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Wind Energy Resource Assessment for Cook Islands With Accurate Estimation of Weibull Parameters Using Frequentist and Bayesian Methods

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ABSTRACT Wind energy resource assessments at two islands in the Cook Islands are carried out in the present work. The wind data were collected for one year from sites on Mauke and Rarotonga Islands in the Cook Islands and the daily, monthly and seasonal average wind speeds, the diurnal variations of the wind shear coefficient, average temperature and turbulence intensity were estimated. Eleven frequentist methods and a Bayesian technique were used to determine the Weibull parameters and the wind power density (WPD) for each site. The best method was determined using the goodness of fit test and error measures. The average wind speeds were 4.65 m/s and 3.86 m/s at 34 m above ground level for the sites on Mauke and Rarotonga respectively. Based on the goodness of fit tests and error measures, the Least Squares Method performed best for estimating the Weibull parameters at the Mauke site, while for the Rarotonga site, the median and quartiles method performed the best. For both the sites, the Bayesian method, which is being used for the first time for wind resource assessments, ranked second of the twelve methods, indicating good potential for this method. The annual energy production (AEP) was also determined which was calculated to be 2192.34 MWh from a total of ten Vergnet 275 kW turbines at the two sites. Finally, an economic analysis, carried out for the two sites, indicated a payback period of 7.72 years.

INDEX TERMS Wind energy, Weibull distribution, wind power generation, energy resources, turbulence intensity, economic analysis.

NOMENCLATURE

Symbols:

A	= scale factor, m/s
k	= shape factor
n	= number of observations
TI	= turbulence intensity, %
U	= wind speed, m/s
$\bar{U}$	= average wind speed, m/s
U_m	= median wind speed, m/s
WAsP	= wind atlas analysis and application program
WPD	= wind power density, W/m^2
U_t	= actual wind speed
$\bar{U}_t$	= predicted wind speed at time t

Acronyms and Abbreviations:

AGL	= above ground level, m
BAYES	= Bayesian method
CEPPD	= combined energy pattern and power density method
COE	= coefficient of efficiency
EMJ	= empirical method of Justus
EML	= empirical method of Lysen
EPF	= energy pattern factor method
LSM	= least squares method

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MAE = mean absolute error
MAPE = mean absolute percentage error, %
ML = maximum likelihood method
MML = modified maximum likelihood method
MO = moments method
MQ = median and quartiles method
NMO = new moments method
PICs = Pacific Island Countries
RMSE = root mean square error, m/s

Greek Letters:

α = wind shear coefficient
r = gamma function
σ = standard deviation of wind speed, m/s

I. INTRODUCTION

Moving to the renewable sources of energy to meet the energy requirements is one of the top priorities of the Pacific Island Countries (PICs). One of the main climate change mitigation policies of the Cook Islands Government is to achieve 100% renewable energy generation by 2025 [1]. This will not only help them reduce their dependence on imported fossil fuels, but will also contribute to a reduction in harmful greenhouse gas emissions. Solar and wind are two proven technologies and are therefore preferred by the PICs. Wind power generation only requires a high initial investment; for the PICs, the returns on such investments are very good considering the high cost of electricity.

The Cook Islands is a country located in the South Pacific with a tropical climate; it has around 15 islands and has a total land area of about 240 km^2. The largest island in the country is Rarotonga which has a population of around 14,000 and also has the capital of the country, Avarua. The two sites at which the wind energy resource assessments were carried out are on Mauke and Rarotonga islands. Mauke is a very small island in the Cook Islands group with distinct features such as lakes, deep caves and a central volcanic plateau. The island has fossilised coral which surrounds the central volcanic plateau and reaches a height of around 1000 m. The island's soil is also very rich because of the volcanic remains and thus is called the garden island [2]. On the other hand, Rarotonga is the main island in the group, which is also the most populated island and the largest among all the islands in Cook Islands. The island is volcanic in nature with the highest peak reaching 658 m. Rarotonga is surrounded by a lagoon which is 100 m away from the reef. The island is heavily populated near the sea-shore. The interior of the island remains unpopulated due to the treacherous and rugged terrain.

Wind energy has become very popular over the years since it is a clean energy source and the cost of wind power generation per unit of electricity has reduced significantly. Substantial research is being done on wind energy mainly in the areas of accurate Weibull parameter estimation from statistical analysis, the overall structure of the wind turbine, blade design, materials used for manufacturing the turbine blades, and the aerodynamics of the wind turbine blade. Some research works have also focused on enhancing the annual energy production by improving the blade design using multi objective genetic algorithms [3], [4].

The current energy trends in the South Pacific call for Scientists and Engineers to search for cleaner and sustainable sources of energy. This comes into light following the increased import and usage of fossil fuels across the region as a whole. The fossil fuels pose a major threat to the environment by contributing to an increase in the greenhouse gas emissions and the associated harmful effects such as rising temperatures, changing rainfall patterns, ocean acidification, stronger cyclones and rising sea levels. The contribution of PICs to current greenhouse gas emissions is below 0.03%; yet they are the ones that are the worst affected and are the ones that may go under water due to the rise in sea level [5], [6].

There is a need for renewable energy technologies to be implemented so that the countries can produce affordable, reliable and sustainable energy. Plans for generating wind power in Cook Islands were made after a feasibility study was carried out for a 2 MW wind farm [7]. The study highlighted the need for wind measurements before installing wind turbines. In 2012, the Renewable Energy Development Division [8] of Cook Islands prepared a renewable energy implementation plan and highlighted the need to firm up the data available for solar and wind energies. A specific study performed for Mauke island in 2004 [9] found that grid-connected wind power is more viable both economically and financially than solar PV and would contribute a higher amount of renewable energy to the system. In a 2016 Conference [10], it was agreed that Rarotonga has a wind resource worth developing. Each country in the South Pacific has its own national sustainable development plan to achieve United Nations' sustainable development goals (SDGs); as an example, Cook Islands aims to have 100% renewable power generation in near future [11]. Although some renewable energy technologies namely wind, solar and hydro are already implemented in the pacific region, energy produced is still not sufficient and the contribution of renewable energy to the total energy production is very small. Thus, in order to extract more energy from renewable sources, resource assessment is essential to identify the real potential of different energy sources especially the wind energy. Wind resource assessment and economic analysis are crucial before installation of any energy harvesting device [5]. There was only one study reported till date on the assessment of wind energy resource in the Cook Islands, which was carried out in 2007-2008 on a hill with the intention of installing a wind farm [12]; however, this was not implemented and a subsequent report [8] emphasized the need for data collection at more sites. It should be noted that till date, no grid-connected wind turbine is installed in the Cook Islands, although most of the above-mentioned reports agreed on the good potential for wind energy harvesting in the country.

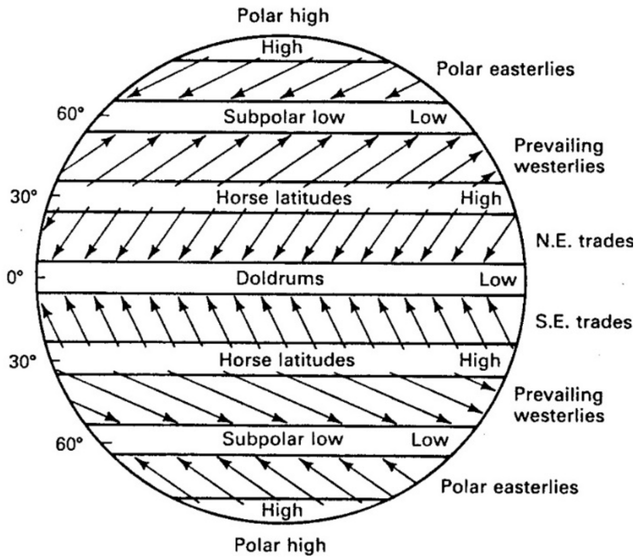

FIGURE 1. Ideal terrestrial pressure and wind systems [14].

The pressure gradient (difference in atmospheric pressure) determines the strength of the wind. The larger the difference between the atmospheric pressures between two points at a relatively short distance, the stronger the wind. The wind also maintains a balance between the equatorial region and the polar region of the earth by transferring energy around. Without winds, the equatorial regions would get hotter and the polar region would get cooler. Fig.1 shows the ideal terrestrial pressure and wind systems. In the Cook Islands region, predominantly south-easterly trade winds are likely to be present. This has been reported in our earlier works in the South Pacific region e.g. for Vanuatu [13].

The Coriolis Effect greatly influences winds. This is due to the earth's rotation and there are two factors that are related to it. Firstly, the earth is constantly moving. Therefore, tracking the wind on any freely moving object would be difficult. Secondly, the rotational speed of the earth changes from polar region to equatorial regions.

As we move towards the equator, the rotational speed of earth increases. Due to earth's rotation, in the Northern hemisphere, anything travelling horizontally would feel being deflected right of its travel direction and vice versa in the Southern hemisphere [15]. Thus the deflection due to this phenomenon of Coriolis Effect influences the winds in the Northern and Southern hemispheres greatly. Frictional drag is also a very important factor that influences wind speed since it is less at greater altitudes but more at lower altitudes due to the presence of buildings, trees and mountainous terrains. The lower wind speed lowers the Coriolis effect with almost no significant impact on the pressure gradient [15].

It is very important to study wind patterns such as wind speeds and directions for a particular region to clearly explain the wind directions that are obtained from wind resource assessment. For example, the expected winds in the South Pacific are the South-Easterly trade winds. However, some earlier studies on wind energy resource assessment in the South Pacific showed some other wind directions such as East or East-North-East [16], [17]. Moreover, obstacles at lower altitudes affect wind speeds and cause turbulence, making it interesting to determine the turbulence intensities under different wind conditions as this may affect the structural integrity of the wind turbine.

Many researchers have carried out wind resource assessments using wind speed data from different locations. Sharma and Ahmed [18] carried out wind energy resource assessment for two sites in Fiji: Kadavu and Suva. They found that the average wind speeds at 20 m AGL and 34 m AGL are 5.65 m/s and 6.38 m/s respectively. They also carried out wind shear analysis and also plotted the wind resource map to find out the AEP from virtual turbines located at suitable locations. The two measurement sites showed very good wind potential. Wais [19] compared the two and three parameter Weibull distribution to study the most appropriate model. In some cases, the frequency of the low wind speeds is greater which cannot be accounted for by any method other than the three parameter Weibull distribution. He compared the wind speeds for three different locations and found out that the three parameter Weibull distribution performed the best when there was greater frequency of lower wind speeds. Lun and Lam [20] studied 30 years of wind data for three locations in Hong Kong which were in city area, open sea area and an exposed city area. With the 30 years of wind data, they calculated the Weibull parameters, which revealed that the parameters varied over the years. They also studied the Weibull distribution of wind speed for each location and it was observed that the distribution curve was wider for the open sea areas. Liu *et al.* [21] studied the wind resource in China and found that the national annual mean wind speed was 4.09 m/s at 10 m above ground level. They used the data from a large number of meteorological stations and identified locations in the country where the potential of wind power is high. Bhuiyan *et al.* [22] studied the Weibull parameters, analyzed the wind speeds and estimated the energy generation for Kuakata region in Bangladesh using a web tool called 'Wind Energy Assessment' which gave an energy output of 2243 kWh/year; the production cost was also calculated. Abdraman *et al.* [23] studied the wind energy potential for N'Djamena in Chad from wind data of 12 months recorded at an airport weather station. They analyzed the wind data to calculate the Weibull parameters, the distributions of the wind speed, the turbulence intensities and the energy production at a height of 100 m using a Vestas V80/1.8 MW wind turbine. It was found that the turbine would produce 50.42 GWh of energy per year Olaofe [24] used 10 years of satellite data at a height of 10 m for a coastal region in Nigeria. He studied the monthly, seasonal and the yearly means as well as the distributions using three mathematical models: Rayleigh, Weibull and Rician. The Weibull and the Rician distributions showed better fit and showed that offshore wind energy potential in Nigeria was good. Rocha *et al.* [25]

analyzed nearly two years of data for two sites in Brazil using seven Weibull approaches and found that the equivalent energy method performed the best in this case. It was also noted that the numerical methods can give better efficiency if the number of iterations is higher thus the numerical methods are also recommended. Tizpar *et al.* [26] studied the wind energy potential for Mil-E-Nader region based on 10 minute average wind speed data, which was measured at a height of 40 m. The analysis was performed to obtain the monthly wind speed variations as well as the diurnal wind speed variations. Based on the wind speed data at 40 m height, the power law was used to extrapolate the wind speed at other heights. Energy analysis was carried out for different heights whereby the best hub height was found by comparing several classifications of wind turbines. Shu *et al.* [27] used six years of wind data that were recorded by five meteorological stations that had varying terrains to carry out the statistical analysis of wind characteristics. The Weibull distribution was used in this study for the estimation of Weibull parameters. The study found that the scale factor (A) varied from 2.85 m/s to 10.19 m/s for the sites whereas the shape factor (k) varied between 1.65 and 1.99. It was seen that the highest Weibull parameters were obtained at a greater latitude at a remote location and the lowest Weibull parameters were obtained in an urbanized area. Dabbaghiyan *et al.* [28] studied the wind energy potential for four locations in Bushehr province of Iran. One-year wind data measured at heights of 10 m, 30 m and 40 m were used to estimate the wind power density using the Weibull approach. It was noted that the Weibull method performed well to give a good fit on the histogram. The annual energy production from twelve wind turbines with generating capacities ranging from 1 kW to 100 kW was also estimated. Chang [29] used a two-parameter Weibull function for evaluating the wind energy potential and compared it with six other numerical methods that are commonly used for estimating the Weibull parameters. The performance analysis was done using parameter error, wind energy error, root mean square error and the Kolmogorov-Smirnov test. From the results, it was observed that the graphical method performed the worst with tests of random variables. It was noted that the maximum likelihood method, modified maximum likelihood method and the moments method performed the best with increasing number of data for the particular location using the simulations based on double checks. However, the maximum likelihood method performed better than the modified maximum likelihood method. Rehman *et al.* [30] carried out an assessment of wind energy potential across geographically distinct locations in the southern part of India. The three cities selected for the study had different elevations. They used three methods of ML, LS and WAsP for estimating Weibull parameters. Guenoukpati *et al.* [31] studied the wind characteristics for three different coastal sites in West Africa. In the study, they used seven numerical methods to find the shape and scale factor. They used similar methods such as EMJ, EML, EPF, ML, MO, graphical method and a hybrid method which is a mixture of EPF and EMJ. According to them, the hybrid method gave accurate results. The numerical methods were used for finding accurate Weibull parameters of the Weibull distribution function so that the wind speed characteristics and WPD can be presented accurately. Saeed *et al.* [32] stated that the numerical methods for estimating the Weibull parameters are inconsistent and that the two-parameter Weibull distribution is one of the best methods for wind data representation. In the work, artificial intelligence optimization techniques were used based on the Chebyshev metric which proves mathematically and guarantees convergence for wind parameter estimation. A site close to the coastal region in Pakistan was chosen to obtain wind data. The wind data were analyzed and showed that the results offer greater accuracy compared to the numerical methods. They also carried out a cost analysis for determining whether the site was worthy for wind power generation Chen *et al.* [33] estimated the wind power potential in Taiwan and carried out an economic analysis. They used ML method only for estimating Weibull parameters and for ranking the sites. Guarienti *et al.* [34] carried out the wind energy resource assessments for 27 stations in the state of Mato Grosso do Sul, Brazil, using hourly wind speed data series. The accuracy analysis for the data were also carried out and six numerical methods (Graphical Method, Maximum Likelihood Method, Modified Maximum Likelihood Method, Moment Method, Empirical Method and Power Density Method) were used to estimate the Weibull distribution parameters. The Maximum Likelihood Method (ML) and Modified Maximum Likelihood Method (MML) performed the best for their case in analyzing most of the data from the 27 stations. In a recent work, Nair and Kumar [35] carried out wind resource assessment at a site on Vanua Levu in Fiji. They used the Weibull parameters from the WAsP software and reported a mean wind speed of 5.91 m/s and a wind power density of 206 W/m^2 at 34 m AGL.

Thus, it can be seen that most of the previous researchers used 6-8 methods for estimating the Weibull parameters and for finding the accurate wind power density. In recent wind resource assessments carried out for Suva [17], Kadavu [36], Vanuatu [13] and Tuvalu [37] in the South Pacific, the authors used 10 different methods for estimating Weibull parameters. This work uses an additional method, called combined energy pattern and power density method (CEPPD) for estimating the Weibull parameters and wind power density. Thus, a total of eleven methods and a Bayesian technique are used in the present work that were never used in the past works. Moreover, wind resource assessment was carried out in Cook Islands just once from May 2007 to May 2008; however, these measurements were carried out on a hill of approximately 80 m height to find a high wind speed hilly site for possible wind farm installation [38]. The measurements were performed at a site close to the North-Eastern coast. However, the plan of a wind farm at the proposed site never materialized. The present measurements were performed close to the North-Western coast near the main hospital and a more populated area with the intention of finding the feasibility of installing 5 wind turbines of 275 kW each at suitable locations across the island. The present work includes a detailed statistical analysis of wind characteristics, accurate estimation of Weibull parameters and wind power density using eleven different methods and a Bayesian technique plus an economic analysis with 10 wind turbines that are commonly installed in the South Pacific countries. Statistical analysis software 'R' and wind resource assessment software 'WAsP' were used in the present work. 'R' is an open-source and free statistical analysis software. It is increasingly being used for data analysis and graphics, and is very useful for exploring, modelling, and visualizing data. Also it is a widely used software by researchers from diverse disciplines. Since it is open-source, the researchers are always able to perform new statistical analyses and apply cutting edge statistical techniques as soon as these are available or anyone thinks of them [39]. In this paper, 'R' is used for the following analyses including data processing, simulations and for graphing and visualizations: (i) calculation of hourly, daily, diurnal, monthly and seasonal parameters, (ii) estimation of Weibull parameters using all the methods, and (iii) calculation of the goodness of fit and error measures (R^2, COE, RMSE, MAE, MAPE, COE). The WAsP software suite is now an industry-standard tool for wind resource assessment, siting of wind turbines and estimation of annual energy production. WAsP software has the capability to predict wind climate and power production based on the currently available wind turbines in the market which makes it advantageous for modeling wind energy. The software calculates its own Weibull parameters using the equations described in Table 4 [40]. Apart from estimation Weibull parameters, WAsP was also used in the present work for drawing the resource grid and for estimating the annual energy production with the selected wind turbines. The main contributions of the present work can be listed as follows:

- Wind resource assessments for two islands (Mauke and Rarotonga) in Cook Islands are carried out by carrying out detailed measurements of wind speed at two heights above ground level, wind direction, and ambient temperature. The daily, monthly, and seasonal variations of wind speed and diurnal variations of turbulence intensity, wind shear coefficient and ambient temperatures are studied in detail.
- For each of the sites, eleven frequentist methods and Bayesian method were used to find Weibull parameters.
- Five goodness of fit/error estimates were used to find the most accurate Weibull parameters and estimate the wind power density.
- Annual energy production from five virtually located Vergnet 275 kW turbines was estimated for both the islands. An economic analysis was also carried out to estimate the payback period. This work will directly contributed to a developing country like Cook Islands meet the sustainable development goals.

II. DATA AND METHODOLOGY

In the present work, an in-depth wind resource assessment was carried out at two locations in the Cook Islands. The data were acquired using "Integrated Renewable Energy Resource Assessment Systems" (IRERAS) which consist of a 34 m tall tower consisting of several sensors and instruments. The information of the sensors, instruments, location of measurements, modelling of the data using Weibull distribution and the Weibull parameters estimation methods, the validation of data and the performance analysis of different methods are presented in the following subsections.

A. METHOD

One IRERAS tower was installed at each of the two sites that were selected for measurements and detailed analysis of wind data. The towers are from NRG systems; they are 34 m in height and are fixed to a base plate and supported by guy wires. Each tower is mounted with a number of sensors that measure wind speed, atmospheric pressure, temperature, rainfall, relative humidity, solar insolation and wind direction. All the useful data are collected in a NRG SymphoniePlus data logger in an SD card. Internet enabled logging system is used to interface the data logger and the Symphonie Pack system. The data were transferred using a mobile network to the main server at the Information, Communication and Technology (ICT) building of the University of the South Pacific (USP) with the help of a GSM iPack combined with a SIM card. The instruments that were mounted on the tower are as follows:

- Cup anemometers at 34 m and 20 m AGL
- Wind vane at 30 m AGL (aligned to true North)
- Barometric pressure sensor
- Temperature sensor (enclosed in a circular six-plate radiation shield) [13], [17].

The raw data files were converted into excel format where the date and time were standardized to be compatible with the algorithm being used for this project. The data were then converted into a valid input file which is a.txt file. The data were then analyzed using R software and the daily, monthly and hourly averages of the data were calculated. The data were recorded at an interval of 10 minutes and sent to the main server once every day. There are 15 channels in the data logger which measure mean values, minimum values, maximum values and the standard deviation of the parameters recorded from the sensors. The measurement sensor' specifications are presented in Table 1.

The data validation steps are as follows:

- Retrieving raw data files
- Developing data validation routines
- Validating the data
- Creating valid data files
- Processing data and generating reports

Data management is an important part of carrying out a wind resource assessment. There are several important steps to be followed in data management. The first step is to check the parameters of the sensor that are arriving at the server against

TABLE 1. Measurement sensor specifications.

Parameter	Sensor type	Range	Accuracy
Wind Speed	NRG #40 Anemometer	1.0 to 96.0 m/s	0.1 m/s in the range 5-25 m/s
Wind Direction	NRG 200P direction vane	0-360°	N/A
Pressure	NRG BP-20 barometric pressure sensor	15.0 to 115 kPa	±1.5 kPa
Tempera ture	NRG 110S	25°C to 65°C	±1.1 °C

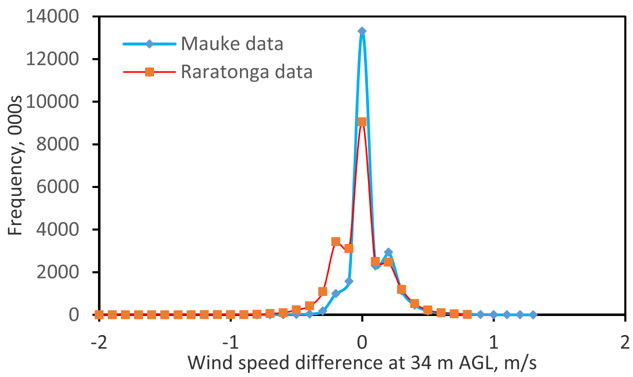

FIGURE 2. Difference of wind speeds for the two anemometers at 34 m AGL in Mauke and Rarotonga.

a manufacturer's catalogue for the sensor. The next step is to measure data for the first few hours and compare it against data from neighbouring meteorological stations. Finally, the data are monitored daily from the server. Some error sources with measured data are:

- wear and tear of sensors and structural components
- lightning strike
- loose or faulty wiring

Developing a data validation routine includes range tests, relational tests and trend tests. A few tests were carried out for validation check. Firstly, the range test was conducted which identifies vague results such as the wind speeds below the offset value of the sensors' threshold. Also, values that are greater than the maximum need to be reviewed for validity [41]. The relational test compares values that are acquired from different heights. Finally, the trend test compares the changes in measured values. For data processing, the range of the wind speed is offset < Average < 25 m/s and the range of the solar radiation is offset < Average < 1300 W/m^2. For the barometric average pressure, the range must fall between 94 kPa and 106 kPa and the average difference in temperature must be greater than 1 degrees Celsius between 1000 hours and 1700 hours, The average change in wind speed for 1 hour must be less than 5 m/s, average temperature variation over one hour must be less than 5°C and the average 3 hours change in barometric pressure must be less than 1 kPa. These validation criteria and the relational test criteria for measured quantities are described in Tables 2-3 respectively [37].

TABLE 2. Validation criteria for measured quantities.

PARAMETER	VALIDATION CRITERIA
Wind speed: horizontal	
Average	Offset < Avg < 25 m/s
Standard deviation	0 < Std.Dev. < 3 m/s
Maximum gust	Offset < Max < 30 m/s
Wind direction	
Average	0 < Avg <= 360°
Standard deviation	3 < Std.Dev < 75
Maximum gust	0 < Max < 360°
Temperature	(Summer Shown)
Seasonal Variability	25°C < Avg < 40°C
Solar Radiation	
Average	Offset <= Avg <= 1300 W/m^2

TABLE 3. Relational test criteria for measured quantities.

Sample Parameter	Validation Criteria
Wind speed average	(All sensor type)
1 hr change	< 5.0 m/s
Temperature average	
1 hr change	±5°C
Barometric pressure average	(Optional)
3 hr change	±1 kPa
Change in Temperature	(Optional)
3 hr change	Changes sign twice

The trend in the measured data must be studied to find out that correct data are being recorded. In this assessment, no significant differences were recorded in the measurement of wind speed, wind direction, barometric pressure and ambient temperature. The difference in wind speeds for the two anemometers installed at 34 m AGL in Mauke and Rarotonga is shown in Fig. 2. The two anemometers placed at 34 m AGL at both the locations were at 22.5° and 202.5°. The wind speeds recorded at the two anemometers has a correlation coefficient of 0.9929. Since the predominant wind direction is North-east and South-east, the results indicate that the difference in the measured wind speeds due to the wake of the measurement tower is within 0.8%.

The diurnal variation was calculated for the wind speed and temperature. The wind shear coefficient, turbulence intensity and accurate wind power density were also calculated. Using eleven different methods and a Bayesian technique, the Weibull parameters were estimated and the performance parameters were compared using various goodness of fit tests. Using the wind speed and the wind direction, a wind map was plotted using WAsP and the annual energy production was estimated. The economic analysis was carried out to estimate the payback period for the investment using the

FIGURE 3. Location of the measurement site in Mauke with coordinates of 20° 09′ 43.20″ S, 157° 20′ 29.66″ W (Source: Google maps).

FIGURE 4. Location of the measurement site at Hospital Hill in Rarotonga with coordinates of 21° 12′ 48.86″ S, 159° 49′ 12.96″ W (Source: Google maps).

net average annual energy production. Fig. 3 shows the location of the IRERAS tower placed in Mauke Island with coordinates of 20° 09' 43.20'' S, 157° 20' 29.66'' W whereas Fig. 4 shows the location of the tower placed near the Hospital in Rarotonga with coordinates of 21° 12' 48.86'' S, 159° 49' 12.96'' W.

B. WEIBULL DISTRIBUTION FUNCTION

Many distributions are used for the estimation of wind energy potential assessment. The most commonly used are the Weibull and Rayleigh distributions. The Weibull distribution is a good fit to mean wind speed. The Weibull distribution function is most commonly defined by the shape factor (k) and the scale factor (A) and has been used widely by researchers.

The function is described as follows [42]:

$$f(U) = \frac{k}{A}\left(\frac{U}{A}\right)^{k-1} e^{-\left(\frac{U}{A}\right)^{k}} \tag{1}$$

where U is the wind speed, k is the shape factor which describes the width of the distribution and how the graph peaks whereas A is the scale factor which indicates how windy the site of study is. The corresponding cumulative distribution function is as follows [42]:

$$F(U) = 1 - e^{-\left(\frac{U}{A}\right)^{k}} \tag{2}$$

C. METHODS OF ESTIMATING WEIBULL PARAMETERS

For the analysis of wind speed, it is not always best to use the normal distribution since wind speed is never negative and is also skewed to the right side thus the Weibull distribution is the best way to represent it. In the two-parameter Weibull distribution, the shape factor (k) and scale factor (A) need to be specified or determined. To determine the k and A values, different methods are used. The best method for each site may be different. In this work, eleven different frequentist methods and a Bayesian component were used from which the best method was selected using a number of performance measures. The eleven frequentist methods used were: the median and quartiles method (MQ) [43], the moments method (MO) [44], the empirical method of Justus (EMJ) [43], the empirical method of Lysen (EML) [43], the least squares method [45], the maximum likelihood method (ML) [43], the modified maximum likelihood (MML) [43], the energy pattern factor method (EPF) [43], the WAsP method [45], [46], new moments method (NMO) [47] and combined energy pattern and power density method (CEPPD) [48]. The description of the methods are presented in our previous publication [13], [17]. Table 4 lists the mathematical expressions for the frequentist methods:

where:

$U_{0.25}$ = 25% wind velocity quartile

$U_{0.75}$ = 75% wind velocity quartile

λ = weights chosen

U_i is the wind speed measured at the interval i

$f(U \geq 0)$ = probability for wind speed equal to or exceeding zero.

The frequentist methods presented above have certain drawbacks such as most of their properties hold if the sample size is large. Thus, in this research we also use a Bayesian approach for estimating Weibull parameters in wind speed data, which is free from such limitations. This is the first work in which Bayesian method is used to find the Weibull parameters for wind resource assessment.

In Bayesian paradigm, data and prior distribution are combined together to estimate the posterior distribution of the parameter of interest. The approach uses the Bayes' rule,

TABLE 4. Eleven frequentist methods used for estimating Weibull parameters.

Methods	Mathematical Expressions
MO	$\overline{U} = A\Gamma\left(1+\frac{1}{k}\right)$ (3) $\sigma = A\left[\Gamma\left(1+2/k\right) - \Gamma^2\left(1+1/k\right)\right]^{1/2}$ (4)
MQ	$k = \frac{\ln[\ln(0.25)/\ln(0.75)]}{\ln(U_{0.75})/U_{0.25}} \approx \frac{1.573}{\ln(U_{0.75})/U_{0.25})}$ (5) $A = \frac{U_m}{\ln(2)^{1/a}}$ (6)
EMJ	$k = \left[\sigma/\overline{U}\right]^{-1.086}$ (7) $A = \overline{U}/\Gamma\left(1+1/k\right)$ (8)
EML	$k = \left[\sigma/\overline{U}\right]^{-1.086}$ (9) $A = \overline{U}\left(0.568+0.433/k\right)^{-\frac{1}{k}}$ (10)
LS	$k = \frac{n\sum_{i=1}^{n} lnUxln\left[-\ln\{1-f(U)\}\right]\sum_{i=1}^{n} lnUx\sum_{i=1}^{n} ln\left[-\ln\{1-F(U)\}\right]}{\sum_{i=1}^{n}\ln U^2-\{\sum_{i=1}^{n}\ln U\}^2}$ (11) $A = \frac{k\sum_{i=1}^{n} ln\ \mathrm{U} - \sum_{i=1}^{n} ln\left[-\ln\{1-F(U)\}\right]}{nk}$ (12)
ML	$k = \left[\frac{\sum_{i=1}^{n} U_i^k \ln U_i}{\sum_{i=1}^{n} U_i^k} - \frac{\sum_{i=1}^{n}\ln U_i}{n}\right]^{-1}$ (13) $A = \left[\frac{1}{n}\sum_{i=1}^{n}(U_i)^k\right]^{\frac{1}{k}}$ (14)
MML	$k = \left[\frac{\sum_{i=1}^{n} U_i^k \ln U_i f(U_i)}{\sum_{i=1}^{n} U_i^k} - \frac{\sum_{i=1}^{n}\ln U_i f(U_i)}{f(U\geq 0)}\right]^{-1}$ (15) $A = \left[\frac{1}{f(U\geq 0)}\sum_{i=1}^{n}(\mathrm{U}_i)^k f(U_i)\right]^{\frac{1}{k}}$ (16)
WAsP	$U = \sqrt{\frac{\sum_{i=1}^{n} U_i^3}{\mathrm{N}\Gamma\left(\frac{3}{k}+1\right)}}$ (17)
EPF	$k = 1+\frac{3.69}{E_{pf}^2}$ (18) $A = \frac{\overline{U}}{\Gamma(1+1/k)}$ (19)
NMO	$\lambda_1\left(A\Gamma\left(1+\frac{1}{k}\right)-\overline{U}\right)^2+\lambda_2\left(A^2\Gamma\left(1+\frac{2}{k}\right)-\overline{U^2}\right)^2+$ (20) $\lambda_3\left(A^3\Gamma\left(1+\frac{3}{k}\right)-\overline{U^3}\right)^2$ $\lambda_1+\lambda_2+\lambda_3=1$ (21) $\overline{U^r} = \sum_{i=1}^{n}\frac{U_i^r}{n}$ (22)
CEPPD	$\frac{\overline{U^3}}{\overline{U}^3} - \frac{\Gamma\left(1+3/k\right)}{\Gamma\left(1+1/k\right)^3}$ (23) $e^{3.\log(A)} - \overline{U^3}$ (24)

which is simply expressed as:

$$p(\theta|U) \ \alpha \ p(U|\theta) \, p(\theta). \tag{25}$$

where $p(\theta|U)$ is the posterior distribution of parameters $\theta = (A, k)$, $p(U|\theta)$ is the likelihood of the data and $p(\theta)$ is the prior distribution of the parameters.

In Bayesian estimation, uniform prior distributions of parameters $\theta = (A, k)$ is used for fitting the wind data. Firstly, a sample of the joint posterior distribution is obtained by simulating a sample from a Markov chain Monte Carlo method using Gibbs sampler. Then, performing a total of 20,000 Gibbs sampler iterations and using a burn-in period of 2000 (i.e. the point after which Gibbs sampler is supposed to attain convergence) the posterior estimates of the parameters are obtained using the R software with **R2jags** package.

Five performance measures were used to find the best method of estimating the Weibull parameters: the root mean square error (RMSE) [44], [49], [50], coefficient of determination (R^2) [49]–[51], mean absolute error (MAE) [44], [52], mean absolute percentage error (MAPE) [44], [49], [50], [53], and coefficient of efficiency (COE) [25], [44], [54]. By ranking the methods based on performance analysis, the best method was obtained.

The performance analysis determined the accuracy of the methods by the following rules:

- The lower the RMSE, the better the Weibull method.
- The higher the R^2, the better the method.
- The lower the MAE, the better the accuracy.
- The lower the MAPE, the better the accuracy.
- The greater the COE, the greater the accuracy of the estimate.

Figure 5 shows a detailed flowchart of the methodology used for the present work. The mathematical expressions used for estimating Weibull parameters are presented in Table 4, while the explanations of the equations are provided in ref. [17].

III. RESULTS AND DISCUSSION

A. WIND SPEED ANALYSIS

Wind speed analysis was also carried out for two locations in the Cook Islands: Mauke Island and Rarotonga Island as discussed in earlier section. One year of wind data were collected from the sites and analysed to study the daily average wind speed variation throughout the year, the monthly average wind speed variation as well as the wind shear diurnal variation and the turbulence intensity diurnal variation. One year of measurements is sufficient for studying the seasonal variations in wind speed, direction, turbulence and wind shear [41]. However, for investments in large wind farms, the correlate and predict steps are performed iteratively with several sources of long-term data. Fig. 6 shows the daily average wind speed variation for the year ranging from 2/08/2013 to 2/08/2014 for Mauke. It can be seen that the wind speed is lower for the warmer months compared to the cooler months. The highest average daily wind speed for the Mauke site was recorded to be 10.26 m/s on the 16th of March, 2014 whereas the lowest average daily wind speed was recorded to be 1.31 m/s on the 17th of May, 2014.

Fig. 7 shows the daily average wind speed variation for the entire year ranging from 11/08/2013 to 11/08/2014 for the Rarotonga site. The highest average daily wind speed for the Rarotonga site was recorded to be 9.25 m/s on the 14th of September, 2013 whereas the lowest average daily wind speed was recorded to be 0.96 m/s on 19th September, 2013. The wind speeds are much lower compared to the previously reported work for Rarotonga [12]. The maximum wind speeds during December and January were recorded to be 29.1 m/s at 29 m AGL; probably caused by a tropical disturbance towards the end of December in the country.

NASA data were obtained from the POWER Project version 2.3.6 [55] for the Rarotonga site for the sake of comparison. For the years 2015-2020, the monthly average wind speeds varied from 4.64 m/s to 8.95 m/s with an overall average for the six year to be 6.48 m/s. This is considerably higher than the measured wind speeds at Rarotonga.

Fig. 8 shows the monthly average wind speeds for the Mauke site whereas Fig. 9 shows the monthly average wind speeds for Rarotonga site. For the Mauke site, the highest monthly average wind speed was recorded in July whereas the lowest monthly average wind speed was recorded in February for both 34 m and 20 m AGL. For the Rarotonga site, the trends for the monthly average wind speed were same as those for the Mauke site. The Cook Islands normally have two seasons which are the cooler dry season and the warmer wet season. The warmer wet season is from November to April whereas the cooler dry season is from May to October. The warmer wet season is also the cyclone season. The variation in atmospheric pressure during winter season is larger compared to the summer season, which leads to higher flow velocities of air between the high and low pressure systems.

The month of July has the highest mean wind speeds for both the sites; similar results were obtained for Tuvalu [37] and Suva [17] with maximum average wind speed recorded in July. The previous work on wind resource assessment in Cook Islands recorded the highest wind speeds from October to December [12]; this is the cyclone season in the South Pacific and some tropical disturbances or depressions may have caused the higher wind speeds reported in that work.

Fig. 10 shows the seasonal average wind speeds at day and night times for both the sites. It is seen that the wind speeds are higher at the Mauke site for both seasons. The average wind speeds are generally higher for winter compared to summer. Higher daytime wind speeds were predicted by [56] from their probabilistic modeling of wind speed variation.

B. WIND SHEAR ANALYSIS

Wind shear is a phenomenon which occurs due to the variation in wind speeds over changing elevations due to the shearing action. The wind shear directly affects the power output of wind turbines at different hub heights. The wind shear coefficient is important for determining the overall energy production of larger wind turbines since

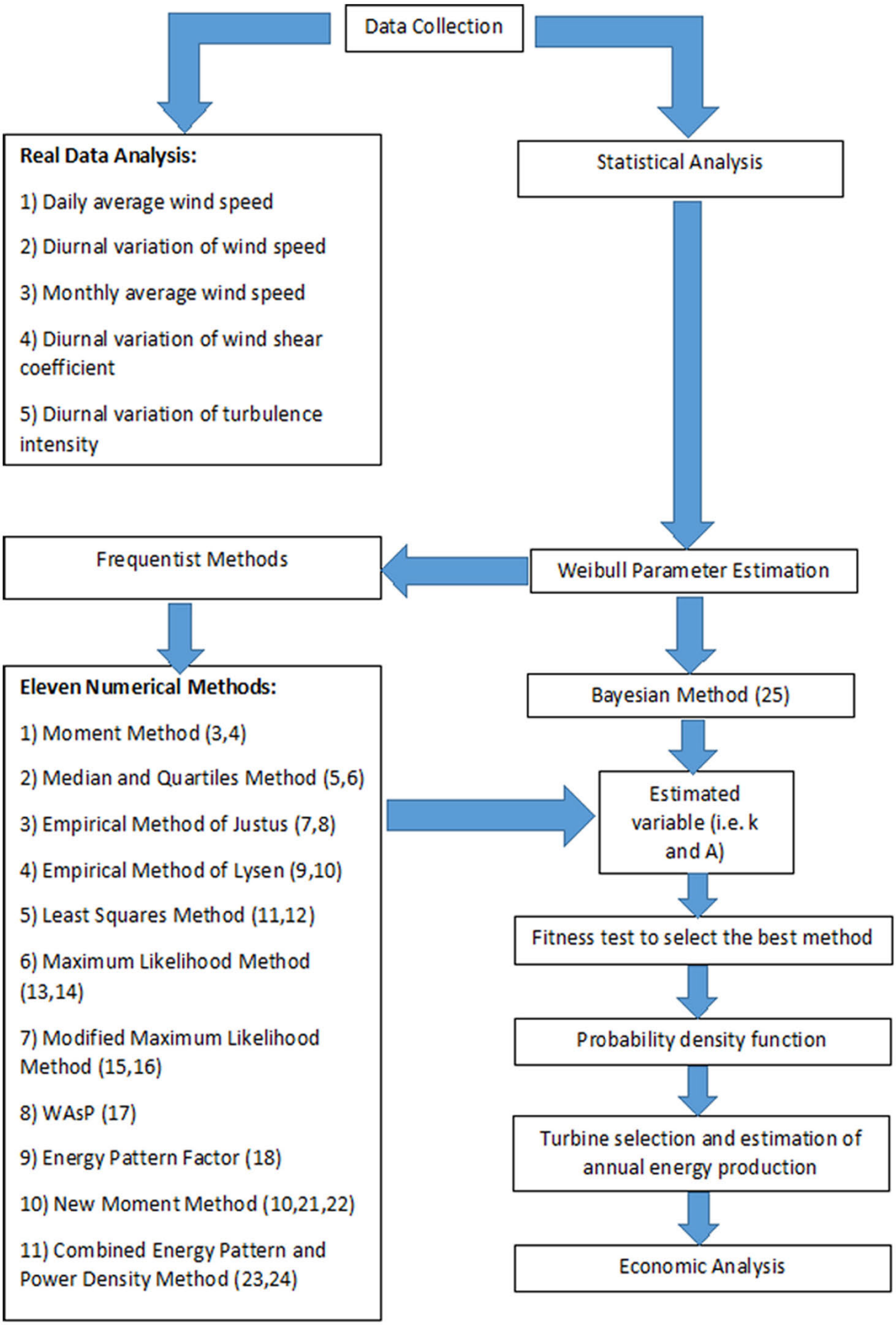

FIGURE 5. Flowchart of the methodology used in the present work.

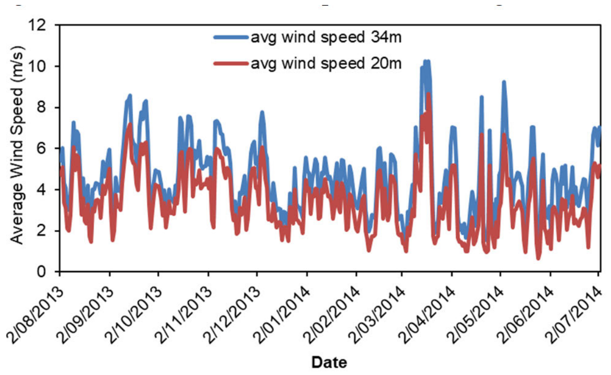

FIGURE 6. Daily average wind speeds for the entire measurement period at 34 m and 20 m AGL for the Mauke site.

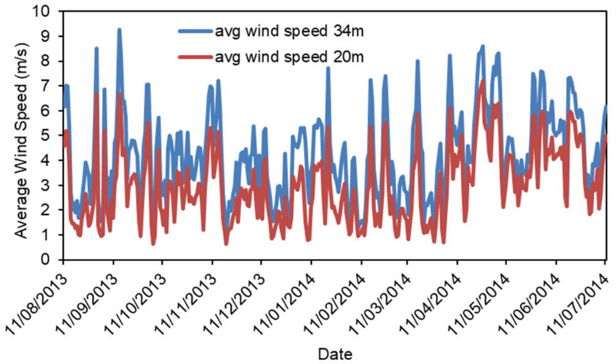

FIGURE 7. Daily average wind speeds for the entire measurement period at 34 m and 20 m AGL for the Rarotonga site.

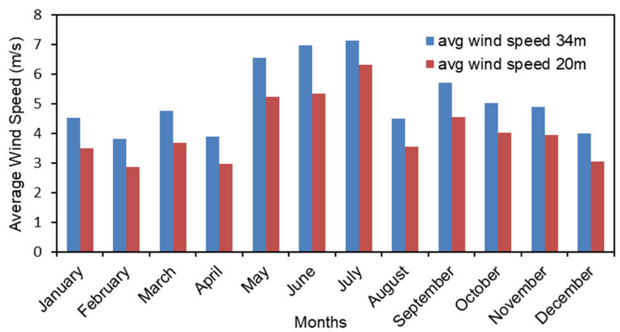

FIGURE 8. Monthly average wind speeds recorded at 34 m and 20 m for the Mauke site.

wind shear is greater at smaller heights. If the coefficient is estimated between two heights, the wind speeds can be extrapolated using the power law to obtain wind speeds and power output at a greater height. The wind shear coefficient (α) can be calculated using the power law as given below [57]:

$$\alpha = \frac{\ln\left(U_2/U_1\right)}{\ln\left(h_2/h_1\right)} \tag{26}$$

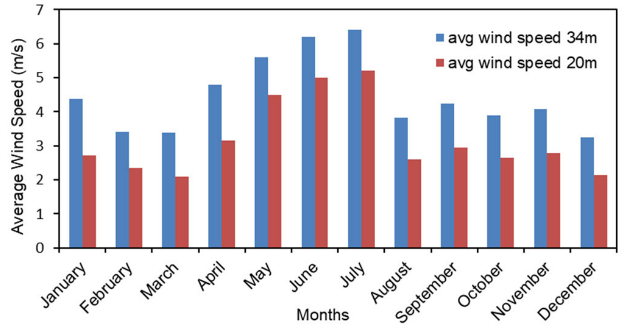

FIGURE 9. Monthly average wind speeds recorded at 34 m and 20 m AGL for the Rarotonga site.

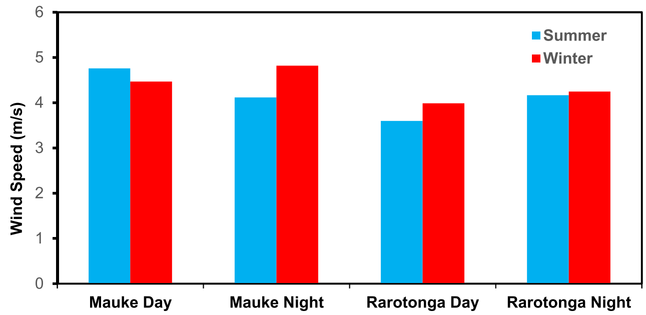

FIGURE 10. Seasonal average daytime and night-time wind speeds for both the sites during summer and winter.

For this work, the wind speeds at two heights of 34 m AGL and 20 m AGL at both the sites were used to calculate the wind shear coefficient. The wind shear coefficients for both the sites were plotted which depict well correlated relationship of wind shear coefficient with the diurnal variation of average temperature for Cook Islands, which can be seen from Fig. 11 and Fig. 12. It is observed from Fig.11 that the wind shear coefficient is greater at night time compared to the day time. This is due to the temperature inversion effect. It is seen that the wind speed variation is greater between 12:00 am – 7:00 am whereas the wind speed variation is significantly lower between 8:00 am – 4:00 pm. It can be seen from several works [13], [17], [18], [44], [57] that the temperature inversion effect occurs when cold air is trapped near the surface due to warm air masses moving above it. The temperature inversion effect mostly occurs at night time at places that have flat terrain or at valleys. When the sun rises, there is a build-up of convective boundary layers after a few hours which results in the elimination of the temperature inversion effect.

From Fig.11 and from other previous works [17], [37], it is clear that the wind shear coefficient varies with time for different sites which could be the effect of factors such as surface roughness, ambient temperatures and atmospheric stability. As seen from Fig.11, higher wind shear coefficient is recorded for the early hours of the day. A few hours after sunrise, the wind shear coefficient decreases steadily and at around mid-day the wind shear coefficient is recorded to be the lowest. Just after mid-day, the wind shear coefficient

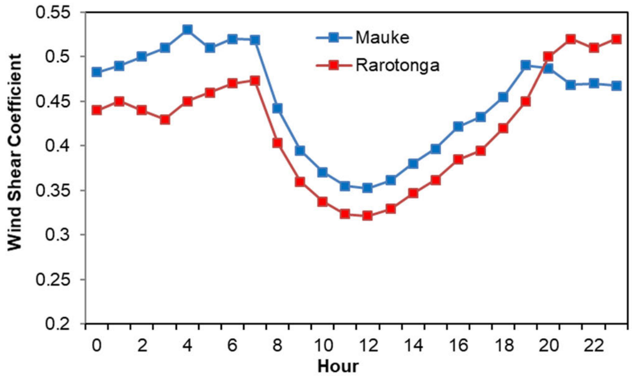

FIGURE 11. Diurnal variation of wind shear coefficient for Cook Islands.

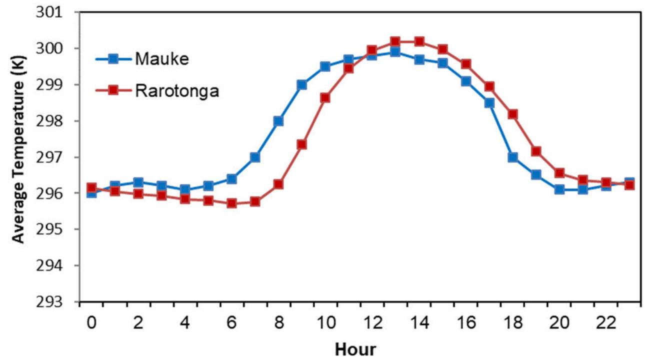

FIGURE 12. Diurnal variation of average temperature for Cook Islands.

begins to rise steadily and becomes almost constant after dusk depending on the case. Fig. 12 shows the diurnal variation of the average temperature for two sites in the Cook Islands. It can be seen from Fig.11 and Fig. 12 that the diurnal average temperature correlated well with the wind shear coefficient for both the sites. It can be seen that for Mauke, the maximum temperature occurs at 1.00 pm while for Rarotonga, the maximum mean temperature is recorded at both 1.00 pm and 2.00 pm. For Nukufetau in Tuvalu, the maximum temperature was recorded at 1.00 pm, while in Funafuti, it was recorded at 2.00 pm [37]. For Suva in Fiji, the average maximum temperature was recorded at 2.00 pm [17]. For the two sites in Vanuatu, the averaged maximum temperature was recorded at 1.00 pm [13]. Interestingly, for almost all these sites, the minimum wind shear coefficient corresponded to the time of maximum temperature while higher values of wind shear coefficient corresponded to times of low temperatures. After the elimination of the temperature inversion effect early morning, the cold air trapped near the earth's surface heats up and starts to rise upwards. This upward movement of air results in bunching of streamlines causing an increase in wind speed above the previously trapped air. This reduces the wind shear which reaches its minimum around mid-day. During the times of higher temperatures, the upward movement of air continues to reduce the velocity difference at the two heights of 20 m and 34 m AGL due to the bunching of streamlines and acceleration of flow at lower heights, which is clear from the figure. In their work on mapping renewable sources for 100% renewable grids in 2050, Al-Ghussain *et al.* [58] made their estimates with a wind shear coefficient of 1/7.

C. TURBULENCE INTENSITY

The turbulence intensity is an important parameter in the design of wind turbines. The turbulence is caused by fluctuating wind speeds with time. The turbulence level depends mostly on the surface roughness of the site, the strength of the wind and the hub height of the turbine. It is known that at the normal wind turbine heights, the sites with greater wind speeds have a higher turbulence intensity since the turbulence intensity is the ratio of the standard deviation

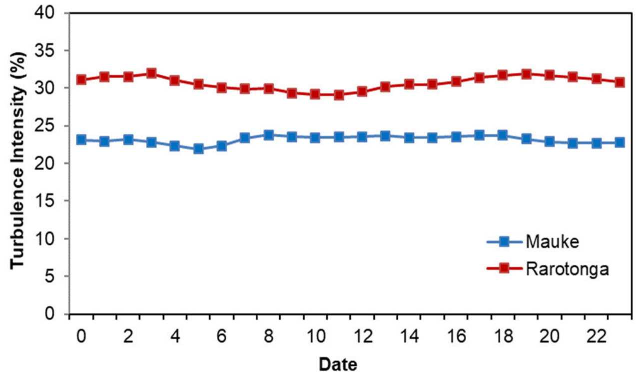

FIGURE 13. Diurnal variation of turbulence intensity for the whole year in the Cook Islands at 34 m AGL.

of the wind speed over the wind speed of the particular site. For wind turbines, very high turbulence intensities may have catastrophic effects to the wind turbine. The turbulence intensity (TI) is calculated using the following equation:

$$TI = \frac{\sigma_u}{\overline{U}} \tag{27}$$

Fig. 13 shows the diurnal variation of the turbulence intensity for the entire measurement period at the two sites in the Cook Islands. It can be seen that the turbulence intensity for the Mauke site is almost constant at 23% throughout the year whereas the turbulence intensity for the Rarotonga site is almost constant at 31% throughout the year. It is noted that the turbulence intensity for the Rarotonga site is higher. It was noted that for average and high wind speeds, the turbulence levels are fairly constant on any given day. At lower wind speeds, the turbulence levels were higher and fluctuating.

D. WIND DIRECTION ANALYSIS

The wind directions for the Mauke and Rarotonga sites were studied in detail and the frequency of counts by wind direction were displayed over a contour plot of 360°. Fig. 14 shows the wind rose plot for the Mauke site. It can be seen from the wind rose plot that the predominant wind direction is from the East at around 27% of the entire duration of measurement. The wind is also coming frequently from South-East and

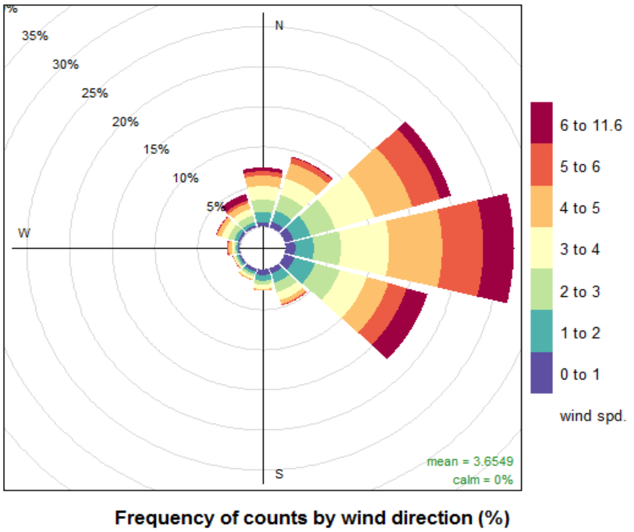

FIGURE 14. Wind rose plot of Mauke Island in the Cook Islands showing frequency of winds received from all directions.

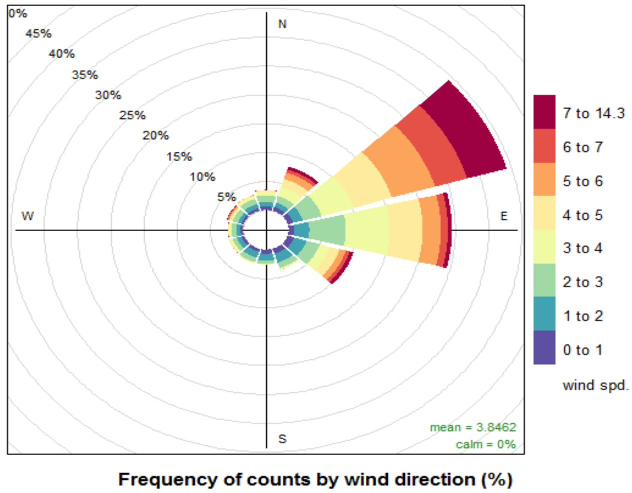

FIGURE 15. Wind rose plot of Rarotonga Island in the Cook Islands showing frequency of winds received from all directions.

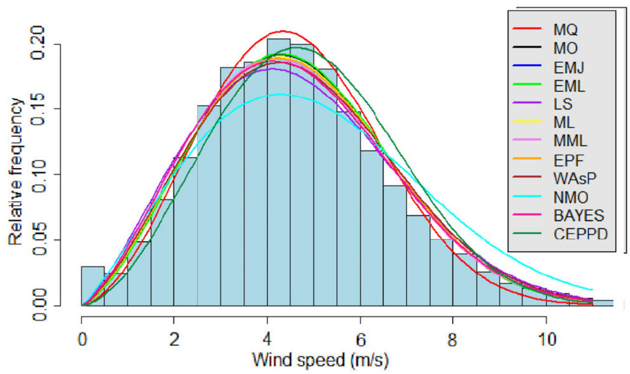

FIGURE 16. Wind frequency distribution and Weibull distribution curve for the Mauke site.

North-East directions. For the two sites in Kadavu and Suva in Fiji whose latitudes are closer to Mauke, the predominant wind direction was found to be easterly [17], [36]. The overall wind direction for the Mauke site (60° to 150°) was very similar to the Suva site. Fig.15 shows the wind rose plot of the Rarotonga site in the Cook Islands. It can be seen from the wind rose plot that the predominant wind direction is from East-North East direction at around 34% of the entire duration.

E. ESTIMATION OF WEIBULL PARAMETERS

The statistical analysis of wind data for the Cook Islands was carried out using the R software with the twelve Weibull parameter estimation methods for estimating the shape factor (k), scale factor (A) and estimating the wind power density. Table 5 presents the values of different goodness of fit tests and error measures for the Mauke site. Table 6 presents the performance ranking for the twelve methods, which show that the best method for estimating the Weibull parameters and the correct wind power density was the Least Squares Method which had the highest correlation coefficient, second highest COE value, the third lowest value for MAPE and relatively higher values for RMSE and MAE. The Bayesian Estimates (BAYES) performed the second best with the second highest value of the correlation coefficient, eighth highest value of COE and relatively lower values of RMSE, MAE and MAPE. In this case, the empirical method of Justus (EMJ) and empirical method of Lysen (EML) performed similarly because the shape factor (k) and the scale factor (A) are the same and the corresponding wind power densities are identical.

However, further analysis may be required to differentiate between the two methods since the k and A values are only in two decimal places. The third best method was the WAsP method which had the fourth highest correlation coefficient, third highest value of COE, fifth lowest value of RMSE, the eighth lowest value of MAE and the ninth lowest value of MAPE. Thus for the Mauke site, the estimated wind power density was 97.77 W/m^2. Fig. 16 shows the wind frequency distribution and Weibull distribution curve for the Mauke site which shows that average wind speeds of around 4.5 m/s to 4.6 m/s are most frequent at around 20% to 21% of the entire measurement period. It is observed that wind speeds greater than 10 m/s are less frequent.

Fig. 17 shows the histograms and the probability distribution function for the Rarotonga site which shows that average wind speeds of around 3.8 m/s are most frequent at around 18% to 19% of the entire measurement period. It is observed that wind speeds greater than 10 m/s are less frequent. It is also observed that the probability distribution function for the Rarotonga site is skewed towards the right compared to Fig. 16. This is because higher wind speeds experienced at the Rarotonga site are less compared to the Mauke site. The effective wind speed for the Rarotonga site was 60.1%. Table 7 presents the goodness of fit test and error measure values for the Rarotonga site whereas Table 8 presents the

TABLE 5. Methods of estimating Weibull parameters, mean wind speed, WPD, and goodness of fit test results for Mauke, Cook Islands.

Method	*k*	*A*	*U*	WPD	R^2	COE	RMSE	MAE	MAPE
MQ	2.71	5.15	4.58	83.37	0.9941	1.2456	0.2995	0.1212	2.2851
MO	2.5	5.26	4.67	93.02	0.9966	1.0136	0.1176	0.0746	1.9934
EMJ	2.51	5.26	4.67	92.78	0.9965	1.0195	0.1207	0.075	1.9885
EML	2.51	5.26	4.67	92.83	0.9965	1.0195	0.1207	0.075	1.9884
LS	2.31	5.25	4.65	97.77	0.9976	0.8816	0.1555	0.1352	3.9065
ML	2.47	5.26	4.67	93.51	0.9971	0.9937	0.1089	0.076	2.1431
MML	2.42	5.2	4.61	92.17	0.9967	0.9684	0.129	0.101	3.0933
EPF	2.46	5.26	4.67	94.13	0.9973	0.9863	0.1047	0.0766	2.1784
WAsP	2.42	5.3	4.7	97.26	0.9973	0.9421	0.124	0.0985	2.5111
NMO	2.2	5.67	5.02	128.32	0.9965	0.6991	0.4634	0.3471	6.7335
BAYES	2.39	5.21	4.62	93.21	0.9974	0.9866	0.1050	0.0818	2.4716
CEPPD	2.72	5.49	4.88	96.95	0.99693	0.996	0.0766	0.06776	2.12096

TABLE 6. Performance ranking of different methods for Mauke, Cook Islands.

Method	*k*	*A*	*U*	WPD	R^2	COE	RMSE	MAE	MAPE	Ranking
LS	2.31	5.25	4.65	97.77	1	2	3	11	11	1
BAYES	2.39	5.21	4.62	93.21	2	8	11	2	6	2
WAsP	2.42	5.3	4.7	97.26	4	3	5	8	9	3
CEPPD	2.72	5.49	4.88	96.95	6	7	12	1	4	4
MO	2.5	5.26	4.67	93.02	8	9	8	3	3	5
ML	2.47	5.26	4.67	93.51	5	6	9	6	5	6
EMJ	2.51	5.26	4.67	92.78	9	11	6	4	2	7
EPF	2.46	5.26	4.67	94.13	3	5	10	7	7	8
EML	2.51	5.26	4.67	92.83	10	10	7	5	1	9
MML	2.42	5.2	4.61	92.17	7	4	4	9	10	10
NMO	2.2	5.67	5.02	128.32	11	1	1	12	12	11
MQ	2.71	5.15	4.58	83.37	12	12	2	10	8	12

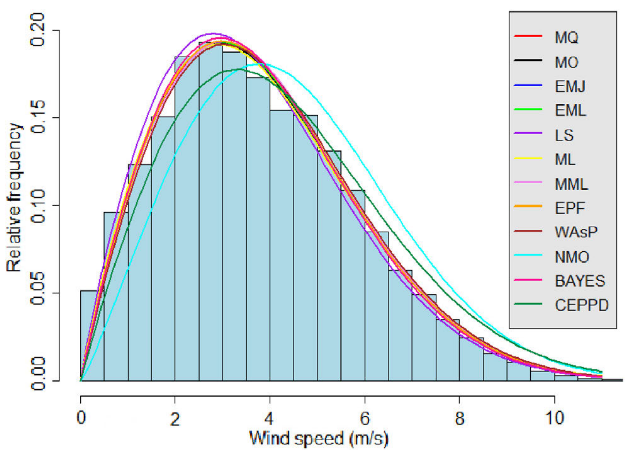

FIGURE 17. **Wind frequency distribution and Weibull distribution curve for the Rarotonga site.**

performance ranking for the twelve Weibull methods at the Rarotonga site. Table 8 shows that the best method for estimating the Weibull parameters and the correct wind power density was the Median and Quartiles method (MQ) which had the fourth highest correlation coefficient, eighth highest COE value, the lowest RMSE value, the lowest MAE value and the third lowest MAPE values. The second best method was the Bayesian Estimates (BAYES) which had the eighth highest correlation coefficient, ninth highest value of COE and the second lowest values of RMSE, MAE and MAPE. The moments method was ranked third for this case. The empirical method of Lysen (EML), empirical method of Justus (EMJ) and energy pattern factor (EPF) method also performed well with almost similar Weibull parameters *k* and *A*. Thus for the Rarotonga site, the estimated wind power density was 66.25 W/m^2. From the performance analysis, it can be said that the average wind speed for the Mauke site was 4.80 m/s whereas the average wind speed for the Rarotonga site was 3.86 m/s. The previous work carried out near the North-eastern coast of Rarotonga [12] reported a mean wind speed of 6.7 m/s and Weibull parameters of 2.1 and 7.51 m/s using only the WAsP method.

Table 9 presents the Weibull parameters *k* and *A*, the average wind speed and the wind power density for the two different seasons in Mauke and Rarotonga. It is known that most of the south pacific countries including Cook Islands have two seasons: the warmer wet season and the cooler dry season. The warmer wet season is from November to April whereas the cooler dry season is from May to October. It can be seen from table 9 that the *k* and *A* values are

TABLE 7. Methods of estimating Weibull parameters, mean wind speed, WPD, and goodness of fit test results for Rarotonga, Cook Islands.

Method	*k*	*A*	*U*	WPD	R^2	COE	RMSE	MAE	MAPE
MQ	1.93	4.35	3.86	66.25	0.9987	1.0062	0.0753	0.0415	1.8992
MO	1.92	4.34	3.85	65.67	0.9987	1.0146	0.0778	0.0474	1.9661
EMJ	1.93	4.34	3.85	65.23	0.9988	1.0219	0.0782	0.0508	2.0841
EML	1.93	4.34	3.85	65.35	0.9987	1.0184	0.0775	0.0492	2.0592
LS	1.89	4.18	3.71	60.18	0.998	1.0574	0.1758	0.1526	4.4104
ML	1.9	4.33	3.84	66.22	0.9985	1.0038	0.0803	0.0448	1.8486
MML	1.96	4.37	3.87	65.63	0.9987	1.045	0.0947	0.0704	3.5756
EPF	1.94	4.34	3.85	64.98	0.9988	1.0318	0.0805	0.0546	2.3215
WAsP	1.95	4.4	3.9	67.5	0.999	1.0219	0.098	0.0674	3.606
NMO	2.17	5.02	4.45	90.24	0.9981	0.9946	0.5749	0.5619	18.5681
BAYES	1.94	4.31	3.82	63.81	0.9986	1.0055	0.0766	0.0438	1.8712
CEPPD	1.96	4.77	4.23	88.32	0.9612398	0.87173	0.0766	0.36135	10.3453

TABLE 8. Performance ranking of different methods for Rarotonga, Cook Islands.

Method	*k*	*A*	*U*	WPD	R^2	COE	RMSE	MAE	MAPE	Ranking
MQ	1.93	4.35	3.86	66.25	4	8	1	1	3	1
BAYES	1.94	4.31	3.82	63.81	8	9	3	2	2	2
MO	1.92	4.34	3.85	65.67	5	7	5	4	4	3
EMJ	1.93	4.34	3.85	65.23	2	5	6	6	6	4
EML	1.93	4.34	3.85	65.35	6	6	4	5	5	5
EPF	1.94	4.34	3.85	64.98	3	3	8	7	7	6
ML	1.9	4.33	3.84	66.22	9	10	7	3	1	7
WAsP	1.95	4.4	3.9	67.5	1	4	10	8	9	8
MML	1.96	4.37	3.87	65.63	7	2	9	9	8	9
LS	1.89	4.18	3.71	60.18	11	1	11	10	10	10
CEPPD	1.96	4.77	4.23	88.32	12	12	2	11	11	11
NMO	2.17	5.02	4.45	90.24	10	11	12	12	12	12

TABLE 9. Estimated Weibull parameters for different seasons in Cook Islands.

Location/Season	*k*	*A*	*U*	WPD
Mauke dry season	2.54	4.93	5.14	89.13
Mauke wet season	1.95	4.22	3.81	68.47
Rarotonga dry season	2.47	4.77	4.84	86.61
Rarotonga wet season	1.91	4.01	3.73	67.8

higher for the cooler dry season; the average wind speeds are also higher along with the corresponding wind power density. This compares well with Fig. 7 and Fig. 8, which show the monthly average wind speeds for both the sites. It is clear from the figures that the average wind speeds are generally higher during the cooler dry season for both the sites.

F. ESTIMATION OF ANNUAL ENERGY PRODUCTION (AEP)

The estimation of the annual energy production was carried out for both Mauke and Rarotonga islands with five 275 kW wind turbines placed virtually on five different locations using the WAsP software which is an industry standard tool. The Vergnet 275 kW wind turbines were used for estimating the annual energy production. There were certain important parameters that were used for the analysis. The Vergnet 275 kW wind turbine has a hub height of 32 m, a rated wind speed of 12.2 m/s, a rotor diameter of 32 m and a cut-out wind speed of 25 m/s at a density of 1.16 kg/m^3 [44]. The power curve of the Vergnet 275 kW wind turbine is shown in Fig. 18.

Since PICs have experience with these turbines and there are no major issues with their maintenance, they were chosen for estimating AEP. The turbines can be lowered easily for repair or when there is a cyclone warning; cyclones are frequent in the South Pacific. These turbines are already in use in countries like Fiji, Vanuatu and Samoa. The Vergnet 275 kW wind turbines are used in EFL's (Energy Fiji Limited) Butoni wind farm in Sigatoka. Other larger commercial turbines are excellent but were not considered since they are not suitable for the pacific island countries. The increased costs associated with logistics, operation and maintenance, and the costs for installation make these unviable in this region. At the same time, it will not be easy to bring down large MW-sized wind turbines if there is a cyclone warning. The hub height of all the five chosen turbines at each location was kept same as the height at which the wind data were measured since there was no significant difference in the wind measurement across the islands [44].

TABLE 10. AEP from the five wind turbines at Mauke, Cook Islands.

Turbine site on Mauke	Location (m)	Power Density (W/m^2)	Net AEP (MWh)	Capacity Factor (%)	Wake Loss (%)
Turbine site 001	(671548.9, -2229978.0)	97	237.48	10	0.0
Turbine site 002	(671556.6, -2230675.0)	98	239.93	10	0.0
Turbine site 003	(671783.9, -2231440.0)	94	230.14	10	0.0
Turbine site 004	(672503.7, -2232448.0)	93	227.69	9	0.0
Turbine site 005	(673041.7, -2232948.0)	96	235.03	10	0.0

TABLE 11. AEP from the five wind turbines at Rarotonga, Cook Islands.

Turbine site on Rarotonga	Location (m)	Power Density (W/m^2)	Net AEP (MWh)	Capacity Factor (%)	Wake Loss (%)
Turbine site 001	(416000,-2350800)	92	225.24	9	0.0
Turbine site 002	(414047.2, 2347127.0)	93	229.56	10	0.0
Turbine site 003	(416196,-2344636)	86	209.25	9	0.0
Turbine site 004	(418955.3,-2345149.0)	80	191.62	8	0.0
Turbine site 005	(421714.7,-2344978.0)	71	166.40	7	0.0

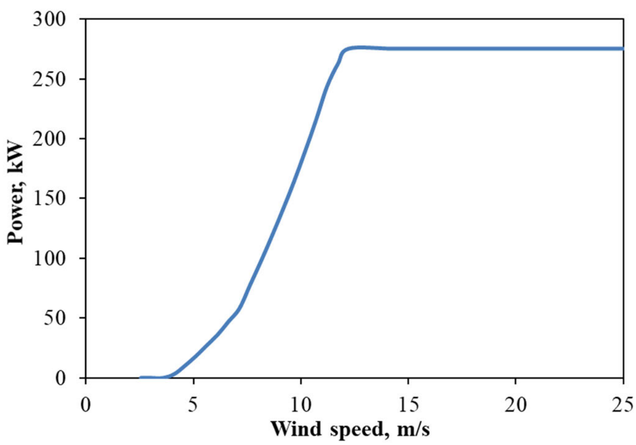

FIGURE 18. Power curve for Vergnet 275 kW wind turbine.

Table 10 shows the annual energy production for Mauke island whereas Table 11 shows the annual energy production for Rarotonga island. The total annual energy production for all the five turbines in Mauke would be 1170.27 MWh whereas the average annual energy production of each turbine would be 234.05 MWh. The capacity factor for the turbines in Mauke varies from 9% to 10%, whereas the wake loss for the turbines is 0% from WAsP since they are located far from each other. Practically, the tip speed ratio of the turbine will be high (above 12), hence the wake losses will be very small [59], [60]. The total annual energy production for all the five turbines in Rarotonga would be 1022.07 MWh and the average annual energy production for each turbine would be 204.41 MWh. The capacity factor for the turbines in Rarotonga from WAsP results varies from 7% to 10% while the wake loss is 0%. The combined power generated from the proposed ten turbines will be able to meet 10% of the country's power requirement.

The wind power density maps were plotted using WAsP mapping and terrain analysis software. The data were imported into WAsP using climate analyst and OWC wizard and analysed for calculating the Weibull parameters k and A. A map of each of the locations was downloaded using the map editor. The coordinates of the locations were specified as well as the roughness lengths and the map extension. The map extension must be kept less than 10,000 m from North to South or West to East to obtain more accurate results. The extensions of the map were kept around 5000 m for these two locations. The maps were saved and imported into WAsP under the 'terrain analysis' and the location of the measurement data site was specified. It is important to specify the measurement site since it acts as the reference point for other virtual turbines that are installed for analysis and estimation of annual energy production.

The wind turbines were placed close to the shoreline as almost all of the population in the two islands is concentrated close to the shoreline. This is in fact, the common trend in most of the PICs. After placing a turbine, the hub height was specified and the calculations were carried out. The results for all the sites were accurate since the wind power density matched with the analysis using the R software.

Fig. 19 shows the wind power density map of Mauke showing the locations of all the five wind turbines whereas Fig. 20 shows the wind power density map of Rarotonga showing the locations of all the five wind turbines. On both the islands, there are region of very high power density; however, it will be impractical to install wind turbines there. Those locations are at hills with high elevations, which will cause practical difficulties for installing wind turbines.

G. ECONOMIC ANALYSIS

The economic analysis of installing ten Vergnet 275 kW wind turbines was carried out with all the amounts in US$ based on the following assumption [34]:

- Lifetime (T) of turbine = 20 years
- Interest rate (r) = 12%

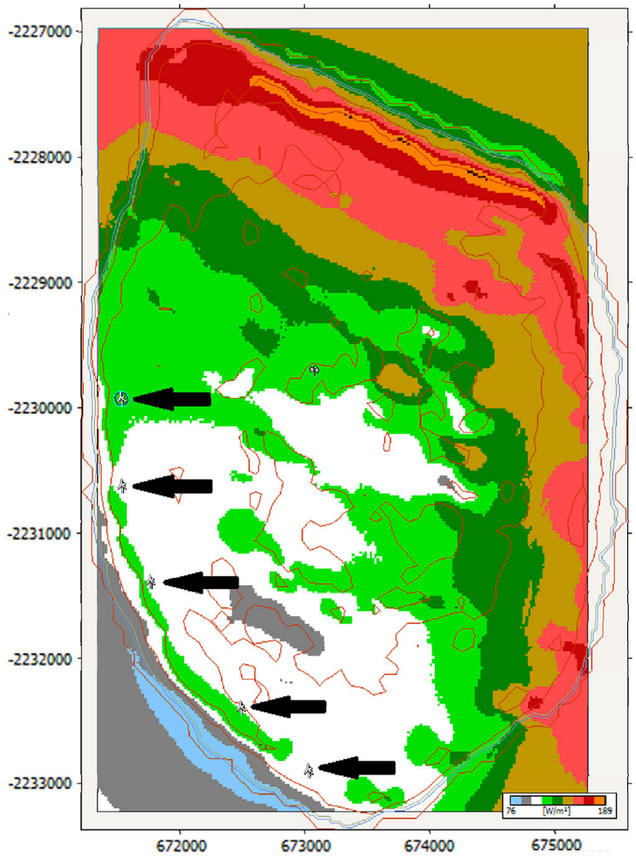

FIGURE 19. Wind power density map of Mauke in Cook Islands showing the locations of the five wind turbines.

- Inflation rate (i) = 3%
- Operation, maintenance and repair works (C_{omr}) = 25% of the annual cost of turbine (machine price/life)
- Scrap value (S) = 10% of the cost of turbine and civil work
- Investment (I) = cost of the turbine + cartage cost + grid integration cost + civil work cost

The equation below shows how the present value of costs is calculated:

$$PVC = I + C_{omr}\left[\frac{1+i}{r-i}\right]\left[1-\left(\frac{1+i}{1+r}\right)^{T}\right]-S\left(\frac{1+i}{1+r}\right)^{T} \tag{28}$$

The cost of the turbine would be $660,000.00, which includes the cost of purchasing the turbine, the cost of civil works, the cartage cost and the cost for grid integration. The average annual energy production was calculated for both the islands Mauke and Rarotonga in the Cook Islands. The average electricity tariff rate for the Cook Islands is $0.54/kWh [61]. The total annual energy production was calculated to be 2192.34 MWh for all the ten turbines which were installed virtually on Mauke and Rarotonga. The average annual energy production for each turbine was estimated to be 219.34 MWh. Thus, the average saving per turbine per year would be $85,443.60 which gives a payback period of 7.72 years. Thus, investing in wind turbines would help improve the economy of the country, as it will result in saving precious foreign exchange. At the same time, it will reduce the GHG emissions from the country.

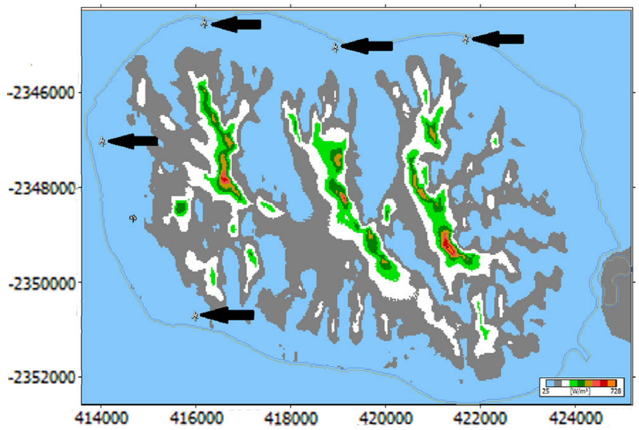

FIGURE 20. Wind power density map of Rarotonga in Cook Islands showing the locations of the five wind turbines.

IV. CONCLUSION

Wind energy resource assessment was carried out for two sites on the islands Mauke and Rarotonga in the Cook Islands. The average annual wind speed at the Mauke site was 4.65 m/s whereas it was 3.86 m/s at the Rarotonga site. The highest wind speeds for both the sites were recorded in the month of July while the lowest wind speeds were in the month of February. Eleven frequentist methods and a Bayesian technique were employed in this work to find the best distribution and accurate Weibull parameters. The Weibull parameters, k and A, from the best method were found to be 2.31 and 5.25 m/s at Mauke (LS method) and 1.93 and 4.35 m/s for Rarotonga (MQ method), while the wind power densities were 97.77 W/m^2 and 66.25 W/m^2 for the two sites respectively. The wind rose plots indicated that the predominant wind directions are from the East and the East-North East for the Mauke and Rarotonga sites, respectively. The total annual energy production for Mauke and Rarotonga from five wind turbines on each island was estimated to be 1170.27 MWh and 1022.07 MWh respectively, indicating good potential for wind power generation. The average saving per turbine per year for the Cook Islands was estimated to be $85,443.60 giving a payback period of 7.72 years, which indicates that it would be highly beneficial to install wind turbines at the two islands. The next step in this work is for the Government of Cook Islands to agree to install wind measurement towers at the ten locations identified in the present work and collect about 3 years of data; based on which they can seek funding from World Bank or some donor countries to install wind turbines and reduce their dependence on imported fossil fuels which will help them improve their economy as well as meet the sustainable development goals of the UN.

DATA ACCESSIBILITY STATEMENT

Sample data for Mauke island are uploaded on to the IEEE DataPort (DOI: 10.21227/y6X3-j007). The full data can be made available upon request and after approval from the respective Governments.

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