predominant wind conditions and optimize the arrangement and spacing of the turbines to reduce wake effects and increase energy capture.
3. Evaluate wind energy projects' potential for grid integration and devise plans to allay grid stability and dependability worries.
4. Examine how energy storage technologies, such as pumped hydro or batteries, can improve the dependability and flexibility of integrating wind power, particularly in regions with erratic wind resources.
5. Investigate the possible ecological and socioeconomic effects of wind energy projects and conduct thorough environmental impact assessments (EIAs).
6. Promote the implementation of regulatory frameworks and supportive policy measures, such as feed-in tariffs, tax breaks, and renewable energy objectives, to encourage investment in wind energy projects.

The stakeholders may optimize the design, operation, and integration of wind energy projects, maximizing their potential for renewable energy generation while reducing environmental and social consequences, by putting these recommendations, which are based on an analysis of wind velocity data, in this study.

Future scope

It will be necessary to develop new methods and technologies to monitor wind speed in renewable energy sources to improve the precision and efficacy of wind resource evaluation. The ability to measure wind velocity in wind energy sources in the future may result in assessments of wind resources that are more accurate and efficient, which will support the expansion and improvement of wind energy projects

for a future powered by sustainable energy.

CONCLUSION

It is becoming increasingly necessary to utilize less non-renewable resources to create energy due to the overuse of renewable resources for various reasons. The search for alternative renewable energy sources is crucial for energy production. This study focused on harnessing wind speed and direction as one of the renewable energy sources to generate wind energy. The current distribution pattern of wind energy was found by statistical analysis of wind speed and direction data. This information is then utilized to estimate the future wind energy availability. Developing sustainable ecosystems powered by renewable energy sources like wind power requires understanding how wind direction and speed affect wind energy availability predictions. Between 1981 and 2023, the average wind speed was determined to be 6.51 m/s, with a standard deviation of 0.280 m/s. For the same timeframes, the wind direction ranged from a low of 3.56 degrees to a maximum of 356.44 degrees. According to this study's findings on the effect of wind speed, higher wind speeds typically translate into more energy being produced. The predictability of wind speed for the years 2024–2050 indicated that precise wind speed forecasts are crucial for maximizing energy production and grid integration. Variability in wind speed, as observed in this study for the period between 1981 and 2050, can impact the dependability and consistency of energy generation. The evaluation of the effect of wind direction revealed that wind direction affects the orientation and efficiency of wind turbines. Since most turbines are made to catch the prevailing winds, knowing which directions the winds are most likely to blow from is essential for best placement and efficiency. Adaptive control systems are necessary since the study's observations of wind direction variations between 1981 and 2050 have the potential to impact energy output's stability and predictability. To determine the precise statistical analysis required for a specific data set, choices about sustainable energy development and environmental management must be made after selecting an appropriate distribution. To evaluate the fit of these parameters for the seasons viz., summer, winter, monsoon, and post-monsoon variation in the Kanyakumari District, this study used wind speed and wind direction as its major data for the aforementioned area. Based on the results of the AD and KS tests on the WD, BD, and 3P WD, the study found that the 3P WD generated less error in the wind speed data distribution pattern than both WD and BD. Only the forecasting of wind speed data beyond the years 2024–2050 was done in this study using 3P WD. This study found that the 3P WD distribution was the best, and the AD test was the most appropriate for forecasting the wind speed corresponding to the wind direction for the periods between 2024 and 2050 to produce sustainable wind energy from the wind turbine. Researchers can test the sensitivity of energy production to varied wind features and get insights into how wind direction and speed influence wind energy availability by selecting a wind speed depending on wind direction and monitoring variations in wind energy output. The research results can be combined with those of stakeholders, energy planners, and local government organizations to provide insightful information. Renewable energy projects that align with the determined acceptable distributions may be easier to implement if these partners are involved. The findings indicate a significant likelihood that the wind direction and speed will be implemented in other nations, which will help with the complementary integration of alternative energy sources. This measure could greatly aid in reducing the use of environmentally hazardous energy sources. This study offers a trustworthy technique for measuring and assessing wind speed, which is advantageous for constructing engineering programs, the design of wind power plants, and assessing renewable energy resources. This data analysis makes finding workable sources for generating sustainable and renewable energy easier. Ultimately, this study concluded that maximizing the availability of wind energy and fostering healthy ecosystems depend on precise wind speed and direction predictions. Societies can maximise the benefits of wind power while reducing its environmental effect and paving the way for a cleaner, more resilient energy future by combining scientific research, technological innovation, and supportive policy.

AUTHOR CONTRIBUTIONS

B. Baranitharan conducted the study and wrote the initial draft of the publication based on data collection and an overview of the literature review.

D. Sivakumar reviewed the paper to ensure that all of the information was accurate and made sense, including how the research was conducted and the data was analyzed, and also offered some very insightful comments. The statistical analysis was completed by M. Perarul Selvan, who also worked with others to guarantee that the study was carried out perfectly and produced essential insights.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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ABBREVIATIONS

%	Percent
γ	Gamma
°C	Degree Celsius
3P WD	Three parameter Weibull distribution
AD	Anderson-Darling
BD	Beta Distribution
CDF	Cumulative distribution function
CSP	Concentrated solar power
CV	Coefficient of variation
E	East
ECDF	Empirical cumulative distribution functions
EIA	Environmental impact Assessment
GW	Gigawatt
KRS	Kurtosis
KS	Kolmogorov-Smirnov
LQ	Lower quartiles
Mt	Metric tonnes
m/s	Meter per second
m^2	Square metre
N	North
PV	Photovoltaic
R^2	Coefficient of determination
SD	Standard deviation
SKW	Skewness
UP	Upper quartiles
$Watts/m^2$	Watts per meter square

WD	Weibull distribution
α	Alpha
B	Beta

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