SOCAR Proceedings

Renewable Energy

journal home page: http://proceedings.socar.az

ASSESSMENT OF ONSHORE WIND ENERGY POTENTIAL IN AZERBAIJAN USING WEIBULL DISTRIBUTION ANALYSIS

M. A. Ismayilov*, A. M. Aliyev, S. H. Abbasov

Azerbaijan State Oil and Industry University, Baku, Azerbaijan

A B S T R A C T

This study provides an in-depth assessment of Azerbaijan's wind energy potential using ERA5 reanalysis data from 1940 to 2023. Using statistical analysis based on the Weibull distribution, the study examines wind characteristics at 24 strategically selected locations across the country. A Python-based automated process facilitated the analysis of over 70 million hourly wind speed observations, yielding detailed estimates of wind power density and providing critical data for renewable energy development planning. Azerbaijan has significant renewable energy resources, with an estimated onshore wind capacity of 3000 MW out of a total renewable capacity of 26940 MW. The analysis identified coastal areas such as Baku, Sumgait and Gobustan as having the highest wind energy potential, with Baku having an average wind speed of 8.01 m/s at 100 meters above ground level (AGL) and a wind power density of 628.5 W/m². Inland regions such as Khizi and Naftalan show moderate potential, suitable for smaller wind energy projects. The methodology integrates long-term meteorological data with advanced statistical techniques to ensure the reliability of the results. Weibull distribution parameters were calculated to characterize wind regimes and effectively predict energy yields. However, the study recognizes the limitations of ERA5's spatial resolution in capturing the complexity of mountainous terrain and highlights the need for localized, high-resolution measurements to improve accuracy. This research outlines priority areas for wind energy development and provides a robust framework for policy makers and stakeholders. By advancing the understanding of wind energy potential, the findings support Azerbaijan's strategic goals of enhancing energy security, achieving sustainable development, and addressing climate change challenges through renewable energy integration.

Keywords: renewable energy; wind energy; Weibull distribution; wind potential; Azerbaijan; ERA5.

Date submitted: 15.11.2024 **Date accepted:** 24.03.2025

© 2025 «OilGasScientificResearchProject» Institute. All rights reserved.

1. Introduction

Azerbaijan's considerable potential in renewable energy sources, particularly wind energy, has garnered increasing attention in recent years. The country's onshore renewable energy potential is estimated at 26940 MW, with wind energy constituting 3000 MW of this capacity [1, 2]. Despite favorable geographical conditions for harnessing wind energy, its full potential has not been thoroughly explored until recently.

In 2022, Mustafayev et al. conducted an extensive literature review in their work «Renewable Energy Status in Azerbaijan: Solar and Wind Potentials for Future Development,» highlighting the scarcity of comprehensive meteorological wind data [3]. They noted that the primary dataset available was presented by Imamverdiyev in 2014 in his study «Wind Energy Potential of Azerbaijan and Prospects for Its Use». Based on these data, they proposed the construction of several wind turbines in selected regions. The study suggested utilizing territories outside the Absheron Peninsula for wind power plant development, emphasizing the need to diversify the locations of renewable energy projects beyond traditional areas.

Historically, analyses of Azerbaijan's wind energy potential have relied heavily on data from international organizations such as the World Bank and the International Renewable Energy Agency (IRENA) [4, 5]. These organizations use datasets like ERA5, which offers a spatial resolution of approximately 31 km [7]. While useful for broader assessments, this resolution may be insufficient for local-scale analyses critical for precise site selection and project planning. Although the World Bank's Global Wind Atlas (fig. 1) attempts to refine these data into smaller spatial steps, the temporal coverage is limited to the period between 2008 and 2017, potentially overlooking long-term wind patterns essential for accurate assessments.

The limitations of relying solely on these datasets have been acknowledged in the literature. For instance, Carta et al. (2009) emphasized the importance of long-term wind speed data and appropriate statistical methods, such as the Weibull distribution, for accurately characterizing wind resources [8]. The Weibull distribution is widely recognized for effectively modeling wind speed frequency distributions, which is

**E-mail:* ismahmud17630@sabah.edu.az

http://dx.doi.org/10.5510/OGP20250101051

crucial for estimating wind energy potential and optimizing turbine performance.

Recent studies have attempted to address these challenges by employing advanced methodologies. Nuriyev et al. (2023) utilized scenario-driven fuzzy multiple-criteria decision-making models to propose solutions for renewable energy transitions in oil-dependent countries like Azerbaijan [9]. Their approach considered economic, environmental, and social criteria under uncertainty, aiding policymakers in strategic decision-making. However, their work did not delve into detailed statistical analyses of wind speed data using long-term datasets or the Weibull distribution.

Similarly, Nuriyev et al. (2022) focused on selecting suitable renewable energy sources for different economic regions within Azerbaijan using a multi-criteria decision-making approach [10]. While providing valuable insights into regional renewable energy selection, this study did not specifically address the statistical characterization of wind energy potential using extensive temporal data.

The purpose of this study is to conduct a comprehensive analysis of Azerbaijan's wind energy potential by utilizing the extended ERA5 database covering the period from 1940 to 2023. By determining the parameters of the statistical Weibull distribution, we aim to accurately estimate the wind power density across different regions of the country.

By processing over 70 million hours of wind measurements from 24 strategically selected locations, we analyze detailed wind speed characteristics and wind power density at both 10 meters and 100 meters above ground level (AGL). This extensive dataset allows for a more precise assessment of wind energy potential, which is essential for optimizing wind turbine placement, maximizing energy output, and advancing Azerbaijan's renewable energy objectives.

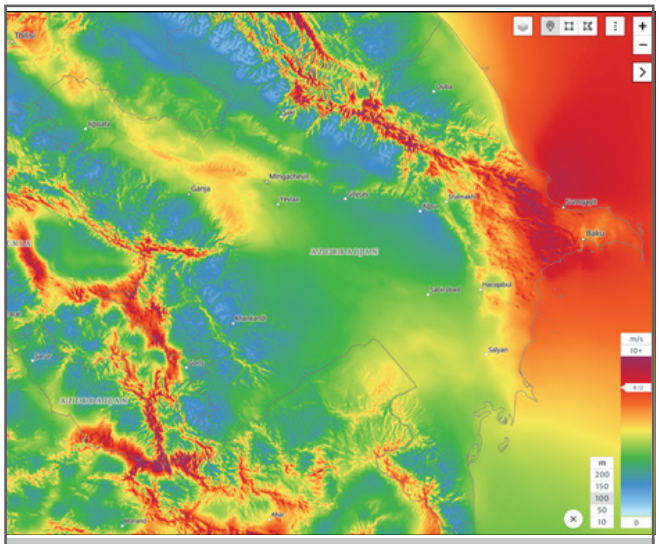

Fig. 1. Wind speed map of Azerbaijan (m/s) provided by the World Bank's Global Wind Atlas [6]

2. Methodology

To assess the wind energy potential of Azerbaijan, a comprehensive methodological approach was adopted, involving data collection, processing, statistical analysis, and visualization. Hourly wind data from the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) were utilized for the period from 1940 to 2023 [7]. ERA5 offers global meteorological data with high spatial resolution (approximately 31 km) and temporal resolution (hourly), enabling a detailed and comprehensive analysis of wind conditions over extended periods. The long-term dataset ensures statistical robustness and captures climatic variability, which is essential for accurate wind resource assessment [12-16].

Twenty-four geographic locations across Azerbaijan were selected for analysis, representing regions with potentially promising wind energy resources. The selection was based on identifying areas with maximum wind potential within a 30 km radius from the central coordinates of key cities and regions in table 1. This approach allows for a balanced representation of different climatic zones and topographical features within the country.

A custom Python program was developed to efficiently process and analyze the extensive dataset. The program utilized libraries such as netCDF4 for reading and processing data from netCDF4 format files, NumPy for numerical operations and manipulation of large arrays and matrices, Pandas for data manipulation and analysis in tabular form, SciPy for statistical analysis including estimation of Weibull

Table 1

Coordinates of selected locations in Azerbaijan

Location	Longitude	Latitude	Location	Longitude	Latitude
Baku	49.86709	40.40926	Tufandag	47.99167	41.16237
Sumgait	49.66861	40.58972	Bazarduzu	47.85833	41.22444
Khizi	49.07333	40.90778	Lerik	48.41497	38.77388
Gobustan	49.375	40.125	Yardimli	48.24052	38.90771
Shamakhi	48.64139	40.63028	Naftalan	46.82398	40.50757
Ismayilli	48.15141	40.78485	Goygol	46.2535	40.5265
Gabala	47.84083	40.9755	Dashkasan	46.07806	40.51917
Oguz	47.46528	41.07128	Gedabey	45.80966	40.55933
Shaki	47.17056	41.19194	Kalbajar	46.25967	39.99033
Babadag	48.30417	41.02	Lachin	46.55	39.63333
Khinalug	48.12667	41.17806	Ordubad	45.6308	38.9558
Nakhchivan	45.40733	39.20533	Julfa	45.6308	38.9558

distribution parameters, Matplotlib for plotting graphs and histograms to visualize data distributions, and openpyxl for reading and writing Excel files, allowing for organized storage and presentation of results, including embedding of graphical plots [17-22].

Wind data from ERA5 for each year from 1940 to 2023 were collected using a Python script that extracts data from netCDF4 files. The necessary wind variables were extracted from each file, specifically the horizontal wind speed components along the X-axis (u) and Y-axis (v) at heights of 10 meters and 100 meters above ground level. These components are essential for calculating the resultant wind speed and direction. The time stamps provided in the files were converted into a standard datetime format to facilitate temporal alignment and time-series analysis.

To associate the wind data with the selected locations, the squared differences between the given coordinates (latitude and longitude) and the grid coordinates of the ERA5 data were calculated. The grid point with the minimum squared difference–the closest grid point–was identified for each location, ensuring that the extracted wind data are as representative as possible of the actual conditions at the selected sites.

For each location, the extracted wind component data were organized into continuous time series spanning the entire study period by concatenating hourly data from all years. The data were then sorted chronologically, and any duplicate entries were removed to maintain data integrity. The wind speed at both 10 m and 100 m heights was calculated using the Pythagorean theorem, combining the horizontal wind components:

$$V = \sqrt{u^2 + v^2}$$

where V is the wind speed (m/s), u is the wind component along the X-axis (east-west direction), and v is the wind component along the Y-axis (north-south direction). This calculation provides the magnitude of the horizontal wind speed at each time step for further analysis.

Statistical analysis involved fitting the Weibull probability distribution to the observed wind speed data to characterize the wind regime of each site. The mean wind speed $\overline{v}$ for each location was calculated:

$$\overline{v} = \sum_{i=1}^{n} \frac{v_i}{n}$$

where n is the total number of wind speed observations, and v_i is the wind speed at the i-th observation. Assuming equal probability for each wind speed observation, the probability p_i is:

$$p_i = \frac{1}{n}$$

The expected value μ was confirmed using the probability:

$$\mu = \sum v_i \cdot p_i = \overline{v}$$

The standard deviation σ of the wind speed data was calculated:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} \left(v_i - \mu\right)^2}{N-1}}$$

The Weibull shape parameter k was estimated using an empirical formula:

$$k = \left(\frac{\sigma}{\overline{v}}\right)^{-1.086}$$

This formula provides an approximation of the shape parameter based on the coefficient of variation of the wind speed data. The Weibull scale parameter c was calculated:

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)}$$

where Γ is the gamma function.

The wind speed data were binned into intervals from 1 m/s to 25 m/s with a step of 1 m/s to prepare for constructing histograms and calculating the probability density function (PDF) [23-30]. The Weibull PDF $f(v)_i$ for each wind speed bin was computed:

$$f\left(v\right)_i = \frac{k}{c}\left(\frac{v_i}{c}\right)^{k-1} \exp\left(-\left(\frac{v_i}{c}\right)^{k}\right)$$

Weibull analysis involves fitting the Weibull probability distribution to observed wind speed data to characterize the wind regime of a site. The shape parameter k describes the variability of wind speeds: a higher k value (k>2) indicates less variability and a more uniform wind speed distribution, while a lower k value (k<2) suggests greater variability and a wider spread of wind speeds. The scale parameter ccc is related to the average wind speed; higher ccc values correspond to higher mean wind speeds. Accurate estimates of k and c allow for predicting the probability of different wind speeds occurring, which is essential for energy yield calculations and turbine selection [31-37].

Wind power density (WPD) quantifies the available wind energy that can be converted into electricity by a wind turbine. It was calculated by first computing the wind power density P_i for each wind speed bin:

$$P_i = \frac{1}{2} \cdot \rho \cdot \overline{v}_i^{\,3} \cdot f\left(v\right)_i$$

where ρ is the air density (assumed to be 1.225 kg/m^3 under standard atmospheric conditions), v_i is the wind speed at the i-th bin, and $f(v)_i$ is the Weibull PDF value at v_i [38-45]. The average wind power density P_w was then computed by summing the contributions from all wind speed bins:

$$P_w = \sum_{i=1}^{N} \frac{1}{2} \cdot \rho \cdot \overline{v}_i^{\,3} \cdot f\left(v\right)_i$$

where N is the total number of wind speed bins.

Wind power density serves as a critical parameter for assessing and comparing the wind energy potential of different sites. It represents the amount of kinetic energy available in the wind per unit area (W/m^2) and is crucial for energy yield calculations, turbine selection, and economic analysis of wind energy projects.

For each location, the results of the analysis were systematically saved in a separate Microsoft Excel file to facilitate accessibility and further examination. The Excel files contained multiple sheets, including data with raw wind component values and calculated wind speeds, histograms of wind speed distributions, Weibull parameters and calculated wind power density values, and graphical representations of the histograms for visual analysis. Visualization techniques

included plotting histograms using Matplotlib to create clear and informative visualizations of wind speed distributions. These visualizations help in understanding the wind profile characteristics at each location, highlighting prevalent wind speeds and the distribution's spread. The histograms and other relevant plots were embedded directly into the Excel files using *openpyxl*, providing a comprehensive report within a single document.

The detailed analysis and visualization of the wind speed data, along with the statistical modeling using the Weibull distribution, enable a thorough assessment of the wind energy potential at each site. The calculated wind power density values serve as a quantitative metric for comparing different locations and identifying the most promising areas for wind energy development. The incorporation of long-term data enhances the reliability of the assessment by capturing inter-annual variability and long-term climatic trends, which are essential for sustainable energy planning.

3. Results and discussion

The analysis of wind energy potential across 24 selected locations in Azerbaijan has provided valuable insights into the spatial distribution of wind resources within the country. Utilizing long-term ERA5 hourly data from 1940 to 2023, key parameters such as average wind speed, Weibull scale parameter *c*, Weibull shape factor *k*, and wind power density were calculated at both 100 meters and 10 meters above ground level (AGL). These parameters are crucial for evaluating the feasibility of wind energy projects and identifying regions with the highest potential.

The coastal regions, particularly Baku, Sumgait, and Gobustan, exhibit the highest wind energy potential. Baku demonstrates an average wind speed of 8.010 m/s at 100 m AGL and a wind power density of 628.5 W/m^2, making it the most promising location for wind energy exploitation. Sumgait and Gobustan also show high average wind speeds of 7.749 m/s and 6.399 m/s at 100 m AGL, with corresponding power densities of 573.7 W/m^2 and 344.5 W/m^2, respectively. These values significantly exceed the threshold of 300 W/m^2 considered suitable for large-scale wind energy development [4].

The Weibull scale parameters (*c*) for these locations further confirm their superior wind regimes. At 100 m AGL, Baku has a *c* value of 9.033 m/s, Sumgait 8.729 m/s, and Gobustan 7.199 m/s. These high c values indicate a higher occurrence of strong winds, which is advantageous for wind energy generation.

Table 2

Wind energy parameters for selected locations in Azerbaijan

№	Location	Coordinates (Location with highest energy potential in 30 km radius)	Average wind speed from 1940 to 2023 (m/sec)		Weibull scale parameter, *c* (m/sec)		Weibull shape factor, *k*		Power density (W/m^2)	
			100m AGD	10m AGD	100m AGD	10m AGD	100m AGD	10m AGD	100m AGD	10m AGD
1	Baku	40.50N 50.00E	8.01	6.437	9.033	7.266	1.917	2.061	628.5	302.8
2	Sumgait	40.75N 49.75E	7.749	6.136	8.729	6.921	1.899	2.025	573.7	266.5
3	Gobustan	40.25N 49.50E	6.399	4.548	7.199	5.129	1.797	1.865	344.5	118.9
4	Khizi	41.00N 49.25E	4.842	3.419	5.452	3.863	1.8	1.94	149.3	48.54
5	Naftalan	40.75N 46.75E	3.808	2.324	4.249	2.591	1.605	1.559	83.6	19.9
6	Sheki	41.00N 47.00E	3.396	2.052	3.812	2.318	1.721	1.889	54.25	10.82
7	Shamakhi	40.75N 48.75E	3.044	1.879	3.42	2.12	1.722	1.839	39.16	8.551
8	Oguz	41.00N 47.25E	2.931	1.786	3.293	2.019	1.737	1.965	34.52	6.833
9	Yardimli	39.00N 48.50E	2.809	1.961	3.152	2.217	1.724	1.917	30.6	9.297
10	Nakhchivan	39.25N 45.75E	2.453	1.71	2.706	1.928	1.441	1.813	26.22	6.545
11	Lerik	38.75N 48.25E	2.647	1.84	2.983	2.08	1.816	1.948	24.2	7.534
12	Ordubad	39.00N 45.75E	2.375	1.573	2.543	1.77	1.447	1.758	21.6	5.27
13	Dashkasan	40.75N 46.25E	2.386	1.541	2.675	1.731	1.657	1.692	19.82	5.209
14	Goygol	40.75N 46.25E	2.386	1.541	2.675	1.731	1.657	1.692	19.82	5.209
15	Kalbajar	40.00N 46.00E	2.536	1.492	2.866	1.684	2.035	1.979	18.83	3.932
16	Julfa	38.75N 45.75E	2.375	1.575	2.673	1.79	1.761	2.068	18.12	4.437
17	Babadag	41.00N 48.50E	2.405	1.519	2.715	1.717	1.887	2.063	17.39	3.993
18	Gabala	41.00N 47.50E	2.239	1.467	2.51	1.658	1.634	2.012	16.74	3.69
19	Ismayilli	40.75N 48.50E	2.222	1.373	2.505	1.55	1.833	1.912	14.15	3.185
20	Lachin	39.75N 46.25E	2.167	1.529	2.445	1.728	1.875	2.208	12.81	3.822
21	Gedabey	40.50N 45.50E	2.076	1.51	2.342	1.705	1.837	2.087	11.53	3.867
22	Khinalug	41.00N 48.25E	2.047	1.148	2.31	1.297	2.175	2.027	9.26	1.751
23	Tafandag	41.00N 48.25E	2.047	1.148	2.31	1.297	2.175	2.027	9.26	1.751
24	Bazarduzu	41.25N 48.00E	1.934	1.069	2.183	1.205	1.907	1.868	8.932	1.539

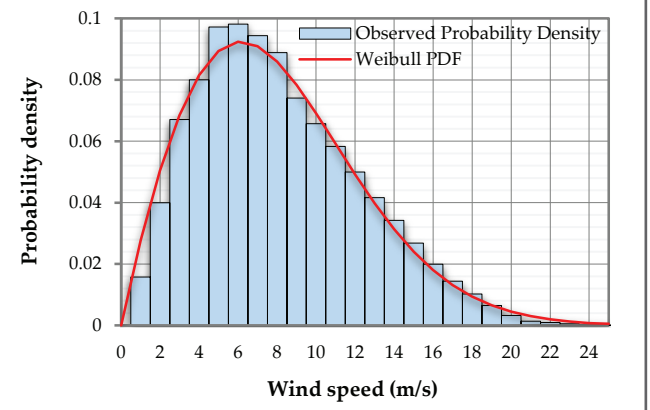

Fig. 2. Hourly wind speed distribution from 1940 to 2023 at 100m – Near Baku at 40.50N, 50.00E]

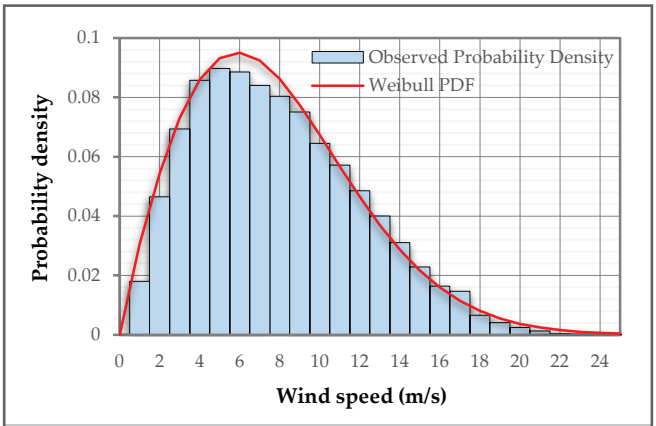

Fig. 3. Hourly wind speed distribution from 1940 to 2023 at 100m – Near Sumgait at 40.75N, 49.75E

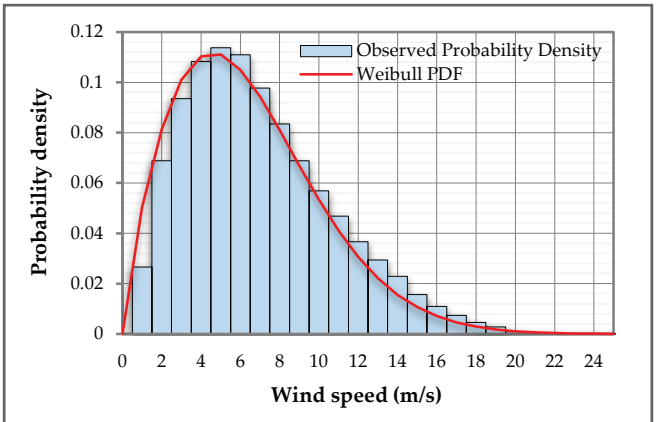

Fig. 4. Hourly wind speed distribution from 1940 to 2023 at 100m – Near Gobustan at 40.25N, 49.50E

The Weibull shape factors (k) for Baku, Sumgait, and Gobustan are close to 2, with values of 1.917, 1.899, and 1.797, respectively, at 100 m AGL. A k value near 2 suggests moderate variability in wind speeds and a relatively consistent wind speed distribution. This consistency is favorable for wind turbine operation, as it implies fewer fluctuations in power generation and more predictable energy output.

The wind speed distributions for these locations are depicted in the histograms provided (fig. 2, 3, 4). The histograms illustrate the frequency of different wind speeds over the long-term measurement period. In Baku and Sumgait, the distributions are positively skewed, with a significant proportion of wind speeds exceeding 6 m/s. This skewness towards higher wind speeds enhances the potential energy yield, as the power available from wind increases with the cube of the wind speed.

Gobustan, while exhibiting slightly lower average wind speeds and c values compared to Baku and Sumgait, still demonstrates a substantial wind energy potential. The wind speed distribution in Gobustan shows a considerable number of occurrences in the 4-7 m/s range, which is adequate for wind turbine operation, especially with turbines designed for moderate wind speed conditions.

Inland regions such as Khizi and Naftalan exhibit moderate wind energy potential. Khizi has an average wind speed of 4.842 m/s at 100 m AGL and a power density of 149.3 W/m, while Naftalan shows an average wind speed of 3.808 m/s and a power density of 83.60 W/m. Although lower than coastal areas, these values are still significant and may support small to medium-scale wind energy projects. The Weibull parameters for these locations indicate slightly higher variability in wind speeds.

The Weibull scale parameters (c) for Khizi and Naftalan are 5.452 m/s and 4.249 m/s, respectively, at 100 m AGL. These values are reflective of their moderate wind climates. The Weibull shape factors (k) are 1.800 for Khizi and 1.605 for Naftalan at 100 m AGL. Notably, these k values are lower than those observed in the coastal regions, indicating a higher variability in wind speeds.

A lower k value signifies a broader distribution of wind speeds and greater fluctuations. For instance, Naftalan's k value of 1.605 suggests that the wind speeds are more dispersed around the mean, which could lead to less predictable wind energy generation. In contrast, Khizi's k value of 1.800 indicates slightly less variability, making its wind regime somewhat more consistent than Naftalan's.

The wind speed histograms for Khizi and Naftalan (fig. 5, 6) illustrate the frequency distribution of wind speeds over the analyzed period. Khizi's histogram shows a relatively balanced distribution with a noticeable number of occurrences in the 3-6 m/s range. Naftalan's histogram displays a similar pattern but with a higher frequency of wind speeds between 2-5 m/s.

These distributions highlight that both locations experience a substantial amount of time with wind speeds suitable for energy generation, especially when utilizing turbines optimized for lower wind speeds. The presence of wind speeds above the cut-in speed of most modern wind turbines (typically around 3 m/s) for a significant portion of time enhances the feasibility of wind energy projects in these areas.

While the methodology yields accurate results for many regions, it relies on ERA5 data, which has a spatial resolution of up to 31 km. This coarse resolution poses challenges in accurately determining the wind potential in mountainous areas, where wind speeds can vary dramatically over short distances due to complex terrain [46-49]. The wind speed data extracted from netCDF4 files may represent low-wind zones on a mountain, providing only a single value for an entire radius of 15 km. As a result, several inland and mountainous regions in Azerbaijan exhibit lower average wind speeds and wind power densities compared to the coastal areas. Locations such as Kalbajar, Khinalug, Tufandag, and Bazarduzu have average wind speeds at 100 m AGL ranging

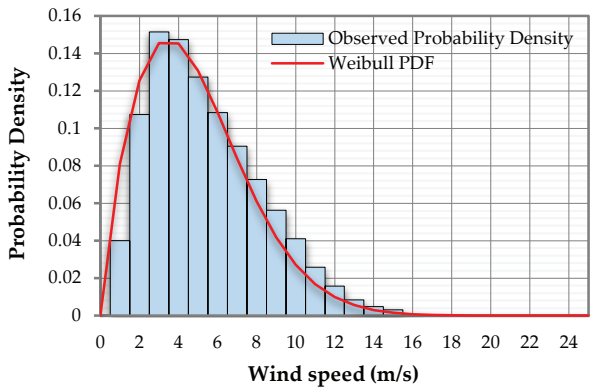

Fig. 5. Hourly wind speed distribution from 1940 to 2023 at 100m – Near Khizi at 41.00N, 49.25E

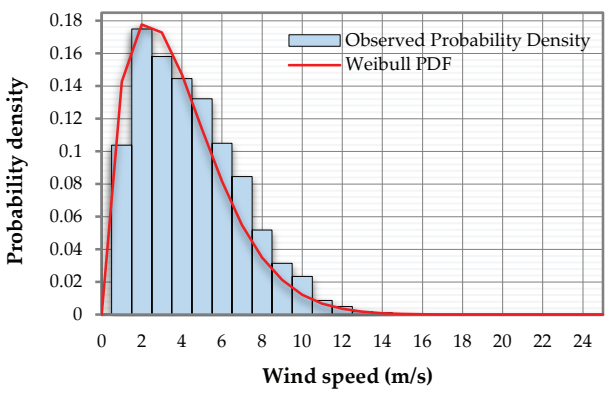

Fig. 6. Hourly wind speed distribution from 1940 to 2023 at 100m – Near Naftalan at 40.75N, 46.75E

from approximately 1.934 m/s to 2.536 m/s and wind power densities below 20 W/m. For instance, Bazarduzu shows an average wind speed of 1.934 m/s and a power density of 8.932 W/m at 100 m AGL.

To achieve a more accurate evaluation of wind potential in mountainous areas, it is recommended to use experimental data. This involves installing an anemometer at the specific mountain location and measuring wind speeds at regular intervals (e.g., every 10 minutes) over the course of one year. Subsequently, applying the Weibull analysis method to this site-specific data will provide more precise and reliable results [31, 33]. For other regions with less complex terrain, the results obtained using this methodology and ERA5 data are valid and sufficiently accurate.

Conclusions

1. Research has proven that the coastal regions of Azerbaijan, especially Baku, Sumgait, and Gobustan, have the highest wind energy potential in the country. Baku's average wind speed of 8.01 m/s and wind power density of 628.5 W/m² at 100 m AGL indicate that it significantly exceeds the 300 W/m² required for large-scale wind energy development. Sumgait and Gobustan also show significant potential with average wind speed of 7.749 m/s and 6.399 m/s, power density of 573.7 W/m² and 344.5 W/m², respectively. The fact that these regions have high Weibull scale parameters and favorable shape factors confirms their suitability for wind energy consumption.
2. Inland regions such as Khizi and Naftalan have moderate wind energy potential. With an average wind speed of 4.842 m/s and 3.808 m/s at 100 m AGL and a power density of 149.3 W/m² and 83.6 W/m², these areas are suitable for small and medium-scale wind energy projects. Although Weibull shape factors show higher variability in wind speed compared to coastal areas, appropriate turbine selection and site optimization can increase energy production in these regions.
3. The study is based on the limitations of ERA5 data with a spatial resolution of approximately 31 km. These limitations make it difficult to accurately capture wind potential in mountainous areas, where complex terrain can cause significant changes in wind speed over short distances. As a result, regions such as Kalbajar, Khinalig, Tufandag, and Bazarduzu show lower average wind speed and wind power density, which underestimates their true wind energy potential.
4. In order to overcome these limitations, in situ wind measurements in mountainous regions are proposed. The installation of anemometers and the collection of high-resolution wind data over long periods of time will allow a more accurate application of Weibull distribution analysis and provide accurate estimates of wind power density. This approach will reveal localized high wind areas not captured by the ERA5 dataset and provide a more reliable basis for wind energy development in these areas.
5. The study identifies key areas for potential wind energy development and offers valuable insights into the spatial distribution of wind resources in Azerbaijan. The results serve as a key resource for policymakers, investors, and energy planners to make informed decisions about expanding the nation's renewable energy infrastructure. By strategically using its wind resources, Azerbaijan can significantly increase its renewable energy potential, contribute to energy security, advance its commitments to sustainable development, and mitigate climate change.
6. There is an important need for integration of higher precision meteorological data and site-specific assessments, especially in complex areas. Assessment of economic feasibility, environmental impacts, and grid integration aspects of potential wind energy projects are important for the practical implementation of research results. Such comprehensive efforts will further improve the understanding of Azerbaijan's wind energy potential and support the strategic expansion of its renewable energy portfolio.

References

1. Azerbaijan Renewable Energy Agency under the Ministry of Energy of the Republic of Azerbaijan. BOEM Potential. https://area.gov.az/en/page/yasil-texnologiyalar/boem-potensiali

2. (2023). The Ministry of Energy of the Republic of Azerbaijan. The official opening ceremony of the 230 MW Garadagh Solar Power Plant was held. https://minenergy.gov.az/en/xeberler-arxivi/00081

3. Mustafayev, F., Kulawczuk, P., Orobello, C. (2022). Renewable energy status in Azerbaijan: Solar and wind potentials for future development. *Energies*, 15, 401.

4. IRENA. (2023). Renewable capacity statistics 2023. *Abu Dhabi: International Renewable Energy Agency.*

5. (2021). World Bank. Offshore Wind Roadmap for Azerbaijan. World Bank, Washington, DC. License: Creative Commons Attribution CC BY 3.0 IGO

6. (2024). Global Wind Atlas: https://globalwindatlas.info/en/about/method

7. Hersbach, H., Bell, B., Berrisford, P., et al. (2023). ERA5 hourly data on single levels from 1940 to present. *Copernicus Climate Change Service (C3S), Climate Data Store (CDS).*

8. Carta, J. A., Ramírez, P., Velázquez, S. (2009). A review of wind speed probability distributions used in wind energy analysis: case studies in the Canary Islands. *Renewable and Sustainable Energy Reviews*, 13(5), 933–955.

9. Nuriyev, M., Nuriyev, A., Mammadov, J. (2023). Renewable energy transition task solution for the oil countries using scenario-driven fuzzy multiple-criteria decision-making models: the case of Azerbaijan. *Energies*, 16, 8068.

10. Nuriyev, M., Mammadov, J., Nuriyev, A., Mammadov, J. (2022). Selection of renewables for economic regions with diverse conditions: the case of Azerbaijan. *Sustainability*, 14, 12548.

11. Imamverdiyev, N. S. (2020). Determining wind energy potential areas in azerbaijan by using gis multi-criteria decision analysis method. *ANAS Transactions, Earth Sciences*, 1, 44-53.

12. Potisomporn, P., Adcock, T. A. A., Vogel, C. R. (2023). Evaluating ERA5 reanalysis predictions of low wind speed events around the UK. *Energy Reports*, 10, 4781-4790.

13. Chisale, S. W., Lee, H. S. (2024). Comprehensive onshore wind energy assessment in Malawi based on the WRF downscaling with ERA5 reanalysis data, optimal site selection, and energy production. *Energy Conversion and Management: X*, 22, 100608.

14. Boretti, A., Castelletto, S. (2020). Trends in performance factors of wind energy facilities. *SN Applied Sciences*, 2, 1718.

15. Ippolito, M., De Caro, D., Cannarozzo, M., et al. (2024). Evaluation of daily crop reference evapotranspiration and sensitivity analysis of FAO Penman-Monteith equation using ERA5-Land reanalysis database in Sicily, Italy. *Agricultural Water Management*, 295, 108732.

16. Liu, X., Zhang, L., Wang, J., et al. (2023). A unified multi-step wind speed forecasting framework based on numerical weather prediction grids and wind farm monitoring data. *Renewable Energy*, 211, 948-963.

17. Rew, R., Davis, G. (1990). NetCDF: an interface for scientific data access. *IEEE Computer Graphics and Applications*, 10(4), 76-82.

18. Jones, M., Blower, J., Lawrence, B., Osprey, A. (2016). Investigating read performance of python and NetCDF when using HPC parallel filesystems /In: Taufer, M., Mohr, B., Kunkel, J. (eds). High performance computing. ISC High Performance 2016. Lecture Notes in Computer Science. *Springer, Cham*.

19. Aizenman, H., Grossberg, M. D., Barnes, N., et al. (2012). Web based visualization tool for climate data using python room 346/347 (New Orleans Convention Center). In: *92nd American Meteorological Society Annual Meeting (January 22-26).*

20. Galiano, V., Migallón, H., Migallón, V., Penadés, J. (2010). PyPnetCDF: A high level framework for parallel access to NetCDF files. *Advances in Engineering Software*, 41(1), 92-98.

21. Gharari, S., Keshavarz, K., Knoben, W. J. M., et al. (2023). EASYMORE: A Python package to streamline the remapping of variables for Earth System models. *SoftwareX*, 24, 101547.

22. Cavaiola, M., Tuju, P. E., Ferrari, F., et al. (2023). Ensemble Machine Learning greatly improves ERA5 skills for wind energy applications. *Energy and AI*, 13, 100269.

23. Wang, H., Feng, L., Wang, J., et al. (2024). Analyzing critical core components' technology opportunities based on multilayer networks from a lifecycle perspective: A case study of offshore wind turbine foundation. *Journal of Cleaner Production*, 477, 143850.

24. Lázár, I., Hadnagy, I., Bertalan-Balázs, B., et al. (2024). Comparative examinations of wind speed and energy extrapolation methods using remotely sensed data – A case study from Hungary. *Energy Conversion and Management: X*, 24, 100760.

25. Alqasem, O. A., Mustafa, M. S., Abdel-Aty, A.-H., et al. (2024). Marshall-olkin extended inverted kumaraswamy distribution for modeling of wind speed data. *Journal of Radiation Research and Applied Sciences*, 17(3), 100931.

26. Ahmad, A., Xiao, X., Mo, H., Dong, D. (2024). Tuning data preprocessing techniques for improved wind speed prediction. *Energy Reports*, 11, 287-303.

27. Alharthi, A. S. (2024). A new probabilistic model with applications to the wind speed energy data sets. *Alexandria Engineering Journal*, 86, 67-78.

28. Yang, X., Tao, Y., Jin, Y., et al. (2024). Time resolution of wind speed data introduces errors in wind power density assessment. *Energy Conversion and Management: X*, 24, 100753.

29. Houndekindo, F., Ouarda, T. B. M. J. (2024). Prediction of hourly wind speed time series at unsampled locations using machine learning. *Energy*, 299, 131518.

30. Younis, A., Elshiekh, H., Yassin, Y., et al. (2024). Historical wind speed dataset of meteorological mast station in Khartoum. *Data in Brief*, 57, 111115.

31. Rüstemli, S., Güntas, O., Şahin, G., et al. (2024). Wind power plant site selection problem solution using GIS and resource assessment and analysis of wind energy potential by estimating Weibull distribution function for sustainable energy production: The case of Bitlis/Turkey. *Energy Strategy Reviews*, 56, 101552.

32. Raza, A., Ali, S., Shah, I., et al. (2024). A comparative analysis of mean charts assuming Weibull and generalized exponential distributions. *Heliyon*, 10(21), e40001.

33. Jahan, S., Masseran, N., Zin, W. (2024). Wind speed analysis using Weibull and lower upper truncated Weibull distribution in Bangladesh. *Energy Reports*, 11, 5456-5465.

34. Nymphas, E. F., Teliat, R. O. (2024). Evaluation of the performance of five distribution functions for estimating Weibull parameters for wind energy potential in Nigeria. *Scientific African*, 23, e02037.

35. Ayua, T. J., Emetere, M. E. (2023). Technical analysis of wind energy potentials using a modified Weibull and Raleigh distribution model parameters approach in the Gambia. *Heliyon*, 9(9), e20315.

36. Aljeddani, S. M., Mohammed, M. A. (2023). An extensive mathematical approach for wind speed evaluation using inverse Weibull distribution. *Alexandria Engineering Journal*, 76, 775-786.

37. Alrashidi, M. (2023). Estimation of weibull distribution parameters for wind speed characteristics using neural network algorithm. *Computers, Materials and Continua*, 75(1), 1073-1088.

38. Chang, T. P. (2011). Estimation of wind energy potential using different probability density functions. *Applied Energy*, 88(5), 1848-1856.

39. Serban, A., Paraschiv, L. S., Paraschiv, S. (2020). Assessment of wind energy potential based on Weibull and Rayleigh distribution models. *Energy Reports*, 6, Supplement 6, 250-267.

40. Liu, L., Wu, M., Mao, Y., et al. (2024). Offshore wind energy potential in Shandong Sea of China revealed by ERA5 reanalysis data and remote sensing. *Journal of Cleaner Production*, 464, 142745.

41. Elfarra, M. A., Kaya, M. (2021). Estimation of electricity cost of wind energy using Monte Carlo simulations based on nonparametric and parametric probability density functions. *Alexandria Engineering Journal*, 60(4), 3631-3640.

42. Faraz, M. I. (2024). Strategic analysis of wind energy potential and optimal turbine selection in Al-Jouf, Saudi Arabia. *Heliyon*, 10(20), e39188.

43. Batran, S., Jama, M., Yousaf, J., et al. (2024). Assessment of wind energy resource in the western region of Somaliland. *Heliyon*, 10(12), e32500.

44. Li, J., Jia, L., Zhou, C. (2024). Probability density function based adaptive ensemble learning with global convergence for wind power prediction. *Energy*, 312, 133573.

45. Zhang, Z., Liang, Y., Xue, X., et al. (2024). China's future wind energy considering air density during climate change. *Renewable and Sustainable Energy Reviews*, 199, 114452.

46. Zhang, G.-F., Azorin-Molina, C., Chen, D., et al. (2024). Variability and trends of near-surface wind speed over the Tibetan Plateau: the role played by the westerly and Asian monsoon. *Advances in Climate Change Research*, 15(3), 525-536.

47. Zha, J.-J., Chuan, T., Qiu, Y., et al. (2024). Projected near-surface wind speed and wind energy over Central Asia using dynamical downscaling with bias-corrected global climate models. *Advances in Climate Change Research*, 15(4), 669-679.

48. Andres-Martin, M., Azorin-Molina, C., Serrano, E., et al. (2024). Near-surface wind speed trends and variability over the Antarctic Peninsula, 1979–2022. *Atmospheric Research*, 309, 107568.

49. Collados-Lara, A.-J., Baena-Ruiz, L., Pulido-Velazquez, D., Pardo-Igúzquiza, E. (2022). Data-driven mapping of hourly wind speed and its potential energy resources: A sensitivity analysis. *Renewable Energy*, 199, 87-102.