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The Calculation of Weibull Parameters by using Five Numerical Methods to Estimate and Study Wind Speed Distribution at Eastern Jerusalem, Palestine

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Jerusalem-Palestine

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Dedication

To my parents

To my sister and brothers

To my friends

Declaration:

I certify that this thesis submitted for the degree of master is the result of my own research, except where otherwise acknowledged, and that this thesis, neither in whole or in part, has been previously submitted for any degree to any other university or institution.

The work was done under the supervision of Dr. Husain Alsamamra from physics department-Al-Quds University.

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Signed:

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Abstract

Wind power offers a feasible and clean solution to generate electricity. The development of wind power applications requires a deep analysis of wind speed data and an accurate wind energy potential at a site. This work explores wind speed distribution to estimate the two Weibull parameters methods that are widely utilized for modeling and providing an accurate and efficient estimation of wind resource and power. The shape and scale parameters are calculated based on measured daily wind speed data from 2008 to 2018, collected in Jerusalem, Palestine. Five methods were selected to estimate shape and scale values: Empirical Method (EM), Method of Moment (MoM), Energy Pattern Factor Method (EPFM), Maximum Likelihood Method (MLM), and Modified Maximum Likelihood Methods (MMMLM). Three assessment criteria were used to assess the goodness of fit; these are Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Chi-Square. The findings revealed that of the five methods, EM followed by the MoM were the most accurate and efficient methods to determine the values of the Weibull shape and scale parameters to approximate wind speed distribution at this site based on the goodness of fit tests. The statistical performance tests rejected the EPFM as an adequate and precise method.

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CHAPTER ONE

INTRODUCTION AND LITERATURE REVIEW

1.1. Introduction

Recently, the demand for renewable energy has increased as a result of environmental factors such as climate change and the global shortage of fossil fuel reserves as a result of the rapid population growth in the world, which causes acceleration of consumption of the limited petroleum resource. In addition to air pollution problem caused by carbon dioxide, as a result of the combustion of this source of energy.

Exploitation of renewable energy sources is critical to meeting the Kyoto Protocol's CO_2 reduction targets. At the world summit on sustainable development in Johannesburg in September 2002, it was agreed that renewable energy's contribution to global energy use should be significantly increased in the future.

Renewable energy should be used in conjunction with fuel-based power generation, intermittent renewable energy can reliably provide 10-30% of the total electricity supply in an area covered by a sufficiently strong power grid [1].

Among renewable energies, wind power is widely regarded as one of the most effective tools for averting global climate change and energy security crises, as well as a potential solution to the problems associated with volatile coal, gas, and oil markets. The oil crisis of the 1970s provided the impetus for the expansion of this field, as well as concerns about the scarcity of fossil fuels [2].

Wind power representing the moving of air molecules to obtain kinetic energy that can be converted into electricity. Produce mechanical energy and then convert it to electricity in a generator. Unlike most other generators, wind turbines can only generate electricity in response to a readily available resource (wind). It is impossible to store the wind and use it at a later time. Thus, the output of wind turbines is inherently volatile and cannot be separated [3]. Any system that connects to a wind turbine must account for this variation.

Wind behavior is described through large scale maps at high altitudes around the world; however, poor information is available about wind speed and its presence in urban areas at low altitudes.

Wind speed is the key factor in the production of wind power. Numerous studies in the literature show wind speed distribution data at a site throughout the world, in addition to many numerical models have been employed in order to estimate the probability of occurrence; distribution; the estimation of wind speed values; and the statistical assessment that compare between observed and estimated wind data.

1.2 Wind Energy in Palestine

Palestine's energy sector is insecure due to the country's unstable political and economic situation, as well as a lack of energy progress. 100 percent of its fossil fuel is imported and 87 percent of its electricity consumption are reliant on other countries [4]. Because of the high density of population growth and rapid industrial growth, there is a huge demand for energy in Palestine, which has resulted in unrealistic energy price controls [5].

Recently, the Palestinian Authority has taken a number of steps to reduce its dependence on energy consumption from other countries, launching a number of initiatives in the field of investment in renewable energy, especially in solar and wind energy, as well as policies aimed at increasing the use of renewable energy resources.

In terms of annual installed capacity growth, wind energy is the most common and fastest-growing renewable energy source [4]. According to the Global Wind Energy Council report, the total global capacity from wind power systems was 793 GW in 2021, with 93 GW of new capacity installed in 2020 [6]. Wind speed is the most important parameter of wind energy because it is a random phenomenon; however, wind resources are rarely consistent and vary with time, height above the ground, and terrain type, so they should be thoroughly investigated [7].

In the Palestinian territories, wind resource assessment has received only sporadic attention, with only a few studies published in the literature. Wind energy industry and delivering energy solutions through small scale wind energy conversion systems require reliable and accurate estimations of wind resources [8]. Large scale maps of wind presence and behavior are used to describe wind behavior at high altitudes around the world; however, information on wind speed and presence in urban areas at low altitudes is limited [9].

In the last few years, activity of research in the area of wind speed distribution modelling has increased considerably and aimed at the development of suitable predictive models to describe wind speed frequency distribution. Statistical models were preferred and employed for the prediction of wind speed distribution, These models provide information about the local occurrence probabilities at a given site [10]. To this task, the choice of a suitable probability distribution function is crucial. Previous studies compared measured wind speed values with statistical distributions in order to examine how well the probability distribution functions describe the statistical properties of the observed wind speed.

The most widely used mathematical functions that reported in the literature which have been successfully used to describe the behavior of wind speed and applied to fit wind speed distributions is the Weibull distribution function [4, 7, 9, 11, 12-13]. In this regard, numerous studies in the literature have been carried out in the world in order to assess the potential of wind energy by using Weibull Probability Density Function (PDF) [11, 14, 15-16]. Researchers concluded that Weibull PDF is an adequate statistical model for describing wind speed frequency distribution in many different locations in the world and provides a real representation of the actual wind frequency distribution for different altitudes above ground level [12, 15, 17-18]. Wind data analysis and accurate wind energy potential assessment are critical for proper and efficient development of wind power applications and are highly site dependent [19]. As a result, knowledge of the statistical properties of wind speed is essential for predicting the energy output. For statistical distribution of wind speed data analysis, Weibull PDF is usually considered as the most qualified function due to its simplicity and high accuracy [20].

The two main parameters used by Weibull PDF to describe the daily average wind speed with a reasonable accuracy [4, 21] are, the dimensionless shape parameter k, and the scale parameter c (in units of m\s), which is a good quality probabilistic model for wind speed at one location [22]. It is obvious that the more appropriate Weibull estimation method can provide accurate and efficient assessment of wind energy potential [10, 13, 16, 23].

Extensive research work in the literature have been done to estimate *k* and *c* parameters of the Weibull PDF, however, various methods have been effectively experimented in this regard, as well as the suitability of each method according to the sample data distribution, which is basically location specific [11, 17, 24].

1.3 Literature Review

Many numerical models have been developed and studied for various areas in order to evaluate the potential of wind energy. These models are extremely useful to energy planners, researchers, and policymakers. Wind power is a function of wind speed ($P=1/2\ \rho v^3$); the methodology is based on the creation of a model for estimating values of wind power by applying appropriate transformations to wind speed values. Worldwide energy consumption is increasing at a rapid rate, but the development of wind projects is hampered by a lack of reliable and accurate wind resource data in many parts of the world, particularly in developing nations [25].

At Luqa international airport in Malta recorded hourly wind data for the year 1993 was analyzed by Cerri and Farrugia 1997. The measurements were taken at a height of 10 meters above ground level and 84 meters above mean sea level. The wind parameters were investigated using a Weibull distribution function for the data collected. The use of a logistic distribution function as an alternative method of calculating mean wind speed is also considered [26].

For some meteorological stations in Palestine, Shabana and Hassan 1997, calculated the Weibull coefficients for the wind speed distribution function. The wind potential was calculated in kWh/m^2 per year, and then the wind potential lines were drawn. Wind power can be generated at a cost of $0.07 per kWh in some West Bank locations [27].

Baban and Parry 2000, conducted a study on wind farm siting criteria and applied them to a $40km^2$ area in England. Topographical constraints, wind magnitude constraints, population, economic, accessibility, and ecological constraints all play a role in siting criteria [28].

Alnaser and Al-karaghouli 2000, investigated and analyzed wind speed in Bahrain, finding that the average annual wind speed is 4.7 m/s, implying that small-scale wind parks (blade diameter less than 2 m) could be used to meet Bahrain's electrical power shortages during the day and night during the summer season. The power that could be extracted ranged from 363 to 160 W m^{-2}. Because of the limited space, the wind direction was found to be so varied, making it unique for the installation of wind parks; this meets the requirement for Bahrain (area of 700 km^2). These wind farms can be built near or far from the coast [29].

Tchinda et al. 2003, studied the distributions of wind speed and energy in the Adamaoua and North regions of Cameron. It was found that the wind energy potential in Cameroon's north and far regions is not suitable for generating electricity, and that installing windmills for community water supply, livestock watering, and farm irrigation would produce a very fruitful result [30].

Celik 2003, used 1-year measured hourly time-series wind speed data to assess the wind energy potential of Iskenderun on Turkey's Mediterranean coast. Time-series data were used to generate probability density distributions, and distributional parameters were identified. On a monthly basis, the two probability density functions were fitted to the measured probability distributions. The location wind energy potential was investigated using the Weibull and Rayleigh models [31].

Using ten selected weather stations in Seri Lanka, the daily wind speed data from 2001 to 2004 collected at altitudes of 6m and 15m was modeled numerically to describe the wind speed frequency distributions over two time periods using a two-parameter Weibull distribution. The annual values of shape parameter k and scale parameter c were calculated and found to range from 0.80 to 3.58 for k and 2.79 to 19.78 m/s for c, respectively. The shape parameter and scale parameter showed seasonal variation values. The two-parameter Weibull distribution accurately described daily average wind speeds frequency distribution [32].

Cellura et al. 2008 analyzed long-term wind speed and direction data collected from several stations in Sicily, Italy, and used it to model wind fields across the region spatially. The parameters of the Weibull distribution were estimated using statistical analysis of wind data. Some traditional deterministic and geostatistical interpolation techniques were also used to validate their results [33].

Ahmed Shata 2008, presented a new analytical method for calculating the wind energy potential available along the Mediterranean Sea's north coast and the Red Sea's east coast in Egypt, as well as estimating the possible electrical power generated by large wind turbines at a cost of 1.26 cents per kWh. The data analysis was expected to aid in the identification of suitable locations in Egypt for the installation of new wind turbines [34].

Zaharim et al. 2009, investigated the probability distribution of wind speed data collected at the University Kebangsaan-Faculty Malaysia's of Engineering. The two-parameter Weibull distribution and the lognormal distribution were used to fit the wind speed data in this study. The maximum likelihood method was used to estimate the scale and shape parameters. To demonstrate that the distribution adequately fits the data, goodness-of-fit tests based on the empirical distribution function were performed. The two distributions were found to be equally appropriate for describing the probability distribution of wind speed data, with the two parameter Weibull distribution outperforming the lognormal distribution [35].

Brahmi and his colleague 2010, devised an algorithm to calculate the monthly wind energy potential of Sfax, Tunisia. To determine the monthly wind potential, the monthly scale and shape parameters were calculated. As a result, they can calculate the monthly wind energy distribution. However, even when non-traditional methods were used, wind distribution estimation has a maximum limit. As a result, the addition of a third Weibull parameter to the distribution was required [36].

Costa Rocha et al. 2012, analyzed and compared the performance of seven numerical methods for determining the parameters of the Weibull distribution, using wind data collected in the northeastern Brazilian cities of Camocim and Paracuru in 2012 [37].

Wind speed data from Hatiya Island in Bangladesh was statistically analyzed 2013 using the Weibull distribution to determine wind energy conversion characteristics. Four methods were used to calculate two important parameters: the Weibull shape factor "k" and the Weibull scale factor "c". The best wind distribution between observed and theoretically calculated data has been described using the probability density function, cumulative distribution function, or Weibull function. Six statistical tools were used to evaluate the accuracy of curve fittings and rank the methods. The Weibull shape factor was found to be very close to the Raleigh function k=2 for a given month, indicating that wind wave characteristics were regular and uniform [38].

Kidmo et al. 2014, used the Weibull Probability Density Function (PDF) with two parameters to evaluate the wind energy for small-scale water pumping in Cameroon's north region. The dimensionless Weibull shape parameter k and the Weibull scale parameter c were estimated using the maximum likelihood method (MLM). In order to forecast applications in the north region of Cameroon, such as providing domestic water, watering farm animals, and small-scale irrigation, the maximum wind power density extracted by the blades, as well as the useful average hydraulic power output and daily water production of a hypothetical windmill, were determined [39].

Kidmo et al. 2014, also investigate how well five numerical methods for estimating Weibull distribution parameters for wind energy conversion system performed in Maroua, Kousseri, Ngaoundéré, Banyo, and Meiganga. The goal of the analysis was to determine which of the maximum likelihood method, modified maximum likelihood method, energy pattern factor method, graphical method, and empirical method was the most accurate two-parameter Weibull probability distribution function method to represent the wind data collected in each of the above mentioned locations. The EPF method was strongly recommended as a more accurate estimation of the Weibull parameters in order to reduce uncertainties in the calculation of wind energy output [30-42].

Soft computing methodologies were used by Petkovic et al. 2014, to evaluate wind speed distribution prediction [43]. In the Niger Delta, Nigeria, however, Adaramola et al. 2014, evaluated the performance of wind turbines for power generation [44].

An investigation was carried out by Dongbum and Kyungnam 2018, on Jeju Island, South Korea, to determine the best method for estimating Weibull parameters. The empirical, moment, graphical, energy pattern factor, maximum likelihood, and modified maximum likelihood methods were reviewed. Five-years actual wind speed data from nine sites with various topographical conditions were used for the estimation [45].

The wind potential was studied at a site in India's Tirumala region using wind data collected for six years (2012 to 2017) at two different hub heights of 10 and 65 meters above the ground. The Weibull distribution function was used to analyze wind speed frequency distribution. The two parameters of Weibull were estimated using multiverse optimization [46].

To sum up, Weibull distribution function was found to be the best method to draw the best representation of wind speed values, however, there are numerous numerical methods that can be used to estimate the Weibull two parameters; shape parameter *k* and scale parameter *c*. In this work five numerical methods will be employed to estimate *k* and *c* parameters, as well as to study the variation of wind speed values. Statistical performance tests will also be used to discuss the goodness of fit.

1.4 Statement of the problem

The motivations behind doing such a study stems from the fact that burning of fossil fuels for energy pollutes in the lower atmosphere, releasing carbon dioxide, sulfur, and nitrogen oxides into the air, these pollutants endanger the global ecosystem and contribute to climate change. The growing global environmental concern about air quality has prompted a shift to green energy sources such as wind and solar, which provide pollution-free electricity [47].

Gaining approval for wind farms with high average wind speeds close to demand will become more difficult over time in many countries, which is a major long-term constraint for wind [48]. Wind power has progressed to the scale-up stage, but there are still some issues and roadblocks to overcome [49]. These include the following: The perceived intermittency of winds and the difficulty in identifying good locations, especially in developing countries, are the two main barriers to large-scale wind power implementation [50].

Indeed, one of the most significant key to the development of renewable energy sources is the scarcity of relevant information available to engineers and technicians who lack the necessary skills [51]. As a result, this investigation is expected to help take one step forward in the sustainable use of wind energy in Eastern Jerusalem, Palestine.

Finally, in the present work, we explore the wind speed distribution to determine the optimal values of k and c using Weibull methods that provide an accurate and efficient estimation of energy prod\uction in East Jerusalem, Palestine. Five common numerical methods for determining k and c parameters were studied, namely, empirical method (EM), method of moment (MoM), energy pattern factor method (EPFM), maximum likelihood method (MLM), and modified maximum likelihood method (MMLM). Suitability for East Jerusalem, Palestine.

We use python scientific language to write a script that enables us to enter the wind speed data, and then perform the data analysis according to the Weibull methods determining the value of *k* and *c* to approximate wind speed distribution. Statistical performance tests, namely, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and the chi-square test (χ2) will be employed to study the goodness of fit of the above mentioned numerical methods.

1.5 Aim and Objectives

This study will be conducted to investigate the available wind speed distribution in Eastern Jerusalem, Palestine, with the following goals:

1. Elucidate and modeling the wind speed distribution and variation using the Weibull distribution function through the estimation of the parameters *k* and *c* by different methods.
2. Distinguish between the five numerical methods through the statistical performance results, which method is suitable to provide best and accurate estimation of wind speed values in East Jerusalem, Palestine

It is obvious that some areas would be preferable compared to others for extracting kinetic energy from the wind in the atmosphere's boundary layer, depending on the earth's surface feature [52].

CHAPTER TWO

MATERIALS AND METHODS

2.1 Wind speed data

Palestine is located west of Jordan on the Mediterranean Sea's eastern coast. The elevation of the West Bank varies from 350 meters below sea level in the Jordan valley to 1000 meters above sea level. Table 1 provides the geographical coordinates of the meteorological station. The West Bank covers an area of 5665 km^2. The climate varies greatly, cold winters and mild summers in the West Bank's hilly areas, with relative humidity ranging from 51% to 83%. Summer months in Jordan valley and Jericho are hot, and winters are mild. In the case of Palestine, the daily average solar radiation intensity on horizontal surfaces is around 5.4 kWh/m^2 per day, with around 3000 total annual sunshine hours [53], with an average daytime temperatures ranging from 14° to 26°.

For the investigation of large-scale wind speeds in this study, the hourly values (one measurement every 3 hours) of wind speed data were provided by the Palestinian meteorological stations network for 11 years; from 1-January 2008 to 31-December 2018. The wind speed data were recorded at a height of 20 m above the ground, continuously by a cup-generator anemometer. In most cases, wind data is gathered in the form of a large number of points, in our case the measured wind speed values were manipulated to obtain the monthly average of daily wind speed values.

Table 1. The study area geographical coordinates.

Variable	**Value**
Latitude	31.7555° N
Longitude	35.2410° E
Anemometer height	20 m above ground level
Elevation	720 m above sea level

2.2 Measured wind speed and standard deviation

In general, measured wind data can be used to investigate a site's wind power potential. The two-parameter Weibull distribution was used by several researchers to fit wind speed frequency distributions [54-55, 51, 56]. This method has a great flexibility and simplicity. However, the main limitation of the Weibull density function is its inability to accurately calculate the probabilities of observing zero or very low wind velocities [57]. The standard deviation σ and continuously recorded wind speed v_m values can be calculated from available monthly wind speed data using equations (1) and (2), as shown below [58].

$$v_m = \frac{1}{N}\sum_{i=1}^{N} v_i \quad (1)$$

$$\sigma = \left(\frac{1}{N-1}\sum_{i=1}^{N}[v_i - v_m]^2\right)^{1/2} \quad (2)$$

Where v_m is the mean wind speed (m/s), σ is the standard deviation of the measured values (m/s), N is the number of measured hourly wind speed values.

2.3 Measured wind speed probability distributions and its frequency format

In order to determine the frequency distribution of wind speed. The wind speed field must first be divided into a number of intervals, the majority of which are of equal widths of 1 m/s [59]. As a result, the wind speed data in time series format were transformed into frequency distribution format for statistical analysis. Using the wind speed classes as a guide, the frequency distribution of the measured wind speed was established and shown by Table 2, where the dash means forbidden values.

Table 2. Mean wind speeds vi calculated for each speed class intervals.

	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11
Jan.	-	1.617275	2.425379	3.395585	4.482955	5.3125	6.489583	7.296875	8.8125	9.9375	10.375
Feb.	0.1042	1.612873	2.474004	3.419271	4.412946	5.538194	6.59375	7.46875	8.875	9.32765	-
Mar.	-	1.666667	2.440988	3.426208	4.408222	5.332237	6.55625	7.0625	-	-	-
Apr.	-	1.705793	2.482582	3.388066	4.441565	5.253906	6.296875	-	-	-	-
May	-	1.743056	2.513558	3.393382	4.296569	5.2875	-	7.1875	-	-	-
Jun.	-	1.725	2.601815	3.477011	4.300156	5.298611	-	-	-	-	-
Jul.	-	-	2.659226	3.494318	4.289409	5.283654	6.0625	-	-	-	-
Aug.	-	-	2.714754	3.492257	4.292067	5.125	-	-	-	-	-
Sep.	-	1.784091	2.584524	3.372076	4.29223	5.177083	-	-	-	-	-
Oct.	-	1.671011	2.489063	3.335965	4.41125	5.05625	-	-	-	-	-
Nov.	0.875	1.618317	2.393452	3.337981	4.417262	5.625	6.875	-	-	-	-
Dec.	0.9375	1.560764	2.41834	3.361638	4.418966	5.496875	6.25	7.625	8.453125	9.0625	-

Table 3 shows the measured wind speed data for the whole year in frequency format and cumulative distribution with equal width of 1 m/s. Given the wind speed in either a time series or a frequency distribution format, Weibull PDF methods can be used to calculate Weibull parameters. Wind speeds were divided into classes; for each speed class interval, mean wind speed *vi* is calculated (the third column). The fourth column shows the frequency with which each speed class occurs (Fi) and the sixth column provides the monthly mean of the measured values. Equations (3) and (4) are also used to calculate the probability of the observed wind speeds and their standard deviation.

$$f(v_i) = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{3}$$

$$\sigma = \left(\frac{1}{N-1} \sum_{i=1}^{N} f_i [v_i - v_m]^2 \right)^{1/2} \tag{4}$$

Table 3. Measured monthly wind speed values arranged in frequency format of equal width of 1 m/s and monthly mean value $v_{m.}$

I	v	v_i	Fi		Month	v_m
1	0-1	0.638889	14		Jan.	2.996945
2	1-2	1.670485	535		Feb.	3.039590
3	2-3	2.516474	1289		Mar.	3.144068
4	3-4	3.407813	1497		Apr.	3.100914
5	4-5	4.371966	503		May	3.229367
6	5-6	5.315568	127		Jun.	3.535265
7	6-7	6.44628	35		Jul.	3.670061
8	7-8	7.328125	15		Aug.	4.484714
9	8-9	8.713542	6		Sep.	3.204545
10	9-10	9.5	3		Oct.	2.730865
11	10-11	10.375	1		Nov.	2.482575
					Dec.	2.750403

As Table 3 depicts, the highest wind speed values are found in August and the lowest values are found in December.

2.4 Methods to estimate Weibull parameters

A number of papers have been published in an attempt to develop a statistical model that can accurately describe the wind speed frequency distribution. Wind speed variations are extremely complex, necessitating sophisticated techniques to optimize power extraction [60]. The Weibull distribution approach can be used to predict wind energy output for preliminary design and evaluation of wind power plants. In the specialized literature on wind energy and other renewable energy sources, it is the most widely used and accepted. This model provides a more reliable fit to empirical wind speed frequency data than the density function with one or two parameters wind power density, as demonstrated by wind speed observations.

The Weibull distribution is a good approximation for many natural phenomena' probability laws. The Weibull distribution has received a lot of attention in the literature because it is found to give a good fit to the observed wind speed data. It's a useful tool for estimating wind speed at various heights above the ground as well as calculating wind energy [61]. Justus et al. 1976 concluded that the Weibull distribution provided the best fit to wind speed data for over 100 stations in the United States National Climate studies have been conducted to develop an adequate statistical model for describing wind speed frequency distribution [62]. Petersen et al. 1981 discovered that the Weibull distribution provided an excellent fit to the wind speed distribution in a study conducted in Denmark [63]. In addition, a number of empirical studies have shown that the two-parameter Weibull distribution can accurately represent surface wind speed distributions on both land and sea [64-65].

The Weibull distribution function was the most widely used model, as it was found to fit a wide range of experimental wind data [66]. This model has been widely applied to wind energy and wind speed analysis. For many years, researchers working on wind speed analysis have almost universally used the Weibull function. Furthermore, because the Weibull probability density function leads to a Weibull model for the distribution of the cube of wind speed, it has been widely used in wind power analysis for decades and accurately predicts mean wind speed [67].

As seen before, it was found that the two parameter Weibull PDF is the most appropriate to express wind speed frequency and to estimate the wind power density distribution function [68-69, 12]. The mathematical form of the Weibull function is characterized by its probability density function $f(v)$ and cumulative distribution function $F(v)$ as follows [14, 31, 47, 70]:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (5)$$

$$F(v) = 1 - exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (6)$$

$F(v)$ is the probability of observing wind speed ν ; ν, wind speed in units of m/s; *c*, Weibull scale parameter in units of m/s; *k*, Weibull shape parameter. The scale parameter determines the abscissa scale on a plot of the distribution, while the shape parameter determines the shape of the distribution.

The fact that a wide range of wind characteristics can be summarized using only two parameters (shape factor, *k*, and scale parameter, *c*) is incredibly useful. These two parameters are sufficient to specify the available wind and to allow assessments and evaluations of the wind power that will be generated [66].

To compute the Weibull PDF, wind speed data were analyzed by using five numerical methods to estimate the Weibull two parameters (*k* and *c*), which are briefly discussed below.

2.4.1. Maximum Likelihood Method (MLM)

The Maximum Likelihood Method is a mathematical expression and known as a likelihood function of the wind speed data in series format and was widely used in the literature to estimate the Weibull parameters [71]. In order to determine the parameters of the Weibull distribution, MLM method is solved through numerical iterations. The shape parameter k and the scale parameter c are estimated according to equations (7) and (8) respectively [69, 72, 43, 73]:

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k . \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} \ln(v_i)}{n}\right]^{-1} \quad (7)$$

$$c = \left(\frac{1}{N}\left[\sum_{i=1}^{n} v_i^k\right]\right)^{1/k} \quad (8)$$

Where n is the number of non-zero data values; i is the measurement interval and v_i is the measured wind speed at the interval *i*.

2.4.2. Modified Maximum Likelihood Method (MMLM)

This method uses the wind speed frequency which is applied to the MLM. MMLM is solved through numerical iterations to determine the parameters of the Weibull distribution [74]. Weibull parameters are calculated as [75]:

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k . \ln(v_i).\ f(v_i)}{\sum_{i=1}^{n} v_i^k . f(v_i)} - \frac{\sum_{i=1}^{n} \ln(v_i).\ f(v_i)}{f(v \geq 0)}\right]^{-1} \quad (9)$$

$$c = \left[\frac{\sum_{i=1}^{n} v_i^k . f(v_i)}{f(v \geq 0)}\right]^{-1} \quad (10)$$

Where $f(v_i)$ is the Weibull frequency with which the wind speed falls within the interval i, $f(v \geq 0)$ is the probability of wind speed for $v \geq 0$.

2.4.3. Method of Moment (MoM)

The Weibull parameters for the MoM method calculated form the mean wind speed and standard deviation of the wind data. The scale parameter equation is given by [17, 76]:

$$c = \frac{v_m}{\Gamma(1 + \frac{1}{k})} \quad (11)$$

The standard deviation of the measured data is calculated by:

$$\sigma = c.\left[\Gamma\left(1 + \frac{1}{k}\right) - \Gamma^2(1 + \frac{1}{k})\right]^{1/2} \quad (12)$$

Where the standard gamma function is given by:

$$\Gamma(\mathrm{x}) = \int_0^\infty t^{x-1} \exp(-t)\, dt \quad (13)$$

By using numerical iteration, MoM method can be solved to obtain *k* and *c* parameters from equations (11) and (12).

2.4.4. Energy Pattern Factor Method (EPFM)

Weibull parameters determination by EPFM is an informal strategy that relies the average of the cube wind speed values to the cube of the average values; that is an energy pattern factor; equation (14) presents the mathematical formula of EPFM [77-78].

$$Epf = \frac{(v^3)_m}{(v_m)^3} = \frac{\left(\frac{1}{n}\sum_{i=1}^{n} v_i^3\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} \quad (14)$$

The Weibull shape parameter is determined from equation (15), while the scale parameter is calculated by substituting the value of *k* (obtained from Eq. 15) in equation (11).

$$k = 1 + \frac{3.69}{\left(E_{pf}\right)^2} \quad (15)$$

2.4.5. Emperical Method (EM)

As a special case of the method of moment, EM method is applicable when the mean wind speed and the standard deviation of wind speed values are calculated. The Weibull shape parameter can be calculated by equation (16), while the scale parameter can be obtained by substituting *k* values (obtained from equation (16)) in equation (11) [17].

$$k = \left(\frac{\sigma}{v}\right)^{-1.086} \tag{16}$$

2.5. Results Evaluation Procedure

To evaluate the performance of the five Weibull methods that are employed in this work, a statistical comparison is performed using three indicators; Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and chi-square test (χ^2), computed as the following equations [79, 66, 80]:

$$RMSE = \left[\frac{1}{n}.\sum_{i=1}^{n}(v_i - v_w)^2\right]^{\frac{1}{2}} \tag{17}$$

where, v_i is the actual speed value, v_w is the estimated wind value from Weibull, and *n* is the number of wind speed dataset.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(v_i - v_w)}{v_i}\right| x100\% \tag{18}$$

$$\chi^2 = \sum_{i=1}^{n}\frac{(v_i - v_w)^2}{v_w} \tag{19}$$

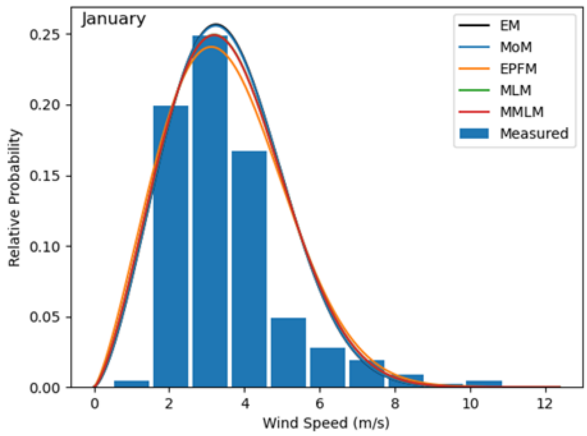
These three assessment methods provide different information about the considered methods reliability. RMSE provides information on the short-term performance of the method as it follows a term-by term comparison of the actual deviation between the estimated and observed values [81], successful estimations correspond to lower values of RMSE [26]. MAPE provides information on the long term performance of the methods studied, it is a measure of accuracy in estimating the values when we have a set of measured values. The percentage error measures how close the data points were presented with respect to the estimated values. The main purpose of MAPE is to show if the wind speed data is stable by means of small variation.

The chi-squared (χ^2) test was used to determine if there exists any difference between the estimated and observed frequencies, lower values of χ^2 provides a goodness of fit. The method generating the best results is established by considering a low value for the chi-square indicator in each case. Since the chi-square value should be as close to zero as possible [82].

It is worth mentioning that any one of aforementioned statistical criteria's can be used to give precise performance analysis that help in ranking Weibull distribution methods.

CHAPTER THREE
RESULTS AND DISCUSSION

The Weibull PDF parameters were generated by the five numerical methods under study (EM, MoM, EPFM, MLM, MMLM). Figs. 1 (a - m) show the Weibull frequency plotted against the frequency distribution of the recorded wind speed values for each month and the whole year, respectively. These plots show that the curves obtained by each numerical method and the histogram generated by the measured wind speed values. As depicted by the plots, the PDfs obtained by all methods approximately cover the histogram in months from January to April, whereas for November and December showing the effectiveness of the modeling, however, EPFM in months from May to October as well as the whole year provides poor representation of the higher values of relative probability. It is clear that EM and MoM methods give the best representation in all months.



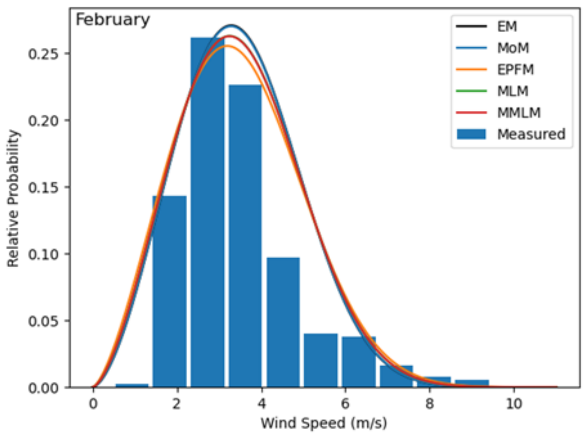


Fig. 1(a) Fig. 1(b)

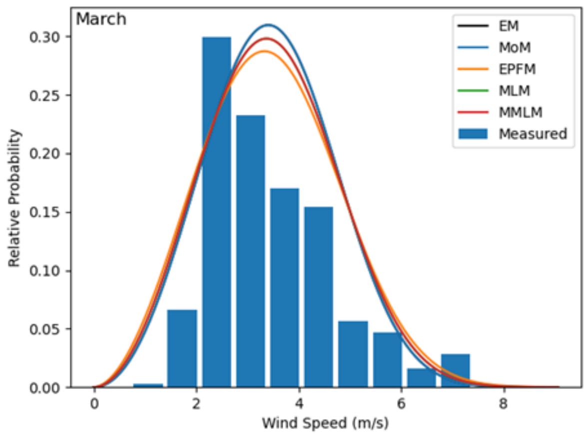


Fig. 1(c)

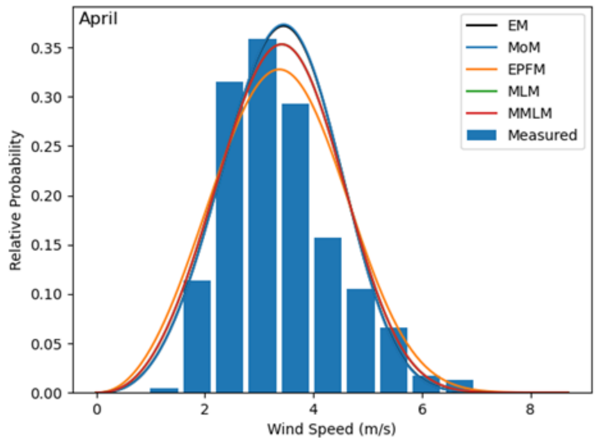


Fig. 1(d)

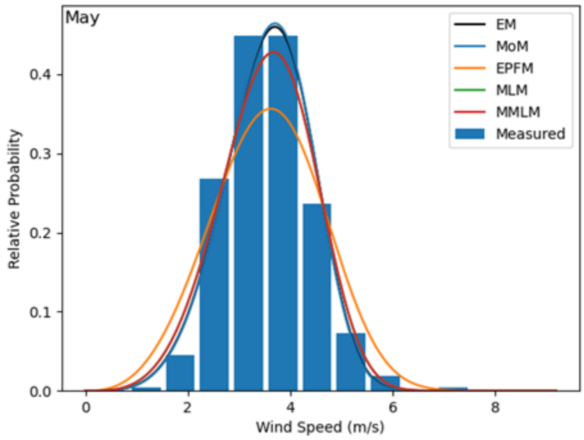


Fig. 1(e)

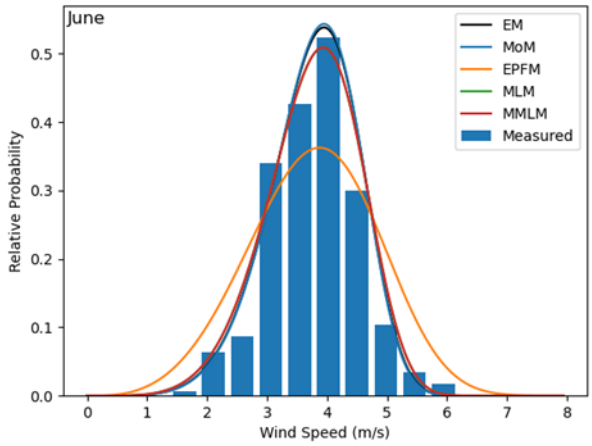


Fig. 1(f)

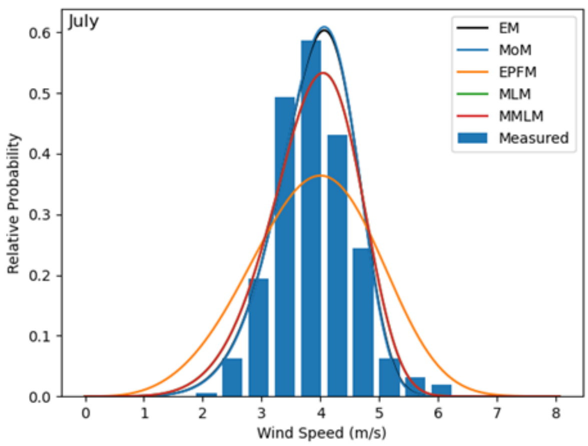


Fig. 1(g)

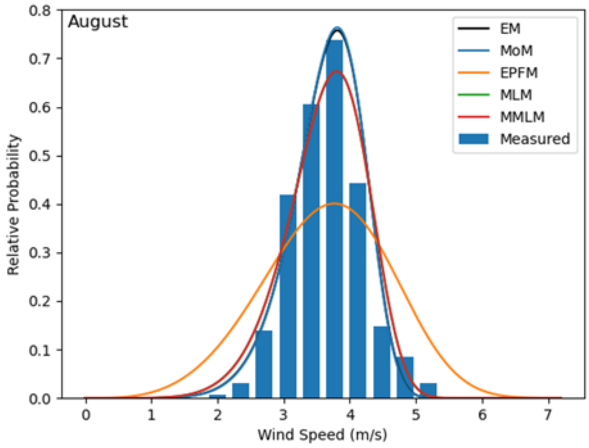


Fig. 1(h)

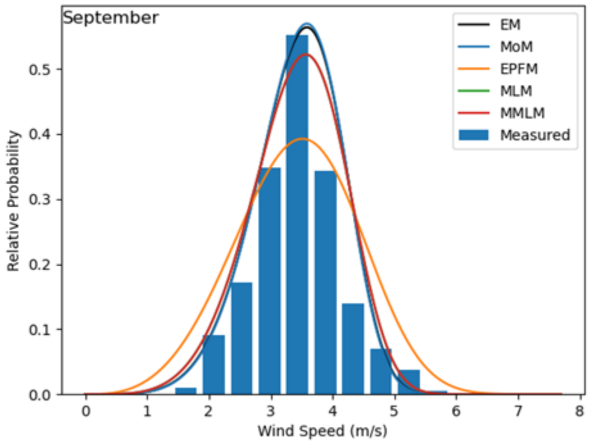


Fig. 1(i)

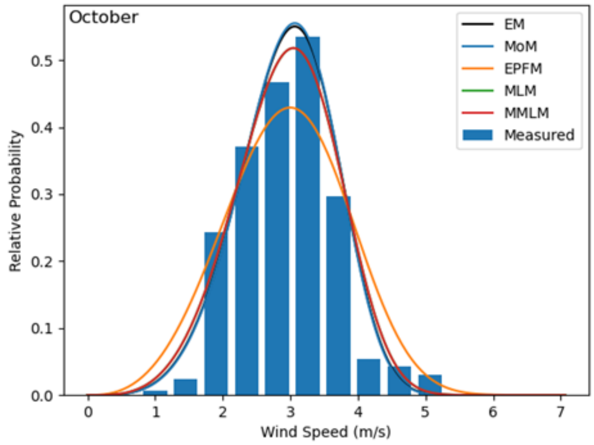


Fig. 1(j)

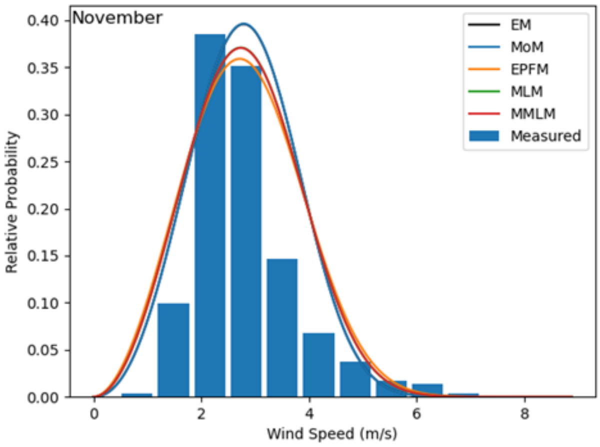


Fig. 1(k)

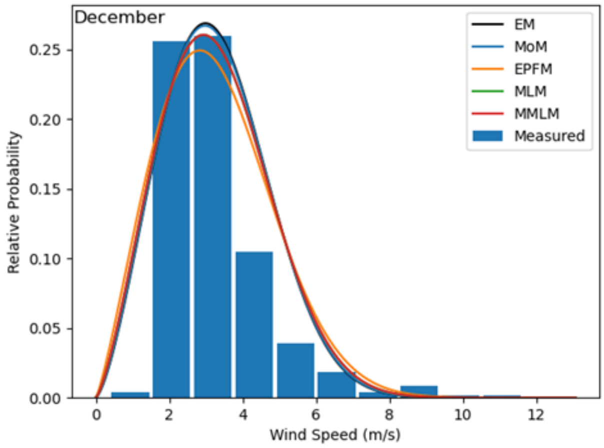


Fig. 1(l)

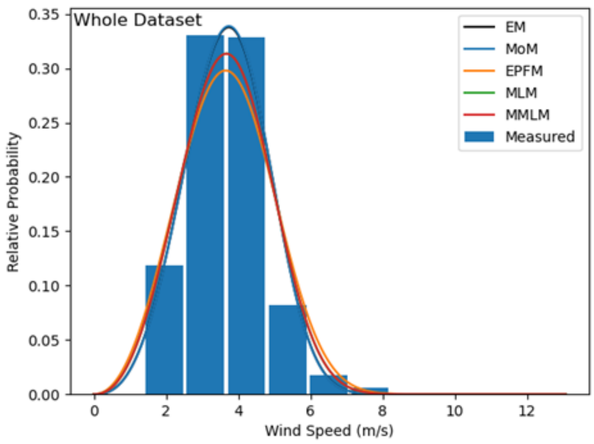


Fig. 1(m)

Fig. 1. The plot of PDFs generated by five methods for estimating Weibull parameters against measured wind speed as histogram, (a, b, c, d, e, f, g, h, i, j, k, l) for months of the year, m for the whole dataset.

Table 4 provides the shape and scale parameters of each numerical method extracted for each month and the whole year, also, the statistical parameters to validate the results were calculated for each method.

Tabulated data of the shape parameter elucidates that the EPFM shape parameter value is the lowest which is consistent with the result obtained in Fig.1. Higher and very close values of shape parameter obtained by the EM and MoM methods. The MLM and MMLM methods shape parameter values are very close and moderate compared to the other methods. A significant difference of the scale parameter values of the EPFM method for the months May to October, it was found to be the highest value compared to other methods. These results clarify that the EPFM did not fit well to represent wind speed data in summer months for this study area. It was found that no significant difference in the scale parameter values for the months November to April, the values obtained by the five methods are very close to each month. For the whole year, the EPFM shape parameter value is the lowest; the scale parameter value is the highest among the others.

The statistical performance values of RMSE and MAPE for EPFM method were found to be the highest in all months with a clear significance in May to October months, lower and very close values of RMSE and MAPE for the EM and MoM methods for all months as well as for the whole year, moderate and approximately equal values of RMSE and MAPE corresponding to both MLM and MMLM methods as compared to others.

Table 4. Assessment accuracy of the Weibull PDF methods.

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	χ^2
	EM	2.523473	3.96306	0.338027	1.695269	0.166511
	MoM	2.513514	3.963461	0.338267	1.705121	0.167077

January	EPFM	2.330362	3.969376	0.342975	1.882031	0.179476
	MLM	2.44044	3.971414	0.340215	1.772495	0.171377
	MMLM	2.436844	3.970177	0.34027	1.777119	0.171656

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
February	EM	2.665283	3.92578	0.333149	2.239279	0.173771
	MoM	2.657658	3.926146	0.333336	2.25101	0.174283
	EPFM	2.48476	3.933593	0.337818	2.559329	0.18827
	MLM	2.576577	3.934374	0.335516	2.381462	0.180059
	MMLM	2.573657	3.933506	0.33556	2.388081	0.180333

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
March	EM	3.070686	3.874294	0.315718	2.39167	0.153875
	MoM	3.072072	3.874214	0.31569	2.389055	0.153812
	EPFM	2.8255	3.888007	0.32128	2.889953	0.168361
	MLM	2.944945	3.882277	0.318455	2.637749	0.160412
	MMLM	2.945695	3.88244	0.318446	2.636062	0.16036

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
April	EM	3.651961	3.765446	0.334281	2.166426	0.163228
	MoM	3.666667	3.764619	0.333953	2.150158	0.162838
	EPFM	3.197019	3.791489	0.34612	2.915868	0.182385

	MLM	3.457457	3.771999	0.338694	2.460302	0.169747
	MMLM	3.456946	3.771921	0.338701	2.46127	0.169771

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	χ^2
May	EM	4.749345	3.889863	0.314048	1.042323	0.125909
	MoM	4.792793	3.887808	0.313046	1.017081	0.12575
	EPFM	3.67122	3.947514	0.345663	2.304411	0.146573
	MLM	4.402402	3.892754	0.322006	1.27504	0.128418
	MMLM	4.40344	3.892854	0.321986	1.274148	0.128407

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	χ^2
June	EM	5.874317	4.075951	0.223633	1.432009	0.07191
	MoM	5.927928	4.073891	0.222254	1.395384	0.071704
	EPFM	3.967186	4.168857	0.28902	3.835175	0.124387
	MLM	5.547548	4.078328	0.231808	1.672815	0.073841
	MMLM	5.546755	4.078279	0.231825	1.673445	0.073847

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	χ^2
July	EM	6.751052	4.164793	0.211213	2.030318	0.06542
	MoM	6.810811	4.162857	0.210003	1.991032	0.06505
	EPFM	4.100352	4.28399	0.295664	5.63232	0.181866
	MLM	5.955956	4.172836	0.22809	2.657751	0.07614

	MMLM	5.954795	4.172769	0.22811	2.659078	0.076166

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
August	EM	7.920942	3.876935	0.132836	2.399365	0.035218
	MoM	7.981982	3.875486	0.13142	2.369258	0.034821
	EPFM	4.241372	4.012651	0.268806	7.495269	0.23373
	MLM	7.037037	3.884446	0.153495	3.111828	0.045183
	MMLM	7.037304	3.884457	0.153491	3.111563	0.045179

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
September	EM	5.59421	3.712358	0.16748	1.548403	0.044083
	MoM	5.648649	3.710328	0.165886	1.525626	0.043839
	EPFM	3.900578	3.7902	0.229319	3.473877	0.087817
	MLM	5.171171	3.716399	0.179232	1.72116	0.046935
	MMLM	5.170717	3.716369	0.179241	1.721368	0.046939

Month	**Numerical method**	**Weibull Parameters**		**Performance tests**		
		Shape k	**Scale c**	**RMSE**	**MAPE**	**χ^2**
October	EM	4.706692	3.224026	0.23978	2.150546	0.087439
	MoM	4.747748	3.222401	0.238458	2.099231	0.086685
	EPFM	3.661135	3.270587	0.281564	3.910052	0.130072
	MLM	4.418418	3.226888	0.248989	2.538455	0.093852

	MMLM	4.419442	3.226968	0.248962	2.536974	0.093827

Month	Numerical method	Weibull Parameters		Performance tests		
		Shape k	Scale c	RMSE	MAPE	χ^2
November	EM	3.195162	3.136302	0.27035	2.325946	0.108407
	MoM	3.198198	3.136158	0.270261	2.32088	0.108242
	EPFM	2.86942	3.151375	0.280795	2.943024	0.133555
	MLM	2.968969	3.14023	0.276974	2.7379	0.124508
	MMLM	2.965697	3.139632	0.277037	2.745406	0.124839

Month	Numerical method	Weibull Parameters		Performance tests		
		Shape k	Scale c	RMSE	MAPE	χ^2
December	EM	2.4519	3.698287	0.342315	1.860845	0.166667
	MoM	2.432432	3.698911	0.342798	1.879153	0.168294
	EPFM	2.225073	3.703286	0.348405	2.233572	0.189443
	MLM	2.36036	3.703926	0.344732	1.977618	0.174656
	MMLM	2.359236	3.703529	0.34475	1.979794	0.174787

Month	Numerical method	Weibull Parameters		Performance tests		
		Shape k	Scale c	RMSE	MAPE	χ^2
Whole year	EM	3.601134	4.092761	0.322903	5.657881	0.147445
	MoM	3.612613	4.092055	0.322657	5.582767	0.146701
	EPFM	3.153275	4.120653	0.333381	9.67098	0.201814
	MLM	3.313313	4.092106	0.328958	8.070614	0.176695

	MMLM	3.312131	4.091886	0.328979	8.083859	0.176883

The Weibull two parameters determine the wind speed for optimum performance of wind energy conversion system as well as the speed range over which it is expected to operate. The breadth of wind speed distribution is shown by the Weibull shape parameter indicator. Lower values of k represents for those winds tend to vary over a large range of speeds while higher values correspond to wind speeds staying within a narrow range. In order to provide a month by month comparison, in Fig. 2, the Weibull shape parameter calculated by the five methods under study have been plotted for each month. The shape parameter values provide a seasonal trend with lower variation (higher values of the k parameter) of wind speeds in summer months.

The highest value of k was found in August for the EM and MoM methods. Higher variation of wind speed was found in winter months (the lower values of k), the lowest value of k was found in December taken from the EPFM method. Also, the results indicated that no significant difference between the shape parameter values calculated by the five methods in winter months from December to February.

The Weibull scale c parameter shows how the wind potential behaves throughout the year. Fig.4 shows scale parameter values calculated by the five methods plotted against each month. The analysis of these figures shows that c values varied from 3.136 in November to 4.283 in July, these values were calculated by the EM and EPFM methods, respectively. A small significance was found in June and July months with small increment of k values compared to the other months, whereas the lowest value of c parameter was found in October and November months.

In general, the results showed that the EPFM method provides highest scale parameter values as compared to the corresponding values of the other methods investigated in this research work. However, $c \geq 3$ indicates that the potential of the wind during the year is sufficient to install a small wind turbine. Upon to the results obtained regarding the c values, there is a possibility to install small wind turbine in the study area.

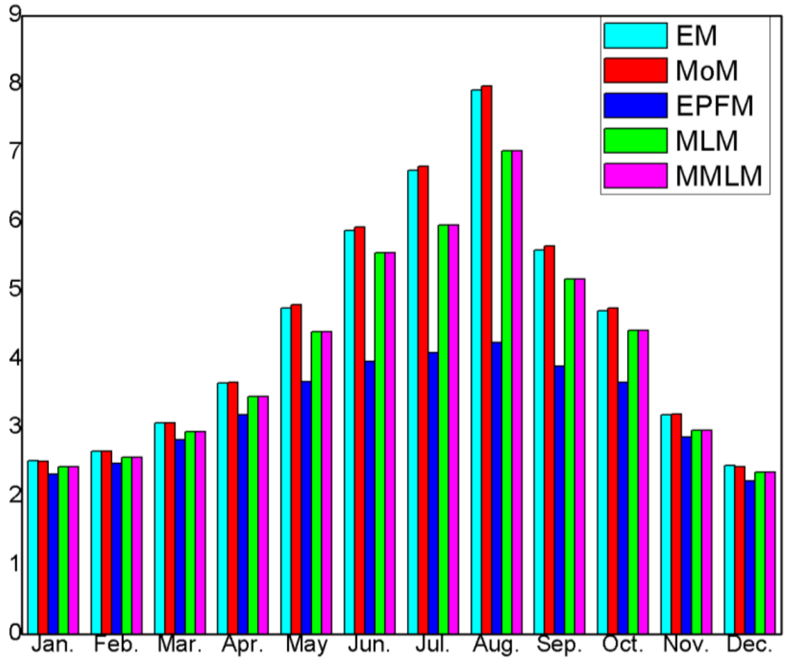


Fig. 2. Plot of the shape parameter of Weibull distribution obtained by the five methods for each month.

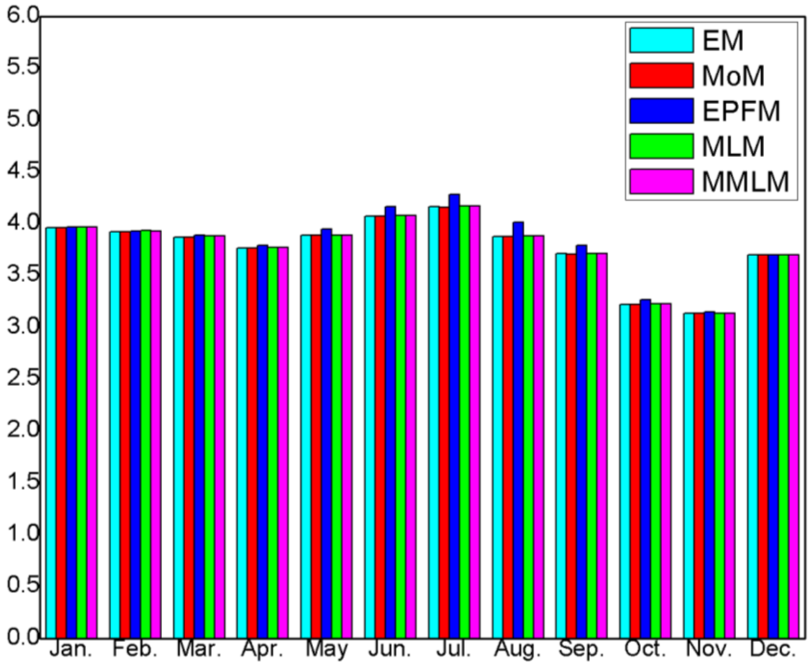


Fig. 3. Plot of the scale parameter of Weibull distribution obtained by the five methods for each month.

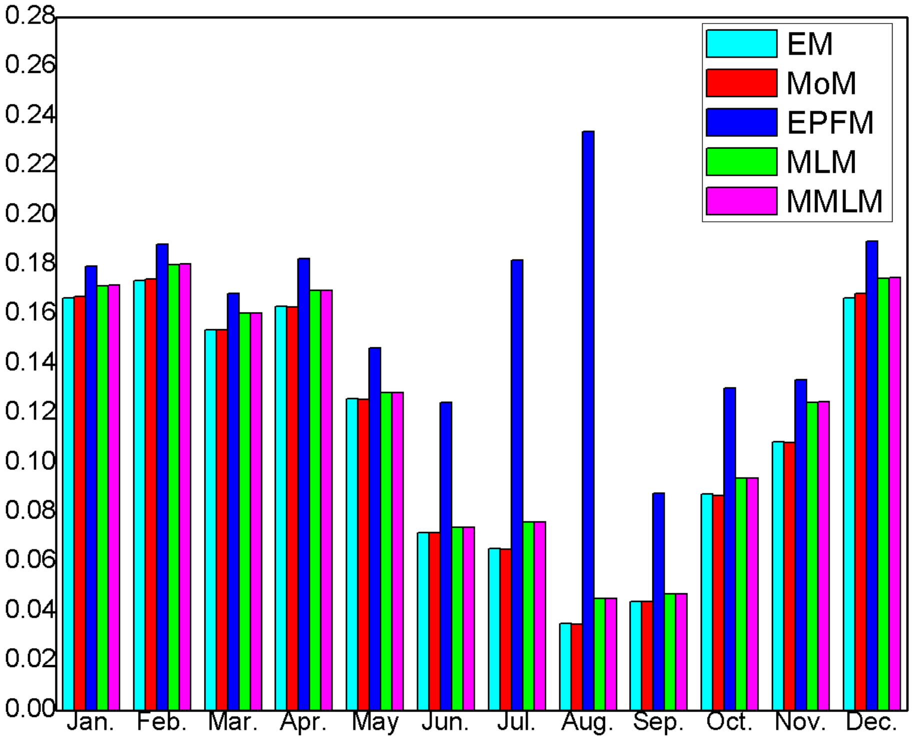


Fig. 4. Plot of the chi-square obtained by the five methods for each month.

For more insights, Fig.4 also presents the results obtained from chi-square per month for the five methods. The chi-square value obtained from the EPFM method is the highest compared to the other methods which shows significant difference in summer months (June to October) as compared to the corresponding values of the other methods. Moreover, the EM and MoM methods showed a lower and acceptable values of chi-square test (0.035 to 0.086) in summer months, as well as for the whole year, with the lowest value (0.035) for the EM method found in August month. The MLM and MMLM present moderate values of chi-square (> 0.1) from November to May.

CHAPTER FOUR

CONCLUSIONS AND FUTURE WORK

The accurate estimation of the Weibull two parameters (k, c) in a study site reduce the uncertainties related to the wind energy output calculation from any wind energy conversion system. In this work, Eleven years (2008-2018) of daily wind speed measured values at Eastern Jerusalem have been processed by python scientific language and statistically analyzed, based on the Weibull two parameters distribution function. The aim of this study was to select the most accurate and efficient methods to ascertain how closely the measured values follow the two parameter Weibull distribution function; the shape and scale parameters were found by applying five numerical methods namely, EM, MoM, EPFM, MLM and MMLM.

The main aim of this work was satisfied since the validity of the five Weibull methods were checked by three statistical tools to find the best method of Weibull distribution. It is worth pointing out that any one of these statistical tools, namely RMSE, MAPE, and chi-square test (χ^2) can be considered as good indicator to rank the Weibull methods, however, analysis using all of them was done to rank the methods more precisely.

Based on the analysis of the obtained results, the least efficient method which performed the worst among the five methods is the EPFM. Furthermore, wind potential was found to be higher with lower variations in summer months.

To sum up, the findings strongly recommend that the EM and MoM are the best estimated methods for getting accurate and reliable results in estimating the Weibull parameters in Jerusalem study site in order to reduce uncertainties related to the calculation of wind energy.

Finally, this study is valuable to wind energy developers and potential wind energy users because it allows them to choose the most accurate and efficient method for ascertaining how closely the measured values follow the two-parameter Weibull distribution function, and generalize this study to other locations in the Palestinian territories with employing other statistical models for fitting wind speed distribution function.

For future work, Wind energy is expected to play a significant role in meeting some of our future energy needs due to its relative simplicity and availability of wind resources. However, there are numerous issues to be resolved if wind resources are to be used effectively and efficiently; among these issues we can summarize:

- Applying this study on wind speed data measured at higher altitudes;
- Estimating wind speed values using other methods such as machine learning algorithms;
- Predicting wind speed values using other meteorological and geographical parameters;
- Calculating the wind energy output and finding the suitable wind turbine;
- Studying the wind direction on the hourly basis;
- Building wind atlas for Palestine through investigating wind velocity at many various locations;
- Investigating the spatial variability of winds throughout Palestine.

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حساب معاملات ويبل باستخدام خمسة طرق رقمية لتقدير و دراسة توزيع سرعة الرياح في القدس الشرقية, فلسطين

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الملخص

توفر طاقة الرياح حلاً مجديًا ونظيفًا لتوليد الكهرباء. ان تطوير تطبيقات طاقة الرياح تتطلب تحليلا معمقا لبيانات سرعة الرياح وامكانات طاقة الرياح بدقة في الموقع. هذا العمل يستكشف توزيع سرعة الرياح من أجل تقدير Weibullمعاملي المستخدمة للنمذجة على نطاق واسع من أجل تقديم تقدير دقيق وفعال لموارد الرياح وطاقتها. Weibullتم حساب معاملي الشكل والقياس لاقتران بناء على بيانات سرعة الرياح التي تم قياسها في الفترة ما بين 2008 الى 2018 والتي تم جمعها في القدس – فلسطين. تم اختيار خمسة طرق لتقدير قيم الشكل والقياس: الطريقة التجريبية (EM), طريقة اللحظة (MoM), طريقة عامل نمط الطاقة (EPFM), طريقة الاحتمالية القصوى (MLM), طريقة الاحتمالية القصوى المعدلة (MMLM), وقد تم استخدام ثلاثة معايير احصائية (RMSE, MAPE, Chi-square) من أجل تقييم اداء الطرق المستخدمة ومعرفة جودتها. أوضحت النتائج انه من بين الطرق الخمسة: أظهرت الطريقة التجريبية (EM)تليها طريقة اللحظة(MoM) نتائج أكثر دقة وفعالية في تقدير قيم معاملي الشكل والقياس لاقتران Weibull من أجل تقريب توزيع سرعة الرياح في موقع الدراسة وذلك بناء نتائج معايير تقييم الاداء. كذلك بينت نتائج الاداء الاحصائية رفضا لطريقة عامل نمط الطاقة (EPFM) باعتبارها طريقة مناسبة ودقيقة.