International Journal of Power Electronics and Drive System (IJPEDS)
Vol.11, No.1, Mar2020, pp. xx~xx
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v11.i1.pp-pg ❐ 51

Numerical analysis for determining the Weibull parameters using seven techniques

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Article Info

Article history:

ReceivedApr 17, 2020
Revised Jul 22, 2020
Accepted Aug3, 2020

Keywords:

Numerical methods
Probability distribution function
Statistical tool
Wind power density

ABSTRACT

This study aimed to compare seven numerical methods to determine the most efficient one for calculating the parameters of the Weibull distribution on the basis of wind speed data. Two approaches were employed: analysis of a set of actual time series data and theoretical Weibull probability function. In this analysis, the parameters Weibull shape factor 'k' and the Weibull scale factor 'c' were adopted. These suitability values were calculated using the following popular methods: method of moments (MM), standard deviation method (STDM) or empirical method (EM), maximum likelihood method (MLM), modified maximum likelihood method (MMLM), second modified maximum likelihood method (SMMLM), graphical method (GM) or least mean square method (LMSM) and energy pattern factor method (EPFM). The performance of these numerical methods was tested by root mean square error (RMSE), index of agreement (IA), chi-square test (X2), mean absolute percentage error (MAPE) and relative root mean square error (RRMSE) to estimate the percentage of error. Among the prediction techniques. The EPFM exhibited the greatest accuracy performance followed by MM and MLM, whereas the SMMLM exhibited the worst performance. The RMSE achieved the best prediction accuracy, whereas the RRMSE attained the worst prediction accuracy.

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1. INTRODUCTION

The electric energy crisis has emerged as a significant global problem in the last decade. Therefore, many governments put an ambitious goal to supply a significant portion of their electrical grid from renewable energy such as PV and Wind energy. In Palestine, traditional energy resources are lacking while the consumption of non-renewable sources in various fields continues to rise. Therefore, the critical situation in this region, the siege imposed and the growing need for alternative sources of energy have become urgent concerns. Such urgency is highlighted by the continued interruption of electric power and fuel supply. In this study will lead to assess the wind energy production in Palestine by analysing wind data using the expert probability function [1-4].

Scale and shape factors are two parameters of the Weibull probability density function that have been widely used in different fields, particularly wind energy assessment, sky clearness index, level prediction of water and rainfall, material life length analysis and classification. Recently, the Weibull distribution becomes the preferred distribution in software designed for commercial wind energy, like Wind

Atlas [5].There is a proportional relationship between Wind power extraction and the cube of wind speed, thus, the distribution of wind speed for a specific wind farm should be determined. The abscissa scale of the Weibull probability distribution is controlled by the scale parameter. The shape parameter characterises the width of the Weibull distribution, such as a large shape factor equates to a less narrow Weibull distribution with a high peak value. The following numerical methods can be used to determine the shape and scale factor for a given data series: method of moments (MM), standard deviation method (STDM) or empirical method (EM), maximum likelihood method (MLM), modified maximum likelihood method (MMLM), second modified maximum likelihood method (SMMLM), graphical method (GM) or least mean square method (LSM) and energy pattern factor method (EPFM)[6-15].

The Weibull distribution is widely utilised to assess wind energy potential and analyse wind for a specific region [9, 16-31]. Seguro and Lambert[13]estimated the parameters of the Weibull distribution by using three different methods. They determined that the MLM gave better efficiency performance than the commonly used GM in Weibull parameters estimation. Akdag and Dinler[12] presented three traditional methods, that are, the GM, MLM and MM, and proposed the EPFM for determining Weibull parameters. They found that the EPFM exhibits better appropriateness than the other methods in comparing power density and mean wind speed MWS. Jowder[32]applied the EM and GM to analyse the wind power density (WPD) at the altitudes of 10, 30 and 60 m in the Kingdom of Bahrain. He calculated and compared two Weibull parameters then noted that the EM more accurately estimates power density and MWS than the GM. M. Sulaiman et al.[33]analysed wind speed record in Oman and referred to the concept of wind speed data following the Weibull probability distribution. Nevertheless, actual observed wind speed are not required in the Weibull distribution. Chang [14] conducted a statistical study to assess the efficiency performance of six different techniques in determining shape and scale factors for Weibull parameters. Costa Rocha et al.[34] compared and analysed seven numerical methods to assess their performance in estimating the parameters of the Weibull probability distribution by using the actual wind speed data of Paracuru and Camocim in Brazil. Bhattacharya and Bhattacharjee [35] and Chu and Ke [36]compared the estimates obtained by the MLM and LSM [37].They concluded that the LSM gave better efficiency performance than MLM. Odo et al. [38]employed a Weibull probability distribution to estimate wind energy potential for 13 years in Nigeria. Oyedepo et al. [39] analysed the actual long-term wind data in southeast Nigeria at a height of 10 m from 24 to 37 years. Abbas et al. [40]statistically analysed the actual wind speed record in Pakistan to estimate the best fitting probability distribution of wind speed record. They used two-parameter Weibull, Rayleigh and other types of probability distributions to fit the data. They also used MLM to determine the parameters of every distribution [37, 41-48]. Mostafaeipour and Mohammadi[49]utilised two methods (PDM and STDM) to assess wind record in Iran. At 2012. Genc et al. [50]and Senoglu and Kantar[51] compared several numerical methods in terms of accuracy in estimating Weibull parameters. However, the scale parameters that they applied were all less than 1.5 m/s, which is likely less than the cut-in wind speed for most small-scale wind turbines. They convened that MWSapproximately10% lower than the scale factor, if the shape factor is approximately 2.Stathopoulos et al. [52] applied statistical and numerical models to estimate wind power. Zhou et al. [53]conducted a case study and comprehensively estimated the wind speed distribution curves for North Dakota.

Wind energy applications require the evaluation of Weibull parameters. Thus, determining the method with superior performance on shape and scale factor values is important. The Kolmogorov–Smirnov statistic test is selected to test the goodness of fit of a Weibull distribution in measured data at the 1% and 5% significance levels[14]. Dorvlo[54] analysed the actual wind speed record from four different stations in Oman. He determined that the chi-square estimation method yields better estimates of Weibull parameters than the MM and GM on the basis of the Kolmogorov–Smirnov statistic.

In examining the feasibility of wind energy at a specific location, the best strategy seen by calculating the wind power density (WPD)according to the measured information of a target meteorological location. Another strategy is the WPD using different frequency distribution functions, such as Weibull distribution, chi-square distribution, Rayleigh distribution, lognormal distribution, generalised normal distribution, gamma distribution, three-parameter lognormal distribution, kappa distribution, inverse Gaussian distribution, wake distribution, normal two-variable distribution, hybrid distribution and normal square root of wind speed distribution [55-57]. Researchers have indicated that the Weibull function is better suited for the wind probability distribution in comparison with other functions[58]. The Weibull function is used to fit time series data. This distribution is essential in maintainability and reliability analyses. The appropriate values for the shape and scale parameters of the Weibull probability distribution are crucial in identifying ideal sites for the installation of wind turbine generators. The Weibull scale parameter, in particular, is essential in determining the effectiveness of wind farms[59, 60].

The available electricity generated by a wind power generation framework in a given wind field depends on the MWS, standard deviation of wind speed and installation location. This paper utilise the information recorded from the coastal city of Ashqelon from January 2012 to December 2015. The wind industry should be able to describe variations in wind speed. Such information benefits the optimisation of the design of wind turbines to minimise the costs of energy generation. In this study wind energy potential can be estimated in south coastal plain of Palestine and describe how varying wind speeds can aid the optimisation of wind energy turbine design for cost-effective wind energy generation[61, 62].

2. ESTIMATION OF WIND POWER DENSITY

WPD indicates the capacity of wind energy resources in a target location[63]. WPD could be measured with two approaches: (1) available power based on the observed MWS of the meteorological station and (2) frequency distribution function (two-parameter Weibull method)[55, 64-66]. In this study, Weibull distribution adopted the to assess wind power.

WPD is an essential indicator that is used to estimate the potential of wind speed data. It also denotes the wind energy amount at different wind speed in a specific location. Moreover, WPD aids the evaluation of the performance of wind turbines to identify the optimum ones. Furthermore, WPD identifies the level of reachable energy at the location. This study WPD had been calculated based on measured wind speed data and calculation using the appropriate distribution function. Although many PDFs for various applications of wind energy have been proposed in the literature, the Weibull function is unarguably one of the most widely used functions in terms of statistical probability distributions. The major advantages of the Weibull distribution function have been characterised extensively in[62, 63, 67]. Accordingly, the Weibull probability distribution function is selected in calculating WPD and is used to illustrate the wind speed frequency distribution. To estimate Weibull parameters, it can be adopted the numerical methods MM, EM, MLM, MMLM, SMMLM, GP and EPFM. The estimation is performed to (a) distinguish past conditions retrospectively,(b) predict future power generation at one site,(c) predict power generation among a grid of wind turbines and (d) calibrate meteorological records [2, 55, 61, 62].

3. CALCULATION USING THE WEIBULL DISTRIBUTION

Wind speed is a random variable that is used to estimate the wind potential of a region. This parameter is generally applied in statistical analyses [17, 68, 69], and its use requires time series records of wind speed data. Based on the wind speed data collected, the Weibull probability distribution can be represented as a cumulative distribution function (CDF) or Weibull function, F(υ), and Weibull PDF, f(υ)[31].The CDF is obtained by computing the integral of the PDF [63, 70, 71], which is ultimately determined using the following equation [10, 31, 59, 63, 68, 70-72]:

$$F(\upsilon) = 1 - \exp\left(-\left(\frac{\upsilon}{c} \right)^{k} \right) . \tag{1}$$

The probability function can be derived as follows:

$$f(\upsilon) = \frac{dF(\upsilon)}{d(\upsilon)} = k \frac{v^{(K-1)}}{c^{K}} e^{-\left(\frac{\upsilon}{C}\right)^{K}} \qquad k > 0, \upsilon > 0,\ c > 1 , \tag{2}$$

Where$v$, c and k are the wind speed (m/s), scale factor (m/s), shape factor (dimensionless), respectively. Parameter k indicates the width of the wind speed probability distribution, which represents the wind probability distribution peak of any specific region[63, 73].Parameter$c$indicates the abscissa scale of the wind probability distribution, which shows the wind in particular location[63, 74]. Shape parameter$k$ and scale parameter $c$are calculated using the methods previously reported in the literature. Parameters c and k can be obtained using MM, STDM (EM), MLM, MMLM, SMMLM, GM (LSM) and EPFM. These methods are frequently compared in the literature on wind energy. However, the results, conclusions and recommendations of previous studies differ greatly due to the change of wind speed data conditions. Hence, it can be verified the most appropriateness of the methods that may change with the sample data distribution, sample data size, , goodness-of-fit tests and sample data format[12, 55].
Based on the Weibull PDF, WPD is determined using equation (3)[63, 75, 76]:

$$\bar{P}=\frac{1}{2}\rho\int_0^\infty \upsilon^3 f_w(\upsilon)d\upsilon=\frac{1}{2}\rho c^3\Gamma\left(1+\frac{3}{k}\right) \qquad \left(\frac{\mathrm{W}}{\mathrm{m}^2}\right) \tag{3}$$

to simulate the required electric power output for wind turbine model[77, 78].

4. NUMERICAL METHODS FOR DETERMINING WEIBULL PARAMETERS

4.1 Method of Moments

The MM is recommended by Justus and Mikhail [79, 80]. The standard and mean deviations of the elements are noted initially at a suitable scale MM. On the basis of the numerical iteration of the equations 4 and 5, the standard deviation σ and mean ($\bar{\upsilon}$) of wind speeds are derived[14, 68, 79, 81-86]. The MM is an effective approach to deriving Weibull parameters. The first moment relates to the origin, and the second moment pertains to the mean. These moments are used to measure parameters k and c, as expressed in Equations (4) and (5), respectively. The calculation includes the MWS and standard deviation which are obtained from the calculated wind speed[86, 87].

$$\bar{\upsilon}=c\Gamma(1+1/k) \quad , \tag{4}$$

$$\sigma=c[\Gamma(1+2/k)-\Gamma^2(1+1/k)]^{1/2} \quad , \tag{5}$$

Where

$$\bar{\upsilon}=\frac{1}{n}\sum_{i=1}^{n}\upsilon i \quad , \tag{6}$$

$$\sigma=\left[\frac{1}{n-1}\sum_{i=1}^{n}(\upsilon i-\bar{\upsilon})^2\right]^{1/2}, \tag{7}$$

Where $\Gamma(x)$ is the gamma function expressed as

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

4.2 Empirical Method or Standard Deviation Method

The EM is also commonly known as the power density method. The EM is easy and simple to implement[86]. The empirical approach involves a straightforward and practical solution that only requires knowledge of MWS $\bar{\upsilon}$ and standard deviation σ[79]. The EM uses the average of the cube of wind speed (υ^3) and the cube of MWS $\bar{\upsilon}^3.\frac{\bar{\upsilon}^3}{\bar{\upsilon}^3}$known as (E_{pf}). The scale factor is determined from the energy pattern factor. The equations used to determine the scale parameter are identical to those used in the MM and EM[88]. Thus, the EM can be categorised as a special case of the MM [14, 68].On the basis of the EM introduced by Justus[63, 89, 90], parameters k and c are computed using equations (9) and (10), respectively[63, 81, 89, 90]. The EM can also be called the STDM. Several studies have adopted the numerical STDM to calculate Weibull parameters. In [49], this method was utilised to assess wind data in Zarrineh, Iranin 2012 as mentioned. Reference [68]analysed and compared seven numerical methods to assess their effectiveness in determining the parameters of the Weibull distribution using wind data collected from Camocim and Paracuru in the northeast region of Brazil in[14], the authors conducted a statistical study to check the efficiency performance by determining the Weibull shape and scale factor for six different numerical methods for wind energy applications. In the STDM, the parameters of Weibull can be estimated as shown below:

$$k=\left(\frac{\sigma}{\bar{\upsilon}}\right)^{-1.086} \quad , \quad 1\le k\le 10 , \tag{9}$$

$$c = \frac{\bar{\upsilon}}{\Gamma\left(1 - \frac{1}{k}\right)} \quad (10)$$

4.3 Maximum Likelihood Method

The MLM was put forward by Fisher[79, 91] and then introduced by Stevens and Smulders as an approach to obtaining wind speed information [79, 92]. The MLM is based on the indirect results of numerical iteration methods for determining parameter k. Therefore, the MLM is effective despite being a laborious and complicated procedure [79]. The MLM is a mathematicalformulation technique also recognized as the likelihood function in time series format for the wind speed data [63]. MLM requires extensive numerical iterations [14]. These numerical iterations are needed to estimate the parameters k and c of the Weibull function. Through the MLM, parameters k and c are calculated using equations(11) and (12), respectively[63, 93, 94].

$$k = \left[\frac{\Sigma_{i=1}^{n} \upsilon_i^k \ln(\upsilon_i)}{\Sigma_{i=1}^{n} \upsilon_i^k} - \frac{\Sigma_{i=1}^{n} \ln(\upsilon_i)}{n}\right]^{-1}, \quad (11)$$

$$c = \left[\frac{\Sigma_{i=1}^{n} \upsilon_i^k}{n}\right]^{1/k}, \quad (12)$$

Where vi the wind speed is in time step i (m/s) and n is the number of non-zero wind speed data points.

4.4 Modified Maximum Likelihood Method (MMLM)

The MMLM is only applicable when the wind speed data are in frequency distribution format. Similar to the MLM, the MMLM entails several iterations when used to determine Weibull parameters. Parameters k and c are obtained using the following equations [34, 63, 95]:

$$k = \left[\frac{\Sigma_{i=1}^{n} \upsilon_i^k \ln(\upsilon_i) f(\upsilon_i)}{\Sigma_{i=1}^{n} \upsilon_i^k f(\upsilon_i)} - \frac{\Sigma_{i=1}^{n} \ln(\upsilon_i) f(U\upsilon_i)}{f(\upsilon \geq 0)}\right]^{-1} \quad (13)$$

$$c = \left[\frac{1}{f(\upsilon \geq 0)} - \sum_{i=1}^{n} \upsilon_i^k f(\upsilon_i)\right]^{1/k} \quad (14)$$

Where vi is MWS central to bin i and n is the total number of bins, $f(vi)$ is the frequency of wind speed falling within bin i, where $f(v \geq 0)$ is the probability distribution curve that wind speed reaches or exceeds zero.

4.5 Second Modified Maximum Likelihood Method (SMMLM)

The SMMLM was developed by Christofferson and Gillette (1987) by replacing the iterative estimation of the shape parameter with [96]

$$k = \frac{\pi}{\sqrt{6}} \left[\frac{N(N-1)}{N\left(\sum_{i=1}^{N} \ln^2 vi\right) - \left(\sum_{i=1}^{N} \ln vi\right)^2}\right]^{0.5}, \quad (15)$$

Which requires neither the iteration nor the sorting of data. Thus, SMMLM was selected by Hanitsch and Ahmed Shata in (2006)[97].

4.6 Graphical Method (GM) or Least Mean Square Method (LSM)

The GM, also called the LSM[98], is employed using the CDF. In GM, the wind speed record ought first be categorised into bins. After using the logarithm of equation (16) twice, the GM equation can be obtained as follows.
.

$$\ln\{-\ln[1-F(\upsilon)]\} = k\ln(\upsilon) - k\ln(c) \tag{16}$$

The GM is used by a logarithmic function of the CDF F(v), that is, the CDF F(v) is modulated for the inclusion of a dual logarithmictransformation [79]

Plotting $\ln(v)$as the x-axis versus $\ln\{-\ln(1-F(v)\}$as the y-axis shows a straight line in which k is the slope and the y-intercept is $kln(c)$[14, 63, 99].

4.7 Energy Pattern Factor Method (EPFM)

The EPFM is related to the mean records of wind speed; it is described by equations(17)[12, 68].

$$E_{pf} = \frac{\overline{\upsilon^3}}{\bar{\upsilon}^3}, \tag{17}$$

where $\bar{v}$ is given as Equation (4).

$$k = 1 + \frac{3.69}{(E_{pf})^2}, \tag{18}$$

where E_{pf} is the energy pattern factor and is the gamma function represented by equation (17).

5. GOODNESS OF FIT

The performance of the five parameter estimation techniques of the Weibull provability distribution for calculating WPD is evaluated using several statistical techniques, including five statistical tools indicators. To achieve a comparative assessment, it can be utilised the root mean square error (RMSE), chi-square test (X^2), index of agreement (IA), mean absolute percentage error (MAPE), and root mean square error (RRMSE), along with some other statistical tools. In the aforementioned subsections, it can be presented a summarise of the statistical tools parameters used in this work[63].

5.1 Root Mean Square Error (RMSE)

RMSE shows the accuracy of a model by comparing the deviations between the values gathered by the Weibull function besides those obtained from measurement data. The positive value of RMSE is calculated by equation(19)[63].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{i,W} - P_{i,M}\right)^2} \tag{19}$$

5.2 Chi-Square Test (X^2)

X^2 is applied to analyse proportions of independent variables, that is, possible inconsistency between the expected frequencies and observed of the events of occurrence. $X^2$is a non-parametric test that is independent of factors like the average population and variance. Two series behave comparably if the variance between the frequencies for every category are negligible, therefore, close to 0. Souza [100] indicated that for this model, the groups should be independent, the items should be randomly selected from each group, the observations should be frequently counted, and every observation should belong to only one group[79].$F(v)$ is the empirical probability distribution estimated from any wind speed record. Then, parameters k and c are determined to be minimum [101].

$$X^2 = \sum_{i=1}^{N} \frac{(y_{i,m} - x_{i,m}}{x_{i,m}}, \tag{20}$$

where y is the observed value and x is the expected value.

5.3 Index of Agreement (IA)

The IA presents the precision degree of predicted values relative to observed values. The IA that change from 0 to 1 is computed by [63, 102]

$$IA = 1 - \frac{\sum_{i=1}^{n}\left|P_{i,W} - P_{i,M}\right|}{\sqrt{\sum_{i=1}^{n}\left|P_{i,W} - P_{M,avg}\right| + \left|P_{i,M} - P_{M,avg}\right|}}. \tag{21}$$

In equations (15)–(21), $P_{i,W}$ and $P_{i,M}$ are the i th calculated wind power density via WDF and the ith calculated WPD by measured data, respectively. $P_{W,avg}$ and $P_{M,avg}$ are the average$P_{i,W}$and $P_{i,M}$ values, and$n$ is the total number of observations.

5.4 Mean Absolute Percentage Error (MAPE)

MAPE presents the average absolute percentage variance between the estimated wind power using Weibull probability function and thatcalculatedfromthe observed data (measured data wind speed). MAPE can be calculated by [63]

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{i,W} - P_{i,M}}{P_{i,M}}\right| \times 100. \tag{22}$$

5.5 Relative Root Mean Square Error (RRMSE)

RRMSE can be acquired by dividing the RMSE with the mean wind power calculated by the observed values.

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{i,W} - P_{i,M}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}P_{i,M}} \times 100. \tag{23}$$

Various domains of RRMSE can be set to demonstrate model precision according to the percentage as clarify below [63, 103, 104].
RRMSE is considered: Excellent if the efficiency performance less than 10%, Good if 10% < RRMSE < 20%, Average if 20% < RRMSE < 30% and Poor if RRMSE more than 30%.
RRMSE, MAPE, IA, X^2, and RMSE with values close to zero are considered satisfactory [31].

6. WIND SPEED FOR COASTAL PLAIN IN PALESTINE AS A CASE STUDY

Palestine is located in Western Asia between the Mediterranean Sea and the Jordan River. It is also surrounded by Jordan and Syria inthe east, Egypt and the Gulf of Aqaba in the south, the Mediterranean Sea in the west and Lebanon in the north. For this study, it can be focused on the Ashqelon sit which lies in the southern coast of the Mediterranean Sea in Palestine. The climate of the coastal area is hot and dry in summer and warm and rainy in autumn. For almost an entire year, the wind speeds in the coastal area are below 7 m/s, with the mean speeds of strong winds not exceeding 25 m/s [105].

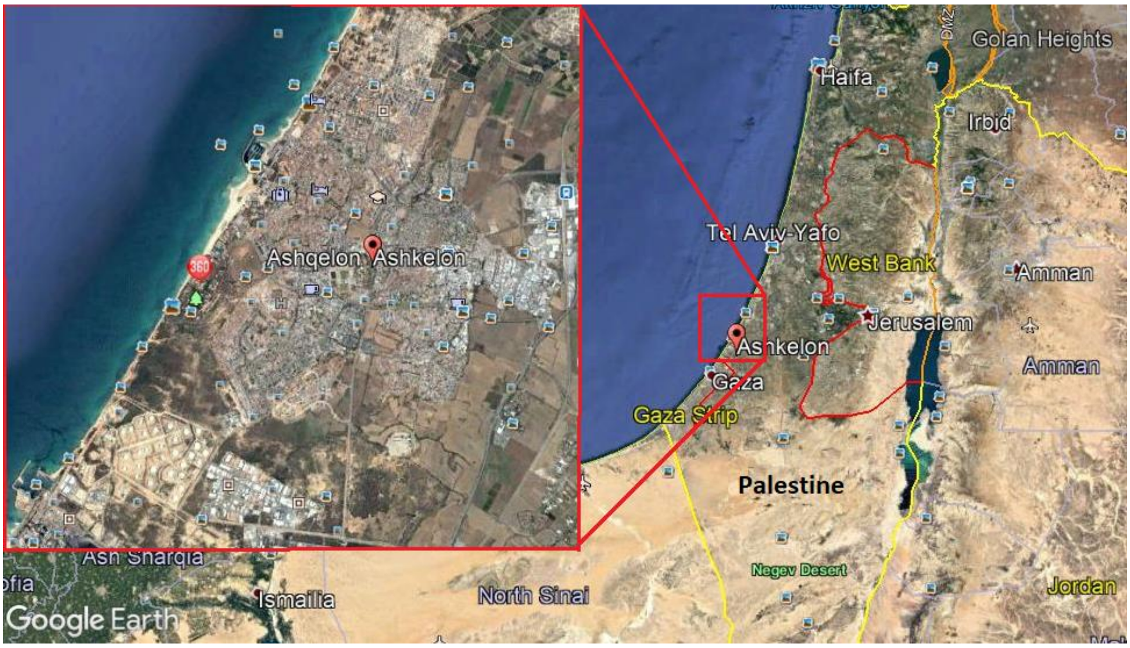

Figure 1. South coastal plain of Palestine (Ashqelon City)[106].

The map in figure 1 shows the site of the data collection. Wind speed in Ashqelon is collected between January 2012 and December 2015. The Mediterranean coastal plains of Palestine exhibit the same weather [105].

7. RESULTS AND DISCUSSION

Wind speed records from wind monitoring stations are adopted to identify the most ideal numerical method for the Weibull distribution. Wind speed data from Ashqelon during the period of January 2012–December 2015 are selected and used in performance testing. Seven methods used in the statistical analysis are employed to estimate the shape factor$k$ and scale factor c of the Weibull probability distribution. These numerical techniques are then compared to clearly determine their efficiency. In the comparison of these methods, it can be used the statistical tools of RMSE, X^2, IA, MAPE and RRMSE. Analysis of efficiency or variance of the method (R^2) is also used. Notably, it can be utilised only 1 column to make ranking for the methods. The ranking is performed using the aforementioned statistical tools to ensure an accurate diagnosis.

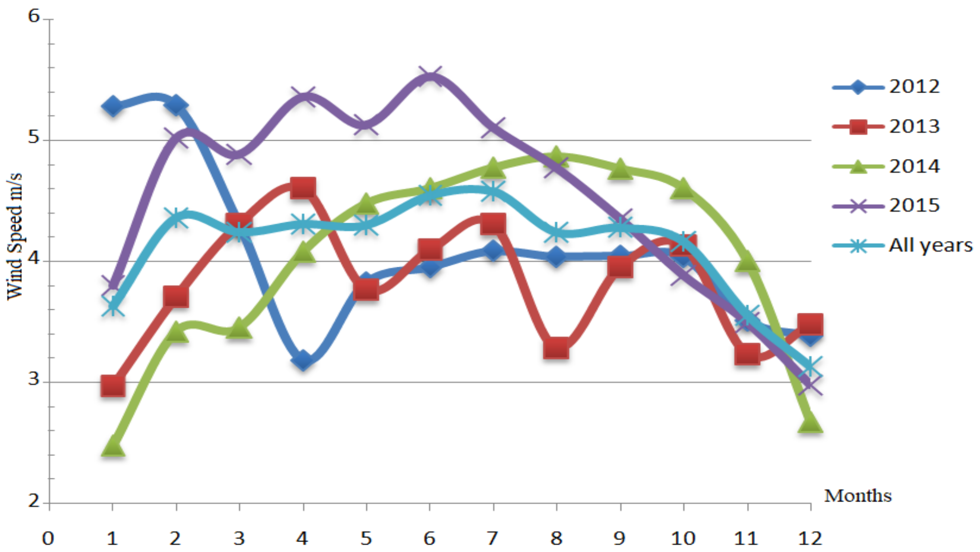

Figure 2 MWS in Ashqelon from January 2012 to December 2015 [105].

Figure 2 shows the percentage of the monthly MWS of Ashqelon in the coastal plain of Palestine between 2012 and 2015. The sources of the meteorological data on Ashqelon, which is adjacent to Gaza City, are recorded on a daily basis according to the MWS that is usually calculated every month. The graph shows that MWS dramatically decreased from February to April 2012, reaching an all-time low of 3.2 m/s. In January, MWS rose as high as or more than 5 m/s. MWS increased steadily and reached approximately 4 m/s. In the last three months, the curve declined. In April 2013, MWS increased dramatically, reaching around 4.7 m/s. The curve suddenly fluctuated during the last eight months of the year. In January to August 2014, MWS significantly increased, reaching 4.8 m/s before finally dropping in the last four months of the year. In January 2015, MWS jumped and reached 5.1 m/s. It then fluctuated significantly and reached the peak point in June. However, MWS gradually declined between July and December, reaching an all-time low of 3 m/s. Overall, MWS fluctuated between 3 m/s to 5 m/s during this period [105].

Table 1. Frequency of actual MWS records from January 2012 to December 2015.

Wind speed (m/s)	Jan	Feb	Mar	April	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1.0615	13	6	5	4	3	1	0	0	1	2	10	11
2.0734	7	2	3	1	0	1	0	0	1	2	3	4
3.0853	3	4	7	4	4	3	1	1	2	3	2	7
4.0972	3	11	11	11	11	12	17	15	9	13	4	6
5.1091	2	2	1	4	4	7	8	8	10	4	1	1
6.121	1	0	2	3	6	5	5	4	6	6	3	2
7.1329	2	2	2	3	3	1	0	3	1	0	3	0
8.1448	0	1	0	0	0	0	0	0	0	0	0	0
9.1567	0	0	0	0	0	0	0	0	0	0	0	0
10.1687	0	0	0	0	0	0	0	0	0	0	0	0
11.1806	0	0	0	0	0	0	0	0	0	0	0	0
12.1925	0	0	0	0	0	0	0	0	0	0	0	0
13.2044	0	0	0	0	0	0	0	0	0	0	0	0
14.2163	0	0	0	0	0	0	0	0	0	1	0	0

Table 1 lists the frequency distribution of the actual MWS records of Ashqelon between January 2012 and December 2015. According to the sample frequency distribution, more than 70% of the total frequency distribution lies between 1 and 7 m/s of MWS. Table 1 can be used to determine the total number of hours for four years at certain wind speeds available monthly.

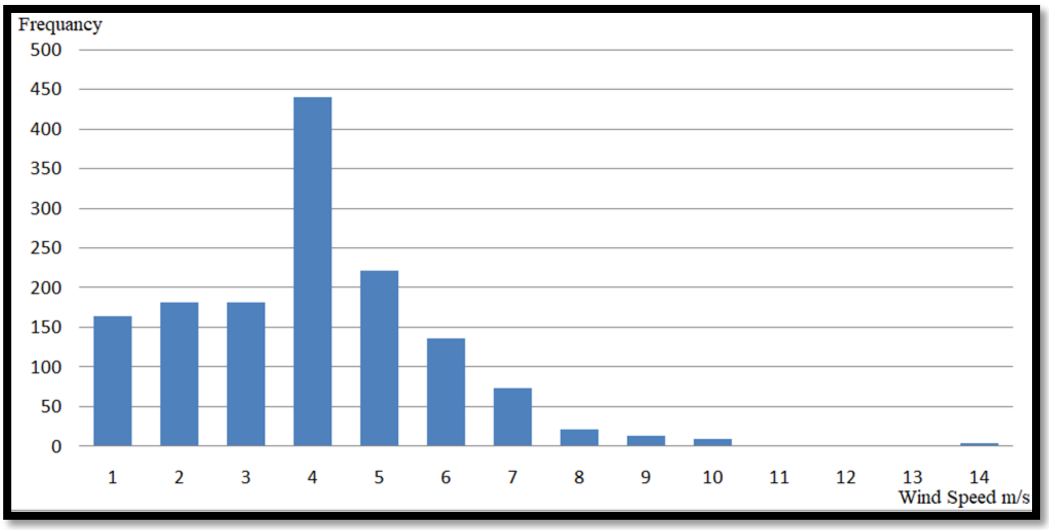

Figure 3. Frequency of actual MWS records from January 2012 to December 2015.

Figure 3 illustrates the frequency distribution of the actual MWS records of Ashqelon between January 2012 and December 2015. The bar graph is extremely close to the PDF of the wind speed data. More than 90% of the frequency lies between 1 and 7 m/s of wind speed for four years.

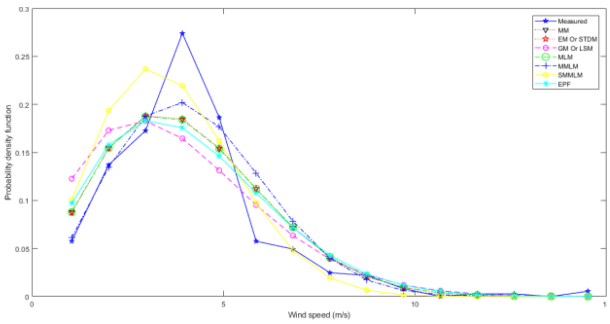

Figure 4. Comparison between observed and estimated PDF curves for Ashqelon in 2012.

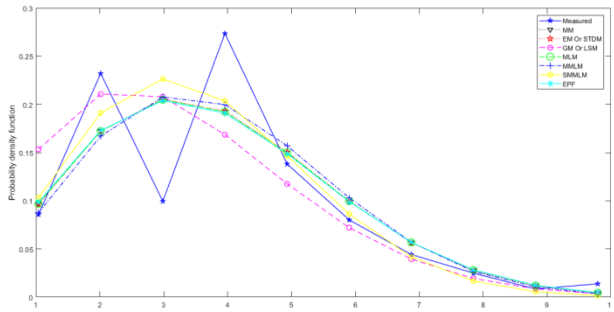

Figure 5. Comparison between observed and estimated PDF curves for Ashqelon in 2013.

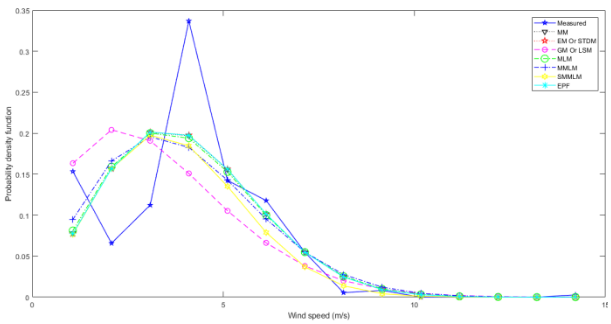

Figure 6. Comparison between observed and estimated PDF curves for Ashqelon in 2014.

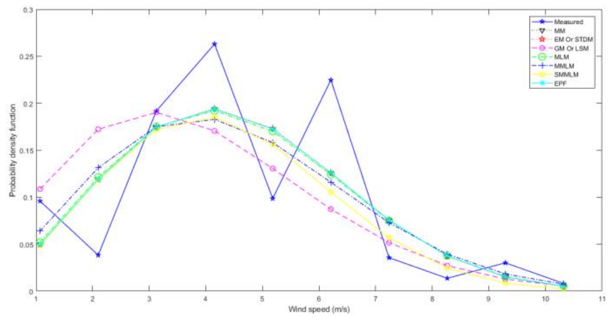

Figure 7. Comparison between observed and estimated PDF curves for Ashqelon in 2015.

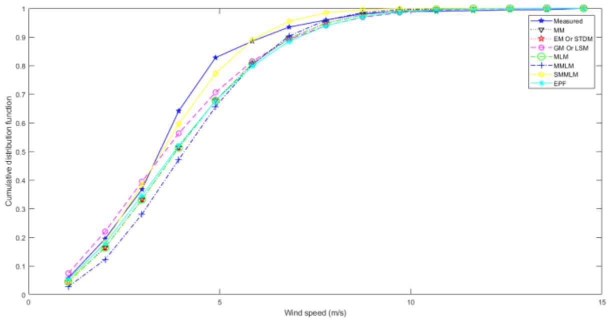

Figure 8. Comparison between observed and estimated CDF curves for Ashqelon in 2012.

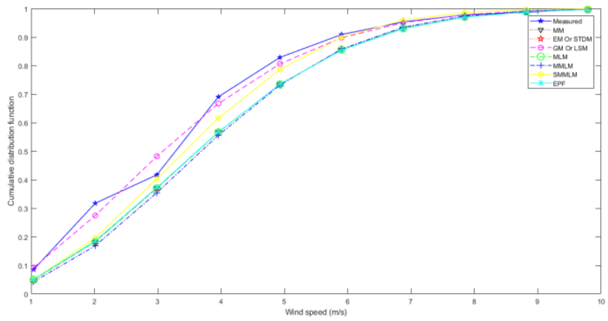

Figure 9. Comparison between observed and estimated CDF curves for Ashqelon in 2013.

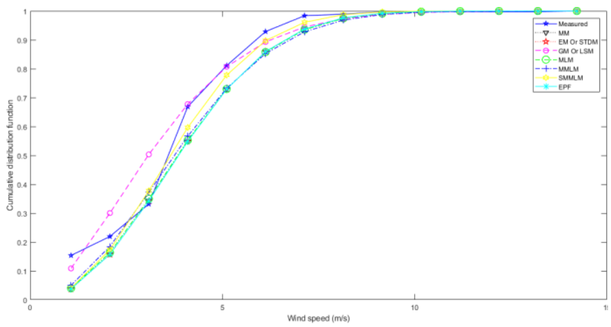

Figure 10. Comparison between observed and estimated CDF curves for Ashqelon in 2014.

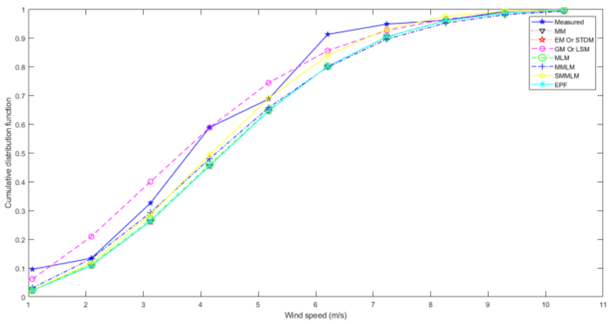

Figure 11. Comparison between observed and estimated CDF curves for Ashqelon in 2015.

Weibull analysis of the wind speed data plots of the CDF and PDF for the entire data and seasons (Figs. 4–7). The results demonstrate that all the wind profiles for these periods follow the same cumulative distribution pattern. Figures 3–7 present a comparison of theoretical PDFs with the observed wind speeds. The corresponding cumulative probability distributions are also plotted in Figures 8–11. The probability density distributions of the yearly wind speed records are obtained from the measured daily time series data of Ashqelon. The observed and theoretical curves of Weibull PDF for 2012, 2013, 2014 and 2015 are shown in Figures 4–7 using actual measured wind speed records. The theoretical estimated curves are plotted based on the data generated using the MM, EM, GM, MLM, MMLM, SMMLM and EPF.

On the basis of the Weibull distribution, it can be calculated several important quantities related to the wind characteristics in Ashqelon for a year. The observed and estimated CDF curves for 2012, 2013, 2014 and 2015 are shown in Figures 8–11 on the basis of the data generated using the MM, EM, GM, MLM, MMLM, SMMLM and EPF.

Table 2: Estimation of Weibull parameters, wind power and energy for maximum wind speed in 2012.

Years 2012	Estimated scale factor and shape factor using seven numerical methods for Ashqelon 2012				
	c(m/s)	k	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %
1. MM	4.5988	2.0608	4.0738	2.0729	50.8836
2. EM, STDM	4.5991	2.0725	4.0738	2.0624	50.6248
3. MLM	4.6053	2.0616	4.0795	2.0751	50.8663
4. MMLM	4.7555	2.3526	4.2142	1.9041	45.1831
5. SMMHM	4.1000	2.2322	3.6313	1.7198	47.3613
6. GM,LSM	4.3642	1.7848	3.8827	2.2492	57.9291
7. EPF	4.5946	1.9559	4.0738	2.1727	53.3336
Observed	4.6053	2.0616	4.0800	1.9873	51.1173

Table 2 presents the variations in the values of the Weibull shape and scale parameters, along with the standard deviations of the measured data and Weibull results for both site analyses in 2012. The shape parameter lies between 2.0608 and 2.2526, and the scale parameter is between 4.1000 and 4.7555 m/s. Different wind parameters reflect dissimilar wind turbine systems and energy potential. Estimating these parameters accurately for a particular time period is necessary in wind energy applications.

Table 3: Estimation of Weibull parameters, wind power and energy for maximum wind speed in 2013.

Years 2013		Estimated scale factor and shape factor using seven numerical methods for Ashqelon 2013				
		c(m/s)	k	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %
1.	MM	4.3076	2.0990	3.8152	1.9095	50.0496
2.	EM, STDM	4.3077	2.1105	3.8152	1.9002	49.8045
3.	MLM	4.3119	2.1006	3.8190	1.9101	50.0166
4.	MMLM	4.3513	2.1937	3.8536	1.8538	48.1071
5.	SMMLM	4.0403	2.1865	3.5781	1.7264	48.2480
6.	GM , LSM	3.7570	1.8225	3.3391	1.8981	56.8458
7.	EPF	4.3074	2.0834	3.8152	1.9224	50.3863
	Observed	4.3119	2.1006	3.8200	1.9179	50.2685

Table 3 shows that the scale and shape factors 4.3119 m/s and 2.1006 for MLM, are completely identical to the observed values in 2013. The standard deviation ranges from 1.7264 m/s to 1.9224 m/s, whereas the observed value is 1.9179 m/s.

Table 4: Estimation of Weibull parameters, wind power and energy for maximum wind speed in 2014.

Years 2014		Estimated scale factor and shape factor using seven numerical methods for Ashqelon 2014				
		c	k	MWS(m/s)	Standard divination σ(m/s)	Variation Coefficient %
1.	MM	4.5376	2.2464	4.0190	1.8927	47.0934
2.	EM, STDM	4.5374	2.2570	4.0190	1.8847	46.8951
3.	MLM	4.5231	2.2089	4.0058	1.9152	47.8094
4.	MMLM	4.4696	2.0668	3.9592	2.0093	50.7497
5.	SMMLM	4.2750	2.2924	3.7872	1.7514	46.2446
6.	GM , LSM	3.8086	1.6942	3.3990	2.0644	60.7359
7.	EPF	4.5375	2.2536	4.0190	1.8873	46.9588
	Observed	4.5231	2.2089	4.0200	1.8993	47.2570

Table 5: Estimation of Weibull parameters, wind power and energy for maximum wind speed in 2015.

2015		Estimated scale factor and shape factor using seven numerical methods for Ashqelon 2015				
		c	k	MWS (m/s)	Standard divination σ(m/s)	Variation Coefficient %
1.	MM	5.0981	2.4321	4.5205	1.9827	43.8593
2.	EM, STDM	5.0977	2.4414	4.5205	1.9759	43.7096
3.	MLM	5.0839	2.3990	4.5068	2.0010	44.3994
4.	MMLM	5.0234	2.2321	4.4491	2.1073	47.3645
5.	SMMLM	4.8565	2.4650	4.3075	1.8666	43.3344
6.	LSM, GM	4.4173	1.9389	3.9174	2.1057	53.7534
7.	EPF	5.0981	2.4315	4.5205	1.9831	43.8692
	Observed	5.0839	2.3990	4.5300	1.9873	43.9606

Tables from 2 to 5 indicate that k and c are nearly the same for the MM, STDM (EM), MLM and EPFM. The results of the MM, STDM (EM), MLM and EPFM are close and better than those of the other methods.

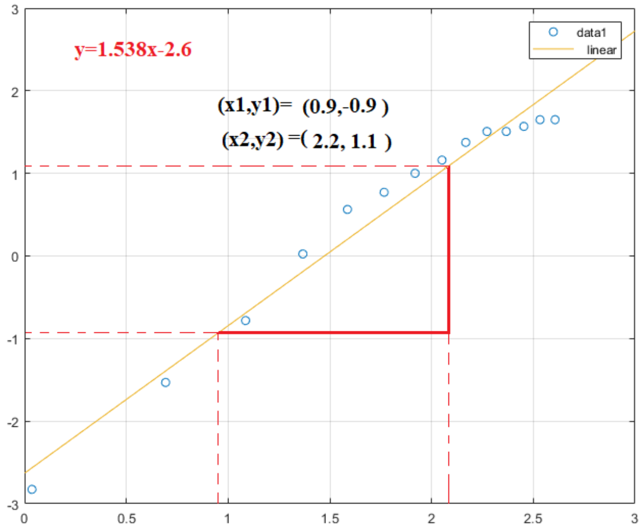

Figure 12. GM estimated results for Ashqelon in 2012.

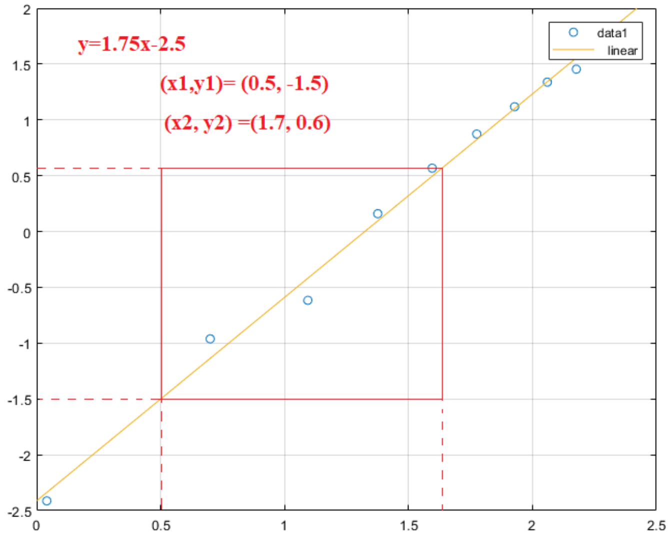

Figure 13. GM estimated results for Ashqelon in 2013.

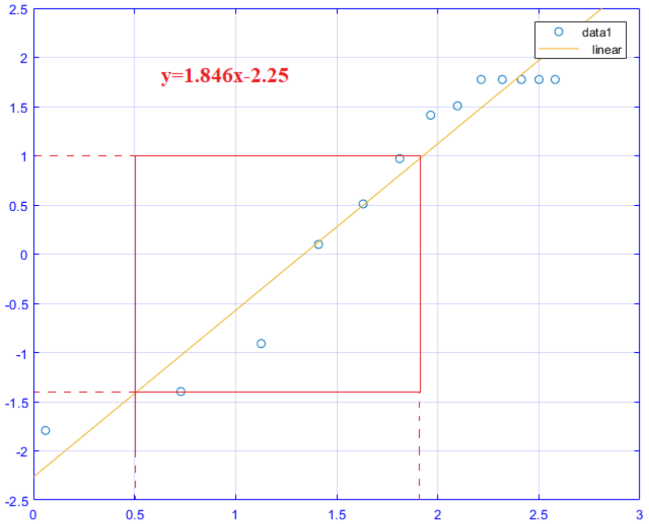

Figure 14. GM estimated results for Ashqelon in 2014.

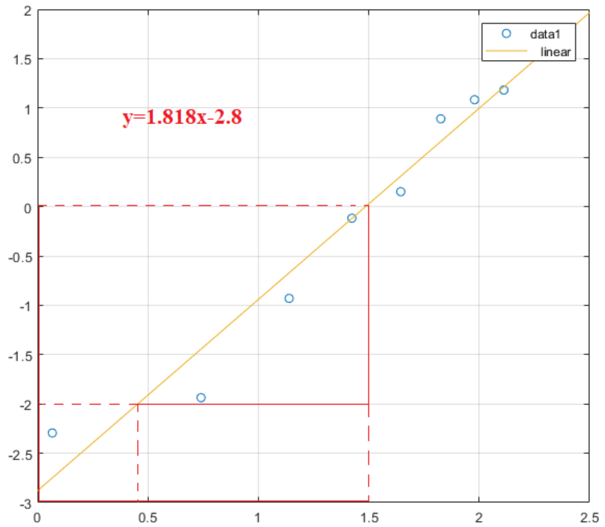

Figure 15. GM estimated results for Ashqelon in 2015.

Weibull parameters can be estimated using the GM of every year presented in Figures 12, 13, 14, and 15. The first step is to plot the natural logarithm of the observed speed versus ln(-ln(1-F(υ)). Then, it can be noted the Weibull parameters by linearly fitting the plotted points; here, k is the slope of the fitted line, and c is equal to exp(b/k), where b is the y-intercept of the fitted line.

Where,

$\ln(\boldsymbol{v})$as x axis versus $ln(-ln(1-F(v))$
$y = mx - b$
where $m = k, \quad b = k\ln(c)$

$$\ln(c) = \frac{b}{k}$$
$$c = e^{\frac{b}{k}}$$

Tables 6–9 show the statistical error analysis of the five statistical techniques.

Table 6: Error percentage for checking accurate numerical methods in 2012.

2012		Goodness of fit tests for Coastal plain Palestine- Ashqelon 2012									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0074	3	0.9780	4	0.7893	3	0.0196	3	11.1391	3
2	STDM,EM	0.0075	4	1.0926	5	0.7912	5	0.0194	2	11.2563	5
3	MLM	0.0074	3	0.9610	3	0.7895	4	0.0196	3	11.1577	4
4	MMLM	0.0089	5	13.5805	6	0.8316	6	0.0158	1	13.3614	6
5	SMMLM	0.0223	6	222.8923	7	0.7795	2	0.0215	5	33.3957	7
6	GM,LSM	0.0043	1	0.3073	1	0.7415	1	0.0239	6	6.4394	1
7	EPFM	0.0066	2	0.4346	2	0.7705	2	0.0212	4	9.9210	2

Table 6 shows that the GM (LSM) yields the greatest efficiency according to the RMSE, X^2, IA and RRMSE in 2012. It is followed by the EPFM, MLM, MM, and STDM (EM). The method with the worst efficiency reflected in the RMSE, X^2 and RRMSE is the SMMLM, followed by the MMLM.

Table 7: Error percentage for checking accurate numerical methods in 2013.

2013		Goodness of fit tests for Coastal plain Palestine 2013									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0053	3	0.1393	2	0.7229	4	0.0317	3	5.2971	5
2	STDM, EM	0.0054	4	0.1402	3	0.7239	5	0.0316	2	5.4297	4
3	MLM	0.0053	3	0.1393	2	0.7224	3	0.0318	4	5.3135	3
4	MMLM	0.0063	5	0.1493	4	0.7254	6	0.0317	3	6.2557	6
5	SMMLM	0.0071	6	0.2126	6	0.7509	7	0.0295	1	7.1193	7
6	GM, LSM	3.2001e-04	1	0.1916	5	0.7027	1	0.0352	5	0.3200	1
7	EPFM	0.0051	2	0.1383	1	0.7214	2	0.0318	4	5.1099	2

Table 7 shows that the GM (LSM) achieves the best efficiency according to the RMSE in 2013. It is followed by the EPFM, MM, MLM and EM (STDM). The MM, STDM (EM), and MLM showed approximately the same efficiency performance according to the RMSE, X^2, IA and MAPE in 2013. The SMMLM shows the worst efficiency performance according to the RMSE, X^2, IA and RRMSE.
The GM (LSM) and EPFM show the highest efficiencyfollowed by MLM and MM, whereas the SMMLM and MMLM show the lowest efficiency for the period of 2012–2013.

Table 8: Error percentage for checking accurate numerical methods in 2014.

2014		Goodness of fit tests for Coastal plain Palestine- 2014									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0046	2	1.9073	6	0.6761	5	0.0323	1	6.4148	3
2	STDM, EM	0.0045	1	2.1563	5	0.6764	6	0.0323	1	6.3530	1
3	MLM	0.0048	3	1.3660	3	0.6751	4	0.0324	2	6.6635	4
4	MMLM	0.0056	4	0.5520	1	0.6723	3	0.0325	3	7.8650	5

5	SMMLM	0.0304	6	22.2735	7	0.6501	2	0.0347	4	42.6080	7
6	GM, LSM	0.0117	5	0.5048	2	0.6119	1	0.0389	5	16.3687	6
7	EPFM	0.0046	2	2.0717	4	0.6764	6	0.0323	1	6.3728	2

In terms of the RMSE in 2014, the STDM (EM) exhibits the best efficiency performance, followed by the EPFM, MM and MLM(Table 8). The SMMLE shows the lowest efficiency performance according to the RRMSE, X^2 and RMSE.

Table 9: Error percentage for checking accurate numerical methods in 2015.

2015		Goodness of fit tests for Coastal plain Palestine- Ashqelon 2015									
Numerical methods		Comparative analysis									
		RMSE	Ranking	X^2	Ranking	IA	Ranking	MAPE	Ranking	RRMSE	Ranking
1	MM	0.0098	2	0.2858	2	0.5991	3	0.0468	5	9.7861	2
2	STDM,EM	0.0097	1	0.2867	4	0.5997	4	0.0468	5	9.7396	1
3	MLM	0.0099	3	0.2838	1	0.5987	2	0.0467	4	9.9406	4
4	MMLM	0.0110	4	0.2863	3	0.5948	1	0.0466	3	11.0351	5
5	SMMLM	0.0384	6	0.3746	5	0.6035	5	0.0462	2	38.4354	7
6	GM,LSM	0.0137	5	0.4159	6	0.6040	6	0.0460	1	13.6533	6
7	EPFM	0.0098	2	0.2858	2	0.5991	3	0.0468	5	9.7892	3

Table 9 shows that in terms of the RMSE in 2015, the STDM (EM) presents the highest efficiency performance, followed by the EPFM, MM and MLM. By contrast, the SMMLE shows the lowest efficiency performance. Between 2014 and 2015, the EM or STDM shows the best efficiency performance, followed by the EPFM, MM and MLM.

8. CONCLUSION

This study presents a first step in determining the feasibility of installing wind turbines in Palestine. Thus, statistically analyses of wind speed data for a period of four years obtained using Weibull probability distribution. The analysis is aimed at estimating the wind energy potential in the Mediterranean coast of Palestine. MWS and coefficient of variation, along with Weibull PDF and CDF are obtained. The parameters of Weibull had been calculated theoretically using the MM, STDM (EM), MLM, MMLM, SMMLM, GM (LSM) and EPFM. Five statistical tools are employed by the author to calculate the percentage error (goodness-of-fit tests) for the seven numerical techniques to check the efficiency performance for each method. GM (LSM) shows the best efficiency performance in the assessment of the low wind speed data, but it is not suitable when high wind speed. On the contrary, the STDM (EM) is applicable for high wind speed data, on the contrary of STDM (EM). The EPFM is applicable to the assessment of any wind speed data and shows the greatest accuracy performance through the years followed by MM and MLM. The SMMLM presents the worst prediction performance followed by MMLM according to all statistical techniques. Among the five statistical tools, RMSE is the most accurately predicted technique. By contrast, the worst predicted technique is RRMSE.

ACKNOWLEDGEMENTS

This research has been supported by the research grant no. RIGS16-041-0104 from the Malaysia Ministry of Higher Education in accordance with the Research Initiative Grant Scheme.

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