MORFAI JOURNAL Multidiciplinary Output Research For Actual and International Issue

Multidiciplinary Output Research For Actual and International Issue (MORFAI Journal) ISSN (e): 2808-6635
Volumes 6 No. 2 (2026)

# STATISTICAL ANALYSIS AND ANN-BASED PREDICTION OF WIND POWER GENERATION: A CASE STUDY OF PEMBA ISLAND, ZANZIBAR, TANZANIA.

**Hamza Khamis Kombo[1*], Ridho Irwansyah[2]**
[1]Department of Mechanical Engineering, Faculty of Engineering, Universitas Indonesia, Campus UI Depok 16424, Indonesia.
[2]Department of mechanical Engineering, Faculty of Engineering, Universitas Indonesia, Campus UI Depok 16424, Indonesia.
E-mails: hamzakhamis305@gmail.com[1]*, ridho@eng.ui.ac.id[2].

| | | | |
|---|---|---|---|
| Received | : 16 February 2026 | Accepted | : 18 March 2026 |
| Revised | : 28 February 2026 | Published | : 01 April 2026 |

**Abstract**
This research work proposes the integrated statistical and ANN approach for the evaluation and prediction of the wind power potential of Pemba Island, Zanzibar, Tanzania. Monthly wind speeds and meteorological data from NASA POWER were used to assess the wind power potential of the region using ten consecutive years of data (2014-2023). From the results, it was evident that the region has marginal to moderate wind power potential since the wind speed averages 6m/s. Wind speed in the region is high between May and August. Wind power density in the region was between 130.46 and 170.43 W/m$^2$. This information proved that the region has the ability to implement small to medium-scale and hybrid wind power systems. An artificial neural network was also developed to predict the wind power density using various parameters such as wind speed, temperature, relative humidity, wind direction, and precipitation. From the results, the ANN has excellent predictive ability since the value of $R^2$ was approximately 0.9998, and very low levels of error for the prediction of the wind energy potential of the islanded grid.

***Keywords: Artificial Neural Network, Pemba Island, Renewable Energy, Weibull Distribution, Wind Power Density.***

## INTRODUCTION

The global energy sector is presently undergoing an unprecedented revolution in the adoption of sustainable energy systems, owing to the impacts of climate change and the increase in greenhouse gas emissions (Pereyra-mari, 2022). Among renewable energy source, wind energy has been made prominence by the level of maturity, decreasing cost of installation, and the possibility of decentralized electricity generation. Wind energy is seen to be more promising, especially for islanded systems, as the high dependency on fossil fuels is causing severe environmental degradation, along with a high cost of electricity (Idris et al., 2020). Nevertheless, the variability and unreliability of wind have posed a great challenge in evaluating wind energy for electricity generation (Mustaffa & Herwan, 2025).

The accurate wind resource assessment is essential in improving the technical and economic potential of wind energy systems. Statistical models, such as the Weibull and Rayleigh distribution models, have been applied to investigate the characteristics of wind speeds and the potential of wind energy (Serban et al., 2020). The models provide valuable information on wind energy, such as wind speeds and wind power density. However, the models are limited in simulating the complex characteristics of wind energy. In East Africa, the country of Tanzania has made notable efforts in diversifying the energy portfolio by promoting renewable energy development. The semi-autonomous region of Zanzibar consists of Unguja and Pemba Islands, and the region faces energy reliability issues, particularly in Pemba Island, which is connected to the mainland using submarine cables (Kombo & Irwansyah, 2025).

Despite the increasing attention of researchers towards the development of renewable energy in Tanzania, research is still limited with regard to the potential assessment and prediction of wind energy in islanded systems. The majority of the research conducted in East Africa is focused on the potential assessment of wind energy sites located in the mainland region, whereas the island location of Pemba Island has received limited attention from researchers (Liu & Yang, 2025; Valdivia-bautista et al., 2023). Additionally, the majority of the research conducted in the field of wind energy potential assessment is based only on the application of statistical models, whereas the potential prediction of wind energy sites is based only on the application of advanced models for the prediction of non-linear relationships between the parameters of the weather.

Therefore, the major objective of this study is to assess and predict wind power potential in Pemba Island, Zanzibar, Tanzania, by integrating statistical analysis and artificial neural networks. For example, the study has employed the application of the Weibull statistical method for evaluating wind speed distribution and power density. On the other hand, the ANN model has been employed for predicting wind power density based on various meteorological factors, such as wind speed, temperature, relative humidity, wind direction, and precipitation. Therefore, it is imperative to deduce that the major contribution of this study, from the scientific point of view, is the presentation of an integrated approach for evaluating wind power, which can improve accuracy for the islanded system.

## LITERATURE REVIEW

Wind energy forecasting and resource assessment is a field that has been extensively researched using different statistical and machine learning approaches. Traditional statistical approaches, persistence, autoregressive integrated moving average (ARIMA), and regression are the most popular techniques used in wind power forecasting due to their simplicity and low complexity. However, these approaches are not able to properly represent the non-linear and stochastic changes in wind speed, which is a major drawback in the accuracy of wind power predictions in complex weather conditions (Preethaa et al., 2023). (Nazir et al., 2020) also pointed out the inability of traditional statistical wind power forecasting techniques to properly represent the changing nature of wind patterns, especially in regions with seasonal wind changes.

To avoid the above-listed disadvantages, Artificial Intelligence techniques such as Artificial Neural Networks (ANN) are being used for wind energy prediction studies. The learning ability of non-linear relationships between wind power and other meteorological parameters is possible using the ANN model. (Andreotti et al., 2021) have proven the superiority of the ANN model for wind power prediction compared to the conventional regression model. This is possible due to the learning ability of the ANN model. (Shafi et al., 2023) proposed a feed-forward ANN model for wind-solar power prediction and proven the improved accuracy of the proposed model compared to conventional statistical models. However, it is observed that the ANN model also has some disadvantages, such as the complexity of computing the model, availability of data, and overtraining of the model during the learning process.

Wind resources are still significantly characterized statistically to evaluate wind energy resources. Probability distribution functions, such as the Weibull distribution and Rayleigh distribution are generally utilized to characterize the distribution of wind speed and determine major wind energy parameters such as wind power density, most probable wind speed, and maximum energy-carrying wind speed (Zhan & Zhu, 2024). Though these statistical models offer good insight into wind behavior and resource potential, they are found to lack predictive power and are unable to address time-variant wind power generation. To overcome these limitations of statistical wind resource characterization models, recent studies have proposed a new class of hybrid models that use a combination of statistical wind resource characterization and ANN-based prediction models.

Recent research indicates the use of hybrid models that incorporate machine learning and statistical models to improve the accuracy of wind power predictions. For instance,(Power et al., 2024) used a Comparative Study on the Estimation of Wind Speed and Wind Power Density Using Statistical Distribution Approaches and Artificial Neural Network-Based Hybrid Techniques. The use of machine learning models can improve the accuracy of wind power estimation by first identifying the wind resource distribution and then using the models for estimation.

Although this has been achieved, the majority of the studies have been conducted for mainland wind farms, with less emphasis being given to the island-based energy systems, especially in East Africa. For instance, (Mangara & Kumwenda, 2023) studied the wind forecasting for mainland Tanzania but did not consider the case for the Pemba Island, which has significant issues with the reliability of the energy being supplied through submarine power cables. Most of the studies have been conducted with either statistical characterization alone, machine learning prediction alone, but not the integration of both approaches.

Therefore, there still exists a major gap in the research for the combination of the statistical wind resource assessment method and the ANN prediction technique for the island energy systems of East Africa. The authors of this study have tried to fill the gap in the research by incorporating the statistical method using the Weibull distribution function and the ANN prediction technique, i.e., the Multilayer Perceptron ANN, for the wind power density of the island of Pemba.

**Table 1:** Comparison of Previous Wind Energy Study

| Author | Study Area | Method used | Key findings | Limitations |
|---|---|---|---|---|
| (Elsoragaby et al., 2020) | Five Cities in Northern Morocco | Weibull and Rayleigh distribution function | Weibull fit wind speed data better then Rayleigh. | Analysis based mainly on Statistical modeling. |
| (Andreotti et al., 2021) | Sicily zone, Italy | Autoregression (AR) statistical model and Artificial Neural Network (ANN) | Both models yielded reasonable forecasts though ANN was superior to AR because of less error values. | Requires large dataset that impacted the performance of ANN training. |
| (Bhatt, 2019) | India | Statistical model (ARMA) and Artificial Neural Network (ANN) | Both models are able to predict the wind power although ANN gave more accurate predictions compared to ARMA, | Short data period. It also relies on few input weather variables, which can interfere with the accuracy of prediction. |
| (Mangara & Kumwenda, 2023) | Mailand Tanzania | ANN forecasting | Adequate prediction of wind speed. | Did not study in island region of Zanzibar. |
| (Kombo & Irwansyah, 2025) | Zanzibar regions | Weibull distribution function. | Effective wind power density for electricity generation | The study based on statistical analysis only without involved ANN for prediction. |
| This study | Pemba island, Zanzibar | Weibull and ANN model | Combined wind characterization and prediction | Addresses island energy system gap |

## METHOD

### Study area and data collection

This study will specifically focus on Pemba Island, which is a semi-autonomous part of Zanzibar, Tanzania. Pemba Island is situated in the Indian Ocean at latitude 5.32° S and longitude 39.74° E. Pemba Island experiences a tropical maritime climate with moderate wind speed due to the effect of monsoon winds. The data of wind speed and other meteorological conditions were taken based on NASA Prediction of Worldwide Energy Resources (POWER) data set, which covers ten-year period (2014-2023)). This data was gathered at a height of 10 meters, with wind speeds, air temperatures, relative humidity, wind direction, and precipitation. As shown in the **Figure 1**.

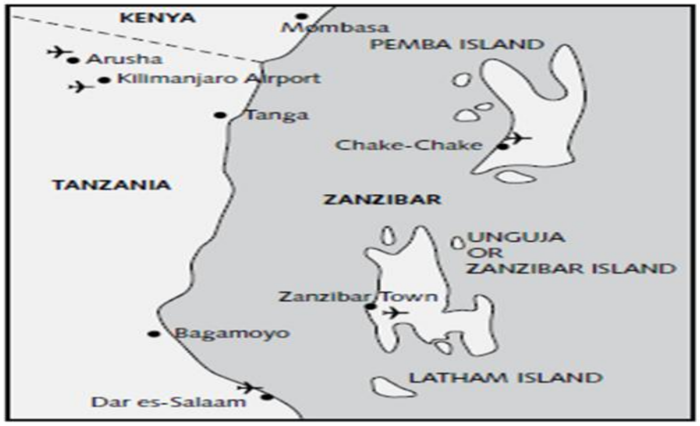


**Figure 1:** Show study area of Pemba Island, Zanzibar, Tanzania.

**Statistical Analysis of Wind Speed Characteristics**

Equations (1) and (2) are used to calculate the monthly mean and Standard Deviation (SD) of the daily wind speed values, respectively (Kombo & Irwansyah, 2025):

$$V_m = \frac{1}{N}\sum_{i=1}^{N} V_i \tag{1}$$

$$\sigma = \left(\frac{1}{N-1}\sum_{i=1}^{N}(V_i - V_m)^2\right)^{\frac{1}{2}} \tag{2}$$

In this equations, mean wind speed is denoted by $V_m$, the standard deviation by σ, while $V_i$ refers to wind speed measured for the i-time interval, and N refers to the total number of recorded wind speed.

Based on the literature, the two Weibull distribution function are normally applicable in the study of the distribution of wind speed for a particular area as described by the equations (3 and 4) (Fitra & Indra, 2023):

Probability distribution function f (v) and given by:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{3}$$

Cumulative distribution function also expressed as:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{4}$$

Further, Equation (5) is used to approximate the mean velocity using Weibull parameters as follows:

$$\bar{v} = c\Gamma\left(1 + \frac{1}{k}\right) \tag{5}$$

Where by c scale parameter (m/s), $\Gamma$ is is gamma, and k, shape factor of the distribution. Weibull distribution function parameters are calculated using the Standard Deviation Method (SDM). Reasons for this are as follows (Kombo & Irwansyah, 2025): (i) this method is suitable when the situation is such that only the value of standard deviation and average wind speed are known, (ii) this method is better than the graphical method, and (iii) this method has a simpler expression than other methods. The equations used to determine these parameters are as follows:(Hasan et al., 2023).

$$k = \left(\frac{\sigma}{V_m}\right)^{-1.086} \qquad (1 \leq k \leq 10) \tag{6}$$

$$c = \frac{V_m}{\Gamma\left(1+\frac{1}{k}\right)} \tag{7}$$

The gamma function ( ) can be calculated using the equation below:

$$\Gamma(x) = \int_0^{\infty} t^{x-1}\exp(-t)dt \tag{8}$$

**Wind speed Indicator**

Two other fundamental wind speed measurement indicators, maximum energy carrying wind speed ($V_{max\,E}$), and most probable wind speed ($V_{mp}$). Most probable wind speed ($V_{mp}$), and maximum energy carrying wind speed ($V_{max\,E}$), are very important indicators that have long been applied in calculating the availability of wind energy in particular site (T et al., 2025).

$$V_{max\,E} = C\left(1+\frac{2}{k}\right)^{\frac{1}{k}} \tag{9}$$

$$V_{mp} = c\left(1-\frac{1}{k}\right)^{\frac{1}{k}} \tag{10}$$

Where by $k$ and c are shape parameter and scale parameter of Weibull.

**Wind Power and Estimation of Energy Density**

Another parameter that is used to evaluate the wind power potential is wind power density (WPD). Wind power density can be obtained using two ways: available power method and two-parameter Weibull distribution method (Power et al., 2024).

$$\frac{P(V)}{A} = \int_0^\infty \frac{1}{2}\rho V^3\, f(V)dV = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) \tag{11}$$

Where ρ is the site's air density (kg/m$^3$), $\frac{P(V)}{A}$ is the wind power density per swept area of the turbine (W/m$^2$), and P (V) is the wind power in watts.

After wind power density calculating in equation. (11) , the wind energy density in the area can be obtained using the equation (12)) for an extended period of time (Hasan et al., 2024).

$$\frac{E}{A} = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) T \tag{12}$$

**ANN Model Process and Data Pre-Process**

The model proposed an artificial neural network using the multilayer perceptron model to make prediction about wind power density depending on some meteorological parameters. The list of input parameters consisted of wind speed, air temperature, relative humidity, wind direction, and precipitation, whereas wind power density was the output parameter. The training, validation, and test sets were constructed to perform an unbiased evaluation of the network (Bhatt, 2019) by standardizing the input and output parameters. The following equation is the normalization equation (Buhan, 2015).

$$y = \frac{(y_{max}-y_{min}) \times (x- x_{min})}{x_{max}- x_{min}} + y_{min} \tag{13}$$

Where by, $y_{max}$ = +1 and $y_{min}$ = -1

**ANN Training and Performance Evaluation**

The model used was an ANN having the feed-forward network of three layers together with one layer of the hidden layer having hyperbolic tangent functions of sigmoid activation. The model that was used was the gradient descent with momentum. The quality of the output of ANN model was elucidated, on the foundation of coefficient of determination ($R^2$) and root mean square error (RMSE) as the indicators of the accuracy and the degree of the estimated values, respectively. The two-performance metrics were used for validating the reliability of the ANN model for wind power density prediction and its applicability for wind energy planning purposes. $R^2$ is given by equation (14).

$$R^2 = 1 - \frac{\sum_{i=1}^{T}(y_\alpha - \hat{y}_\alpha)^2}{\sum_{i=1}^{T}(y_\alpha - \hat{y}_\alpha)^2} \tag{14}$$

The value ranges between 0 and 1. The higher the value, the higher the accuracy of the predictions.

Root means square error is also defined as stated in equation (15):

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{1}(y_\alpha - \hat{y}_\alpha)^2} \tag{15}$$

Where $y_\alpha$ and $\hat{y}_\alpha$are the measured and forecasted densities of the wind power, respectively. These measures were employed to determine the predictive power and reliability of the model.

## RESULTS AND DISCUSSION

### Months average wind speed analysis

From the **Figure 2**, it can be noted that the data show seasonal as well as interannual variations. It is quite evident that the wind speeds are high between the months of May and August, which indicating that the wind speeds are high, i.e., above 7 m/s. This indicates that the time of the year is suitable for the generation of wind energy. It is also evident that between the months of February and April, the wind speeds are quite low. The interannual variation of the data between the years 2016-2018 indicates an increase in wind speeds. A declining trend in the wind speeds is also evident in the data from the year 2019.

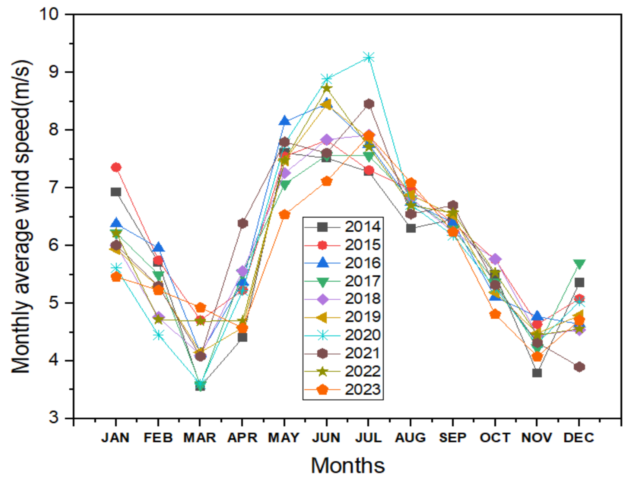


**Figure 2:** Monthly average wind speed for ten years from 2014-2023.

### Weibull Statistical Modelling of Wind Characteristics

From **Table 2** and **Figure 3**, the shape parameter ranges from 3.70 to 6.16. This implies moderate variation in the distribution of the wind speed. On the other hand, the scale parameter ranges from 6.21 to 6.71 m/s. This implies consistent strength of the wind throughout the years. The increased power and energy density are also exhibited by the year 2020. This is because the year with the highest energy-carrying wind speed of 7.51 m/s is the same year. This implies superior wind energy potential is exhibited the year 2020 compared to other years. The most probable wind speed ranges from 5.97- 6.50 m/s. This implies minimal variation throughout the years.

Comparing the wind characteristics recorded in the region to other parts of the African continent, it can be established that the wind characteristics recorded in Pemba Island are similar to or slightly higher than those recorded in the East African Community countries. For instance, (Buhan, 2015) established that the highest wind energy siting suitability is recorded in Kenya, while Rwanda receives lower wind speeds of 4.0-5.1 m/s and wind power density of 13.17-22.42 W/m². In Uganda, wind speeds of 3.7-6.0 m/s are recorded in the Lake Victoria Region and the Karamoja Region, classified as wind power class 1. Higher wind power density is recorded in North Africa, particularly in Somalia and other coastal regions, which receive wind power density of 300-700 W/m². In the southern coastal regions of Africa such as Namibia, South Africa, and Mozambique, wind power density ranges from 75 to 320 W/m².

**Table 2.** Weibull parameters (k and c), wind energy and wind power density, and wind speed indicators.

| Years | Mean ($V_m$) | Shape parameter k | Scale parameter c (m/s) | Wind power density (WPD) W/m$^2$ | Wind energy density (WED) kWh/m$^2$ | Maximum energy-carry wind speed ($V_{max E}$) | Most probably wind speed ($V_{mp}$) |
|---|---|---|---|---|---|---|---|
| **2014** | 5.87 | 4.7318 | 6.4118 | 144.95 | 1269.77 | 6.91 | 6.10 |
| **2015** | 6.22 | 6.1587 | 6.6905 | 162.50 | 1423.51 | 7.00 | 6.50 |
| **2016** | 6.16 | 4.8931 | 6.7138 | 165.90 | 1453.32 | 7.20 | 6.41 |
| **2017** | 5.96 | 5.5224 | 6.4462 | 145.75 | 1276.80 | 6.82 | 6.22 |
| **2018** | 5.95 | 5.1052 | 6.4607 | 147.37 | 1290.95 | 6.89 | 6.19 |
| **2019** | 5.97 | 4.6547 | 6.5273 | 153.18 | 1341.88 | 7.05 | 6.20 |
| **2020** | 6.03 | 3.6963 | 6.6775 | 170.43 | 1492.95 | 7.51 | 6.13 |
| **2021** | 6.04 | 4.5430 | 6.6113 | 159.61 | 1398.15 | 7.16 | 6.26 |
| **2022** | 6.01 | 4.6748 | 6.5657 | 155.83 | 1365.11 | 7.09 | 6.24 |
| **2023** | 5.73 | 5.3599 | 6.2095 | 130.46 | 1142.81 | 6.59 | 5.97 |

(a) Weibull parameters k and c (b) Wind speed indicators

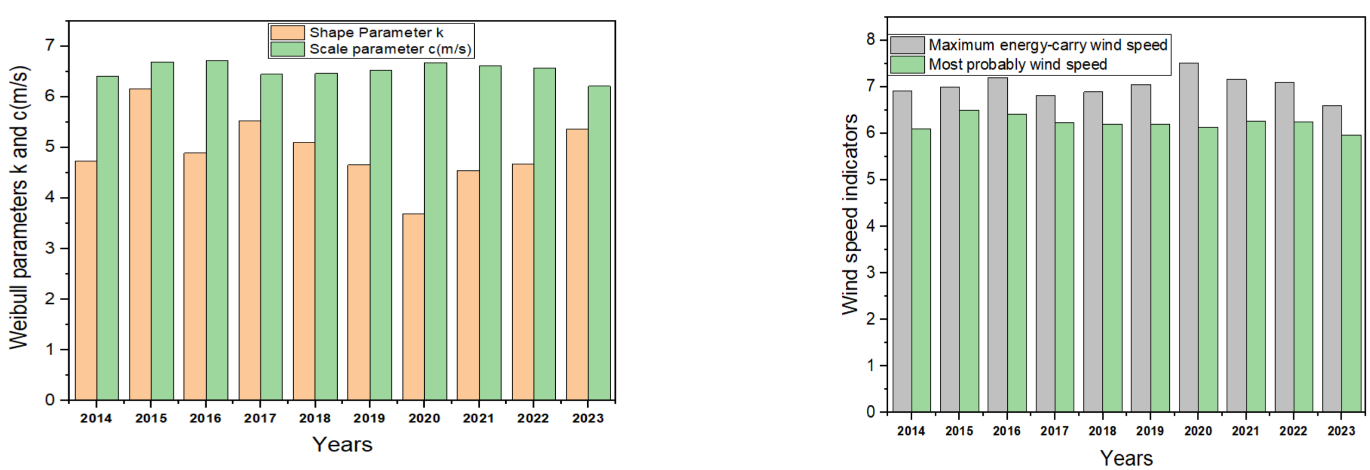


**Figure 3:** Yearly Weibull parameters and wind speed indicator for ten years from 2013-2014.

### Wind Energy and Power Evaluation

From the data presented in **Table 2** above, it showed that the annual wind power density varies between 130.46 W/m² and 170.43 W/m², while the wind energy density varies between 1142.81 kWh/m² and 1492.95 kWh/m². Based on the values presented in the Table 2, it can be noted that the highest annual wind power density was recorded in the year 2020, which had the highest values of WPD and WED, while the lowest values were recorded in the year 2023. Based on the PNL classification of wind power in **Table 3**, the values of the annual wind power density (WPD) obtained in this research falls in class 2 (Marginal) and class 3 (Moderate) of the PNL classification of wind power, which corresponds to the height of 10 m. Thus, the location is suggested as Marginal–Moderate wind class that can be used to generate small to medium-scale wind power, hybrid systems, and localized energy sources instead of the large utility scale wind farms.

In comparison, it is found that in mainland Tanzania, wind power potential is found to be much higher in some regions. In their study, (Kombo & Irwansyah, 2025) assessed three sites in Zanzibar and discovered the mean annual wind intensities in the range of 5.43 to 5.81 m/s, which are equal and slightly below the 6 m/s average in Pemba. Singida region in mainland Tanzania is the best wind location in the country with the mean wind speed of 7.29–8.2 m/s and the mean power density of wind 237.30 W/m$^2$ at 10 m high whereas Dodoma Airport site had low mean wind speed of 4.50 m/s and 55.32 W /m$^2$ power density at 10 m height (Kumwenda et al., 2024).

**Table 3.** Classification of wind power by PNL (Kombo & Irwansyah, 2025).

| **Wind power class** | **Wind power density (WPD)** | | | **Resource potential** |
|---|---|---|---|---|
| | At 10m (W/m$^2$) | At 30m (W/m$^2$) | At 50m (W/m$^2$) | |
| **1** | 0 – 99 | 0 – 159 | 0 – 199 | Poor |
| **2** | 100 – 149 | 160 – 239 | 200 – 299 | Marginal |
| **3** | 150 – 199 | 240 – 319 | 300 – 399 | Moderate |
| **4** | 200 – 249 | 320 – 399 | 400 – 499 | Good |
| **5** | 250 – 299 | 400 – 479 | 500 – 599 | Very good |
| **6** | 300 – 399 | 480 – 639 | 600 – 799 | Excellent |
| **7** | 400 – 1000 | 640 – 1600 | 800 – 2000 | Superb |

**Results and performance evaluation of ANN Prediction**

ANN model showed very good results in the prediction of wind speed in months. As **Figure 4** portrays, the data on the wind speed were split into training, testing, and validation where the model successfully learned the wind speed patterns. The fact that the values of the observed and predicted values are very close implies that the model is very reliable with very few deviations in all the phases. It can be justified by the fact that the coefficient of determination is very high ($R^2 = 0.99989$) meaning that there is almost perfect fit. The predictive accuracy found in this research is similar to or better than the findings reported in another research carried out using tropical and island setting where ANN models have been found to perform better and have smaller prediction errors than other traditional statistics methods, which usually need bigger datasets (Andreotti et al., 2021). The predictive accuracy obtained with a high level of predictive accuracy with Pemba Island indicates that ANN models are useful in capturing the non-linear dependencies amongst meteorological factors to wind power density in an island-based setting to aid in resource planning in analogous islanded grid systems.

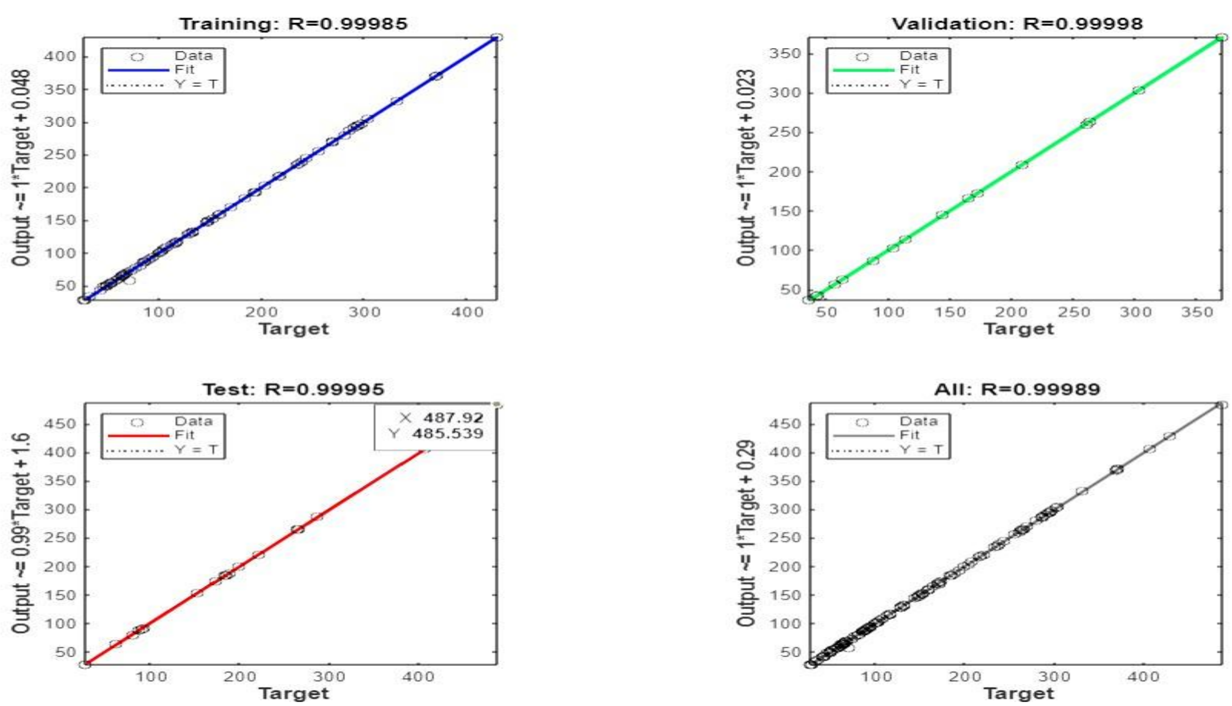


**Figure 4:** Show Training, Validation and Test data of ANN model.

As per **Figure 5**, the results indicate that there is a very strong agreement between the actual values and predicted values in terms of wind power density. The actual values indicate that there is a considerable variation in terms of months, which indicates that the data is seasonal. The minimum values are around 28 W/m², and the maximum values reach up to 488 W/m², which indicates that the data is showing periods of high levels of wind energy. The predicted values indicate the same trend, but the data is smooth. The statistical results indicate that the level of prediction accuracy is very high, as indicated by the high value of $R^2$, which is around 0.9998, and the levels of error are very low. As per the above discussion, it is very clear that the model is capable of accurately representing the low and high values of wind power density.

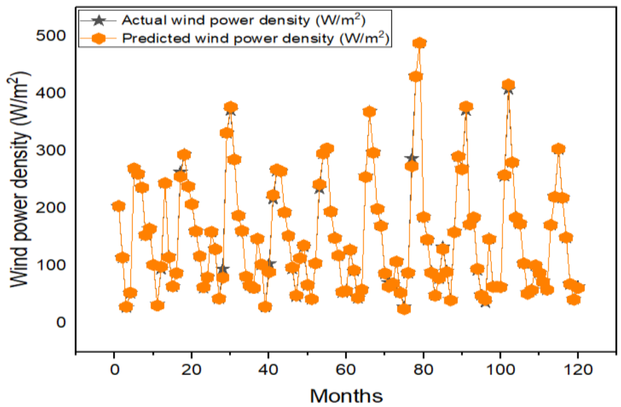


**Figure 5:** Actual value and predicted value of wind power density for ten years (120 months).

## CONCLUSION

This research demonstrates that wind energy potential in Pemba Island, Zanzibar is marginal to moderate with an average wind speed of approximately 6 m/s with higher winds during May to August. Weibull distribution analysis reflected that the wind is stable, and ANN model was used to confirm good predictability with a high level of accuracy ($R^2$ = 0.9998). These findings indicate that the region can be developed to have small to medium wind energy and a hybrid renewable energy system in an effort to enhance energy supply locally. Nevertheless, the research is restricted by the application of NASA POWER satellites data and wind measurements to the height of 10 m. The next research can involve ground measurements over a long period of time, as well as multi-height data on the wind.

## ACKNOWLEDGEMENTS

This article has been funded with support of the Kemitraan Negara Berkembang (KNB) Scholarship from Ministry of Higher Education, Science, and Technology of Republic of Indonesia on behalf of the Government Republic Indonesia. This publication reflects the view only of the author, and the Ministry of Higher Education, Science, and Technology of Republic of Indonesia cannot be held responsible for any use which may be made of the information contained therein.

## REFERENCES

Andreotti, A., Caiazzo, B., Pasquale, A. Di, & Pagano, M. (2021). On Comparing Regressive and Artificial Neural Network Methods for Power System Forecast. *2021 AEIT International Annual Conference (AEIT)*, 1–6. https://doi.org/10.23919/AEIT53387.2021.9626938

Bhatt, G. A. (2019). Statistical and ANN based prediction of wind power with uncertainty. *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, *Icoei*, 622–627.

Buhan, S. (2015). *Multistage Wind-Electric Power Forecast by Using a Combination of Advanced Statistical Methods*. *11*(5), 1231–1242. https://doi.org/10.1109/TII.2015.2431642

Elsoragaby, S., Yahya, A., Mahadi, M. R., Nawi, N. M., Mairghany, M., M Elhassan, S. M., & Kheiralla, A. F. (2020). Applying multi-objective genetic algorithm (MOGA) to optimize the energy inputs and greenhouse gas emissions

(GHG) in wetland rice production. *Energy Reports*, *6*, 2988–2998. https://doi.org/10.1016/j.egyr.2020.10.010

Fitra, M., & Indra, C. (2023). *Evaluation and analysis of wind speed with the Weibull and Rayleigh distribution models for energy potential using three models Evaluation and Analysis of Wind Speed with the Weibull and Rayleigh Distribution Models for Energy Potential Using Three Models*. https://doi.org/10.32479/ijeep.12775.This

Hasan, W. S. A., Hassan, A. S. M., & Shukri, M. A. (2024). Assessment of wind power potential and economic viability at Al-Hodeidah in Yemen: Supplying local communities with electricity using wind energy. *Energy Reports*, *12*(April), 2981–2996. https://doi.org/10.1016/j.egyr.2024.08.073

Hasan, W. S. A., Saif, A., Hassan, M., & Shukri, M. A. (2023). Assessing the performance of several numerical methods for estimating Weibull parameters for Wind Energy Applications : A case study of Al-Hodeidah in Yemen. *Energy Reports*, *10*(5), 2725–2739. https://doi.org/10.1016/j.egyr.2023.09.081

Idris, W. O., Ibrahim, M. Z., & Albani, A. (2020). *in Nigeria*. 1–16.

Kombo, H. K., & Irwansyah, R. (2025). *Evaluation of Wind Energy Potential for Electricity Generation in Three Locations of Zanzibar , Tanzania*. *5*(1), 148–165.

Kumwenda, M. J., Mangara, R. J., Hasan, W. S. A., Hassan, A. S. M., & Shukri, M. A. (2024). Assessment of Wind Speed Characteristics and Available Wind Power Potential for Electricity Generation in Tanzania. *CC BY-ND] Tanzania Journal of Engineering and Technology (Tanz. J. Engrg. Technol.)*, *12*(April), 2981–2996. https://doi.org/10.1016/j.egyr.2024.08.073

Liu, H., & Yang, R. (2025). Artificial intelligence for wind speed forecasting_ A review on multi-scale decomposition and intelligent fusion strategies. *Advances in Wind Engineering*, *2*(2), 100055. https://doi.org/10.1016/j.awe.2025.100055

Mangara, R. J., & Kumwenda, M. J. (2023). *Wind Speed Forecasting Using Wavelet Analysis and Recurrent Artificial Neural Networks Based on Local Measurements in Singida Region ,*. *49*(3), 754–763.

Mustaffa, Z., & Herwan, M. (2025). Random forest based wind power prediction method for sustainable energy system. *Cleaner Energy Systems*, *12*(December 2024), 100210. https://doi.org/10.1016/j.cles.2025.100210

Nazir, M. S., Alturise, F., Alshmrany, S., Nazir, H. M. J., Bilal, M., Abdalla, A. N., Sanjeevikumar, P., & Ali, Z. M. (2020). *Wind Generation Forecasting Methods and Proliferation of Artificial Neural Network : A Review of Five Years Research Trend*.

Pereyra-mari, C. (2022). *Wind energy potential assessment of selected locations at two major cities in the Dominican Republic , toward energy matrix decarbonization , with resilience approach*. *32*(November 2021). https://doi.org/10.1016/j.tsep.2022.101313

Power, W., Using, D., & Distribution, S. (2024). *applied sciences A Comparative Study on the Estimation of Wind Speed and Wind Power Density Using Statistical Distribution Approaches and Artificial Neural Network-Based Hybrid Techniques in*.

Preethaa, K. R. S., Muthuramalingam, A., Natarajan, Y., Wadhwa, G., Abdi, A., & Ali, Y. (2023). *A Comprehensive Review on Machine Learning Techniques for Forecasting Wind Flow Pattern*.

Serban, A., Paraschiv, L. S., & Paraschiv, S. (2020). Assessment of wind energy potential based on Weibull and Rayleigh distribution models. *Energy Reports*, *6*(April), 250–267. https://doi.org/10.1016/j.egyr.2020.08.048

Shafi, I., Khan, H., Farooq, M. S., De, I., Diez, T., Miró, Y., Galán, J. C., & Ashraf, I. (2023). *An Artificial Neural Network-Based Approach for Real-Time Hybrid Wind – Solar Resource Assessment and Power Estimation*. 1–18.

T, M., K, T., O, J., T, S., & A, W. (2025). *Characterization of Wind Energy Potential in Ladeba , Lagos State , Nigeria*. *27*(7), 28–52.

Valdivia-bautista, S. M., Dom, A., Marco, P., Jesahel, C., & Castillo-t, B. (2023). *Artificial Intelligence in Wind Speed Forecasting : A Review*.

Zhan, Y., & Zhu, J. (2024). Response surface methodology and artificial neural network-genetic algorithm for modeling and optimization of bioenergy production from biochar-improved anaerobic digestion. *Applied Energy*, *355*(September 2023), 122336. https://doi.org/10.1016/j.apenergy.2023.122336.