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Research paper

A comparative study of five numerical methods for the estimation of Weibull parameters for wind energy evaluation at Eastern Jerusalem, Palestine

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ABSTRACT

Wind power provides a clean and feasible solution to generate electricity. The development of wind power applications requires a deep analysis of wind profiles and an accurate prediction of wind energy at a study site. This work explores the distribution of wind speed to estimate the two Weibull parameters (shape and scale) that are widely utilized for modeling and providing an accurate and efficient estimation of wind resource and power. These two parameters are calculated based on measured daily wind speed data from 2008 to 2018, collected in Jerusalem, Palestine. Three assessment criteria were used to assess the goodness of fit; they are Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and chi-square. The findings revealed that of the five estimation methods being considered in this study, both the Empirical Method (EM) and the Method of Moment (MoM) were the most accurate in determining the values of the Weibull shape and scale parameters to approximate wind speed distribution at the study site. Based on the goodness-of-fit tests, both methods provide lower values of the used assessment criteria. The statistical performance tests rejected the Energy Pattern Factor Method (EPFM) as an adequate method due to the higher values of chi-square and revealed that the Maximum Likelihood (MLM) and the Modified Maximum Likelihood (MMLM) methods ranked third and fourth, respectively.

1. Introduction

Palestine has an insecure energy sector due its unstable political and economic conditions, as well as the lack of energy progress. It is fully dependent on nearby countries to cover its fossil fuel needs and more than two-thirds of its electricity consumption (Alsamamra and Shoqeir, 2020). The high density of population growth and rapid industry development resulted in a huge demand of energy leading to an unrealistic price control of energy in Palestine (Kitaneh et al., 2012). Recently, the Palestinian authority has taken many steps to reduce the dependence of energy consumption taken from other nearby countries and lunched many initiatives in the investment of renewable energy mainly in solar and wind energies, as well as the adoption of policies that aim to increase the use of sustainable energy resources.

Among the sustainable energy sources, wind energy is among the top fast-growing technologies in terms of the percentage of annual growth of the total installed capacity (Alsamamra and Shoqeir, 2020). The global wind energy council report presents that the electricity generating capacity worldwide from a wind power system was 793 GW in 2021 with an increment of 93 GW compared with the year 2020 (Global Wind Energy Council (GWEC), 2021). As a random phenomenon, wind speed plays an important rule in characterizing wind power generation (Waliu et al., 2018). The assessment of a potential wind energy requires a deep analysis of the wind speed data gathered from a metrological station being installed in the same geographical coordinates to get the optimal estimation accuracy (Resen et al., 2019; Faleh et al., 2020). However, wind resources induce high variations in speed measurements due to several factors: time period, height of the metrological station, and type of terrain, among other factors. Hence, wind speed data should be carefully examined and analyzed (Rehman et al., 1994).

Wind resources assessment has been received only a little attention in the Palestinian territories with a few works reported in the literature. Reliable and accurate estimations of wind resources are necessary for wind energy industry in delivering energy-based solutions through installing small to medium scale

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List of abbreviations

CDF	Cumulative Distribution Function
EM	Empirical Method
EPFM	Energy Pattern Factor Method
MAPE	Mean Absolute Percentage Error
MLM	Maximum Likelihood Method
MMLM	Modified Maximum Likelihood Method
MoM	Method of Moment
PDF	Probability Density Function
RMSE	Root Mean Square Error
SD	Standard Deviation

wind energy conversion systems (Basel and Yaseen, 2007). Wind presence and behavior are 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 (Azad et al., 2014; Habali et al., 2001).

In the last few years, the activity of research in studying the wind speed distribution and modeling its nature has been significantly increased and aimed at the development of suitable prediction models to describe the frequency distribution characteristics of the wind speed. Statistical models were preferred and employed for the prediction of wind speed distribution (Kitaneh et al., 2012; Rehman et al., 1994; Fadare, 2008; Chang, 2011), these models give detailed information about the local probabilities that could occur at a given site (Persaud et al., 1999). To this task, the choice of a suitable probability distribution function plays a vital role in obtaining long-term benefits of wind speed profiles. 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 (Drobinski et al., 2015; Mostafaeipour et al., 2014; Baseer et al., 2015).

The most widely used mathematical function that provides the optimal fit of characterizing wind speed profiles is the Weibull distribution function. It can parameterize the distribution of the wind resources to find the best fits, but the estimation process itself gets more complicated, especially with high diversity in wind speed distribution (Ali et al., 2018; Kang and Huh, 2018; Bingol, 2020). Various probability functions were coupled with the wind speed data to find the appropriate statistical distribution that perfectly represents the wind regime. Researchers concluded that the level of accuracy of the Weibull Probability Density Function (PDF) is acceptable, and thus it can be applied to describe the wind variations in a specific wind regime (Sadullayeva et al., 2019; Gungor et al., 2020), and it can provide a real representation of the actual wind frequency distribution for different altitudes above the ground level (Choi and Wette, 1969). As a result, exploring the statistical properties of wind speed is vital for estimating the energy production. For the statistical distribution of the wind speed data analysis, the Weibull PDF is typically considered due to its implementation simplicity and high accuracy (Celik, 2003).

The two main parameters used by the Weibull PDF to describe the daily average wind speed with an acceptable accuracy (Kitaneh et al., 2012; Azad et al., 2014; Jowder, 2009) are the dimensionless shape parameter (k) and the scale parameter (c) in units of m/s, which show accurate and valid probabilistic model for wind speed at a specific geographical area (Carta and Ramírez, 2007). Extensive research work in the literature has been done to estimate k and c parameters of the Weibull PDF in many different locations in the world (Serbana et al., 2020). Moreover, various methods have been effectively tested in this regard (Zhang et al., 2018), as well as the suitability of each method according to the sample wind data distribution and the location of the metrological station. Justus et al. (1978) suggested the Empirical Method (EM) to calculate the Weibull parameters based on data average and Standard Deviation (SD). Stevens and Smulders (1979) proposed the Maximum Likelihood Method (MLM) that uses numerical iterative mechanisms to estimate the two Weibull parameters. Deaves and Lines (1997) presented the graphical method which applies a linear least-squares regression to find the best estimated values of the Weibull parameters. Akdag and Dinler (2009) proposed another method called the Energy Pattern Factor Method (EPFM) to estimate the available wind power density of a study site by considering the wind speed variation.

Also, several comparative studies among the Weibull parameters estimation methods were conducted using the statistical analysis. For example, Seguro and Lambert (2000) made a comparative study between the MLM, the Modified Maximum Likelihood Method (MMLM), and the graphical method to estimate the Weibull parameters using sample wind speed and made a comparison among them. Mohammadi et al. (2016) analyzed the wind speed data in a study site located in Canada to calculate the most appropriate estimation method of the Weibull parameters. They compared five methods: EM, GM, MLM, MMLM, and EPFM. The EPFM and EM were very favorable while the graphical method was shown to be the worst. Similarly, Shabana et al. (2020) analyzed six methods for estimating the Weibull parameters: SD, MLM, ML using modified iterative method, ML using iterative method, EPFM, and equivalent energy method. They used four statistical indicators to assess the method's accuracy. The experimental results have shown that the equivalent energy method outperforms the others with the highest estimation accuracy.

Bingöl (2020) used wind speed data gathered from a meteorological mast located at a height of 101 m above the sea level to compare several Weibull estimation methods. The results have shown that the MLM provides better estimation, especially with a high diversity in wind speed. Kaplan (2022) examined the performance of six estimation methods applied to estimate the coefficients of the Weibull distribution function to determine the best-performing method in a study site located in Adana region in Turkey. The Root Mean Square Error (RMSE) was used as statistical indicator to compare the accuracy of the six methods. The obtained results have shown that all the methods give an acceptable performance with minor variations in the considered time period.

In the present work, we aimed to explore wind speed distribution to select the optimal values of k and c using Weibull methods that can provide efficient wind speed estimation for energy considerations in Eastern Jerusalem, Palestine. Five common numerical methods were studied to select the optimal values of k and c, they are: EM, MoM, EPFM, MLM, and MMLM. These five methods are explored to test their suitability for Eastern Jerusalem, Palestine.

The importance of this work comes from the limited energy sources in the region, since Palestine depends mainly on three sources (Egypt, Jordan, and Israel) to cover the energy demand. The Palestinian Government has begun to stimulate the investment in renewable energy projects and in order to invest safely in renewable energy, it is necessary to carry out analytical studies and modeling of renewable energy resources including winds. Despite the availability of other related studies worldwide, the literature emphasized that wind estimation and modeling are site dependent. This means that a proper estimation of the Weibull parameters at one site might not be suitable for other sites. Also, depending on the previous studies, the presented work is

Table 1
The study area's geographical coordinates.

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

considered the first study in the Eastern Jerusalem that analyzes long-term wind data. This analysis approximately elucidates the wind status in the region and provides strong benchmark for those who invest in wind energy in the region.

2. Materials and methods

In this section, we first provide some exploratory analysis about the wind speed dataset used in this study. Next, we discuss the five estimation methods experimented in this work: EM, MoM, EPFM, MLM, and MMLM. We end this section by discussing the process of evaluating the performance of the five Weibull methods using three assessment indicators: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and chi-square (χ^2).

2.1. Wind speed data

The hourly values of wind speed data were provided by the Palestinian meteorological stations network for the time period between 2008 to 2018 (11 years). The wind speed data were measured continuously at a height of 20 meters by a rotating cup generator anemometer with an accuracy of (3.0%), and the calibration was done using a linear regression uncertainty with a percentage of (0.2% to 5.0%). The raw dataset consisted of (32,131) records. During the preprocessing steps, we have found out that a very few records (120) having zero wind speed values, which is around (0.03%) of all the available data records. To ease the process of evaluating the five estimation methods and to avoid the miss representation of zero values by the Weibull distribution, these records were filtered out form the dataset before applying the estimation methods. The remaining observed wind speed values were analyzed to estimate the Weibull parameters in order to develop the Weibull distribution model which fits with the considered site. Table 1 shows the meteorological station coordinates considered in this study.

2.2. Measured wind speed and standard deviation

The monthly average wind speed data and the SD of the measured daily wind speed values are calculated according to the following equations (Eqs. (1) & (2), respectively) (Petkovic et al., 2014a).

$$v_m = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{1}$$

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

where v_m is the average wind speed (m/s), σ is the SD of the measured values (m/s), and N is the number of wind speed records.

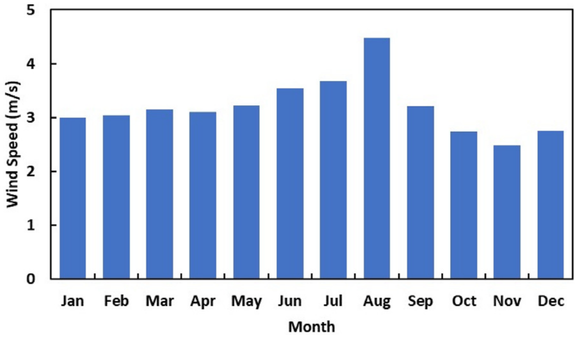


Fig. 1. Average monthly measured wind speed data.

2.3. Measured wind speed probability distributions and its frequency format

The frequency distribution of the observed wind speed data was determined and presented in Table 2 by dividing the wind speed values into a set of regular class intervals of the same width (1 m/s) (Kidmo et al., 2015), then time-series wind speed data were converted into their frequency format based on the class intervals.

To obtain the Weibull PDF for the whole year; as presented in Table 3, the measured wind speed values are arranged in equal width of 1 m/s frequency and in a cumulative format. Then, mean wind speed (v_i) is calculated for each class interval where f_i is the frequency of occurrence of each interval. The probability of the observed wind speed and its SD are also calculated according to Eqs. (3) and (4), respectively.

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

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

Fig. 1 presents the average monthly wind speed values. Referring to this figure, the highest values of wind speed are found in summer months where August is the highest, while the lowest values are observed in November for the whole dataset. Moreover, Fig. 1 agrees with the analysis obtained from Table 3 where the highest frequency distribution occurred in the intervals [2–3] and [3–4] m/s, with 1289 and 1497 records, respectively. In addition to that, the small values of wind speed are more feasible for installing small wind turbines at the study site. As Fig. 2 illustrates, the cumulative frequency distribution, which determines the frequency of wind speed classes up a certain threshold, shows that more that 80% of the wind speed classes are lower than 4 m/s.

2.4. Methods to estimate Weibull parameters

Numerous studies in the scientific literature have been conducted to obtain accurate representative models to characterize wind speed data (Zhang et al., 2018; Kidmo et al., 2015). They provide a convenient representation of the potential wind energy in order to assess the economic feasibility of a wind farm in producing energy (Azad and Alam, 2012). Thus, it is essential to determine how closely the estimated data from the Weibull distribution matches with the data gathered from the actual wind speed distribution (Bhattacharya and Bhattacharjee, 2009). Nevertheless, it was found that the two Weibull PDF parameters are the most appropriate to describe the frequency of the wind

Table 2
Calculated average wind speed (νi) for each class interval.

Month	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	–
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
Measured monthly wind speed value in frequency format and monthly mean value (ν_m).

i	v	ν_i	Fi	Month	ν_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

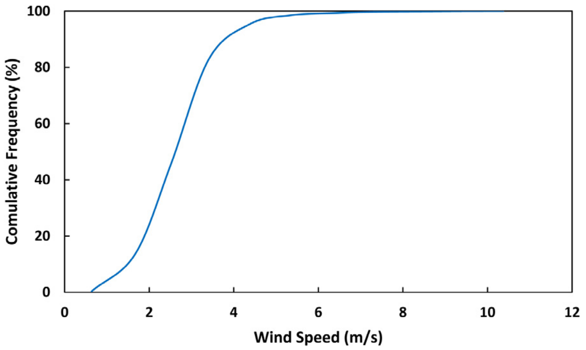


Fig. 2. Cumulative frequency distribution of the wind speed derived from the measured data.

speed and to estimate the wind power density distribution function (Kidmo et al., 2015; Arslan et al., 2014). However, the Weibull distribution has some limitations in describing real scenarios when wind speed is zero (calm), the calm hours in the dataset was found to be less than (0.3%), and they were removed from the analysis (Drobinski et al., 2015; Shu and Jesson, 2021)

The mathematical form of the Weibull function is characterized by its PDF $f(\nu)$ and Cumulative Distribution Function (CDF) $F(\nu)$ (Kitaneh et al., 2012; Baseer et al., 2015). They are calculated following Eqs. (5) and (6), respectively (Choi and Wette, 1969; Celik, 2003; Bagiorgas et al., 2011).

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

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

where $F(\nu)$ is the probability of observing wind speed; ν is the wind speed in units of (m/s); c is the Weibull scale parameter in units of (m/s); and k is the Weibull shape parameter. The scale parameter describes the abscissa scale on a plot of the distribution, whereas the shape parameter describes the shape of the distribution.

To compute the Weibull PDF and its two parameters (k and c), wind speed data were experimented using five numerical methods. A brief overview of each method is given below.

2.4.1. Maximum likelihood method (MLM)

The MLM is a mathematical-based expression being known as a likelihood function of wind speed data presented in time-series format, and it is widely utilized in the literature to estimate the Weibull parameters (Manwell et al., 2002). This method considers the maximization of likelihood function, which is mainly used in statistics to estimate probability distribution parameters by assuming that the best value of any parameter is the one that gives the maximum value of likelihood function (Ombeni, 2020; Chaurasiya et al., 2018). In order to determine the Weibull distribution parameters, the MLM method is solved using numerical iterations. Both Weibull PDF parameters (k and c) are estimated according to Eqs. (7) and (8), respectively (Ali et al., 2018; Arslan et al., 2014; Shu and Jesson, 2021):

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

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

where n is the number of nonzero 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)

The MMLM method is based on wind speed frequency which is developed from the MLM to deal with wind data arranged in bins format (Sumair et al., 2020). The MMLM is also solved using numerical iterations to find the optimal values of k and c (Maatallah et al., 2013), which are calculated using Eqs. (9) and (10), respectively (Rajabi and Modarres, 2008).

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

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

where $f(v_i)$ is the Weibull frequency of wind speed in interval i, and $f(v \geq 0)$ is the probability of wind speed for $v \geq 0$.

2.4.3. Method of moment (MoM)

The Weibull parameters of the MoM method are calculated from the average wind speed and the SD of the wind data. The scale parameter is given by Eq. (11) (Carta et al., 2009).

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

And the SD of the measured data is calculated using Eq. (12).

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

where the standard gamma function is given by Eq. (13).

$$\Gamma\,(\mathrm{x}) = \int_{0}^{\infty} t^{x-1}\exp\left(-t\right)dt \tag{13}$$

By using numerical iterations (Sumair et al., 2021), the MoM method can be solved to obtain k and c parameters from Eqs. (11) and (12), respectively.

2.4.4. Energy pattern factor method (EPFM)

The EPFM determines the Weibull parameters following an informal strategy that relies on the ratio of the wind power energy to the third power of the average wind speed values (Kang et al., 2021). Eq. (14) presents the mathematical formula of the EPFM (Basumatary et al., 2005; Justus and Mikhail, 1976).

$$EpfM = \frac{\left(v^{3}\right)_{m}}{\left(v_{m}\right)^{3}} = \frac{\left(\frac{1}{n}\sum_{i=1}^{n} v_{i}^{3}\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} v_{i}\right)^{3}} \tag{14}$$

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

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

2.4.5. empirical method (EM)

The EM method is considered as a special case of the MoM which is applicable when the average wind speed and the SD of wind speed values are calculated. The Weibull shape parameter can be calculated by Eq. (16), while the scale parameter can be obtained by substituting k values- obtained from Eq. (16) - in Eq. (11) (Petkovic et al., 2014b).

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

2.5. Evaluation procedure

To assess the performance of the aforementioned five Weibull methods, a statistical comparison is performed using three performance indicators: RMSE, MAPE and chi-square test (χ^2), which are computed following Eqs. (17), (18), and (19), respectively (Indhumathy et al., 2014; Kollu et al., 2012).

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

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

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\left(v_{i}-v_{w}\right)}{v_{i}}\right| \times 100\% \tag{18}$$

$$\chi^{2} = \sum_{i=1}^{n}\frac{\left(v_{i}-v_{w}\right)^{2}}{v_{w}} \tag{19}$$

These three assessment methods provide different information regarding the reliability of the considered methods. The RMSE provides statistical error measurements on a short-term performance since it follows a term by term comparison of the actual deviation between both estimated and observed values (Gualtieri and Secci, 2012), and successful estimations correspond to lower values of the RMSE (Lun and Lam, 2000). The MAPE provides statistical information on the long-term performance of the studied methods, it is a measure of accuracy in estimating the values when there exists 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 the MAPE is to show whether the wind speed data is stable by means of a small variation.

The chi-squared (χ^2) test is used to determine if there exists any difference between the estimated and observed frequencies, lower values of χ^2 provide a goodness of fit. The method that generates the best results is determined by considering a low value for χ^2 in each case, since χ^2 should be as close to zero as possible (Weisser, 2003).

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

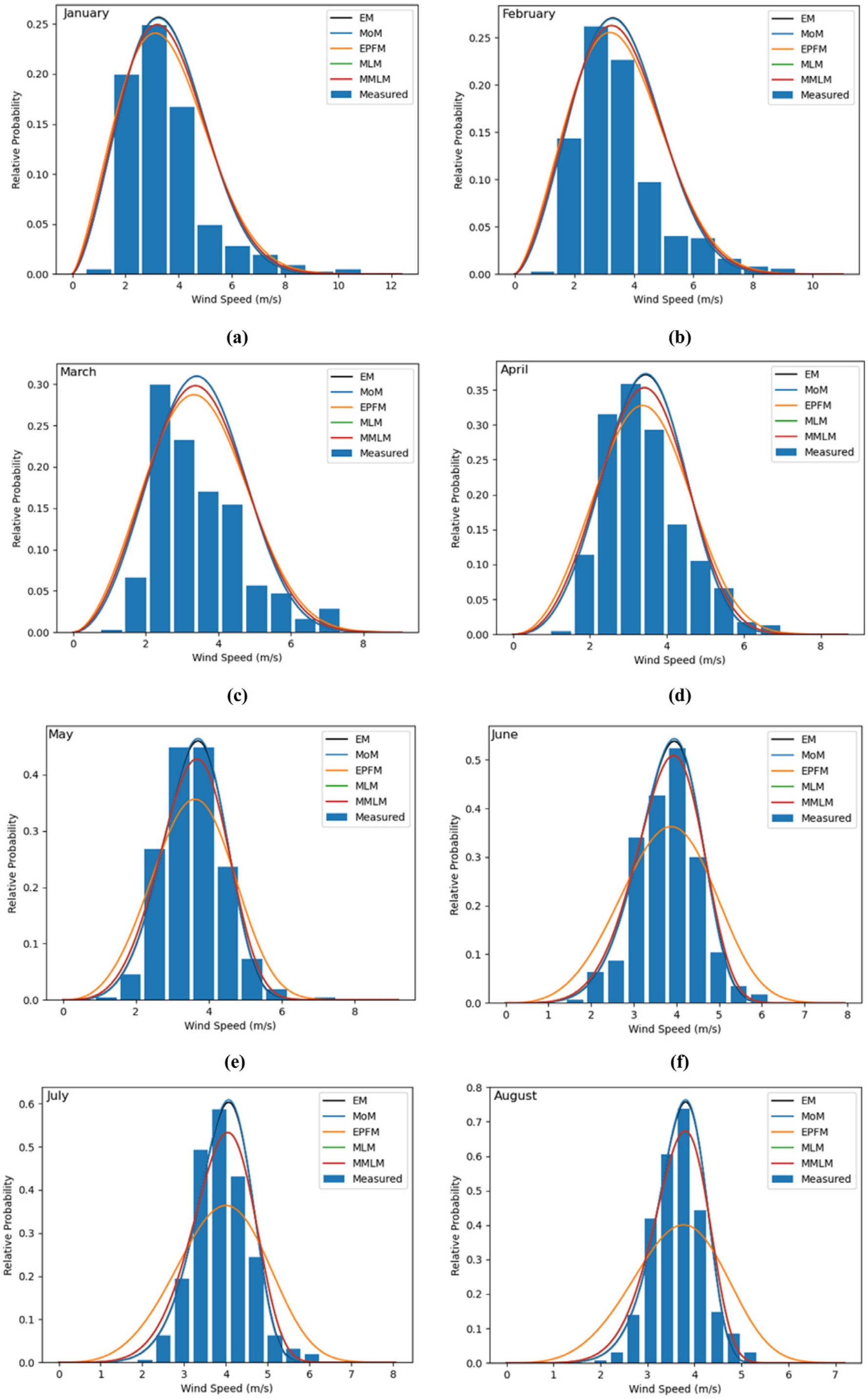
3. Results and discussion

The Weibull PDF parameters were experimentally computed from the five numerical methods under consideration (EM, MoM, EPFM, MLM, MMLM). Subplots of Fig. 3(a–m, l) 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 curve 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, it is clearly shown the effectiveness of the model, however, the estimation of the EPFM in May to October as well as the whole year provides poor representation of the higher values of the relative probability. It is clear that both the EM and MoM methods give the best representation in all months.

Table 4 provides k and c parameters of each numerical method extracted for each month and the whole year, as well as 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 results obtained in Fig. 3. Higher and very close values of the shape parameter were obtained from the EM and MoM methods. The k values of the MLM and the MMLM methods are very close and moderate compared to the other methods. A significant difference of the c values of the EPFM method is observed for May to October, it was found to be the highest value compared to the other methods. These results clarify that the EPFM did not fit very well to represent wind speed data in summer months for this study site. It was found that no significant difference in the c values for November to April, the values obtained by the five methods are very close for each month. For the whole year, the EPFM shape parameter value is the lowest and the scale parameter value is the highest among the other methods.

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

The best estimation of the Weibull parameters of the wind speed helps in getting the optimal performance of any 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

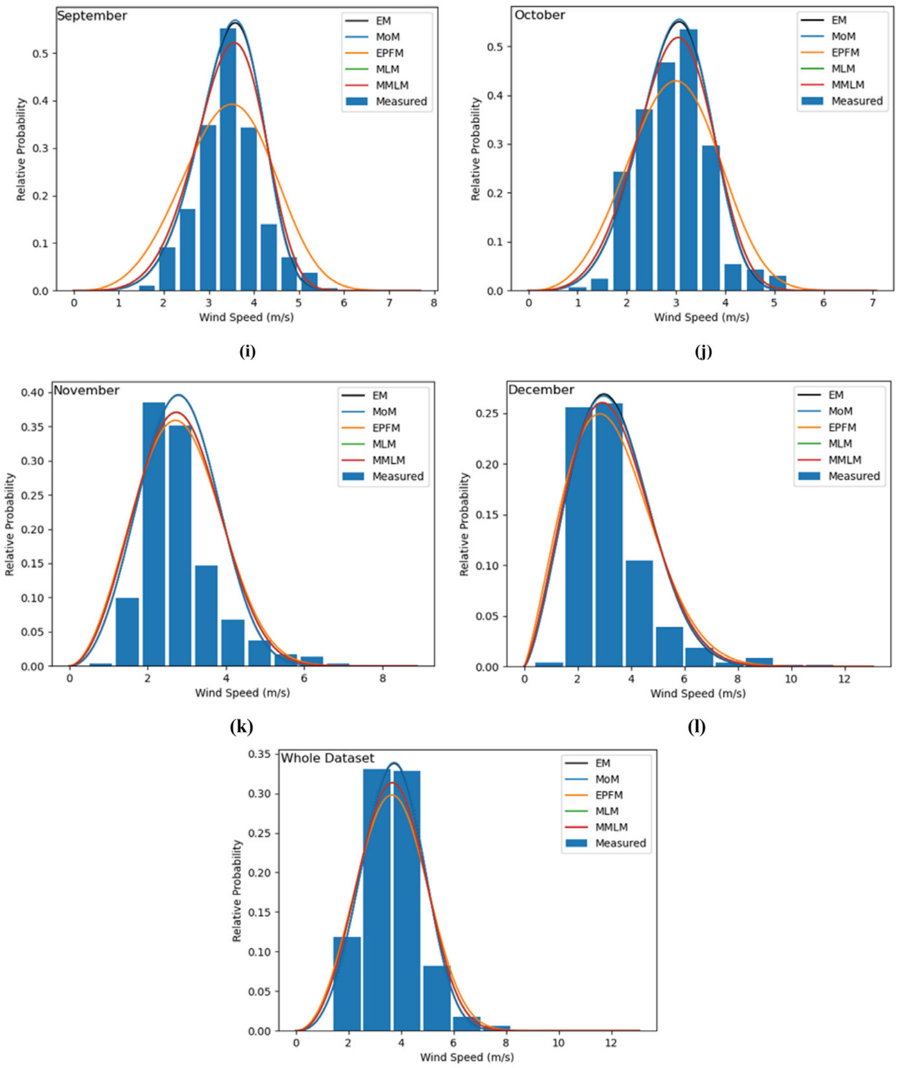


(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 3. Plot of the PDFs generated by the five methods for estimating the Weibull parameters against measured wind speed as histogram.

of k represent high wind speed variations, while higher values represent low wind speed variations. In order to provide a month by month comparison, in Fig. 4, 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 speed in summer months. The highest value of k was found in August for the EM and the 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 which is extracted from the EPFM method. Also, the results indicate 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. 5 shows the 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 both the EM and the EPFM methods, respectively. A small



(i) (j)

(k) (l)

(m)

Fig. 3. (*continued*).

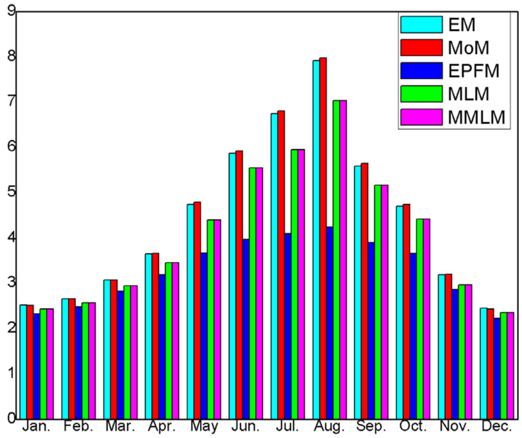


Fig. 4. A plot of the shape parameter of the Weibull distribution obtained by the five methods for each month.

significance was found in June and July with small increment of k values compared to the other months, whereas the lowest value of c parameter was found in October and November. In general, the results show that the EPFM method provides the 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.

For more insights, Fig. 6 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 a significant difference in summer months (June to October) as compared to the corresponding values of the other methods. Moreover, the EM and the MoM methods show 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. The MLM and MMLM present moderate values of chi-square (> 0.1) from November to May.

4. Conclusion

The estimation of the Weibull distribution parameters plays a vital role in renewable wind energy development. Five different Weibull estimation methods have been evaluated in this

Table 4
Assessment accuracy of the Weibull PDF methods.

Month	Num. method	Weibull parameters		Performance tests		
		Shape k	Scale c	RMSE	MAPE	χ^2
January	EM	2.523473	3.96306	0.338027	1.695269	0.166511
	MoM	2.513514	3.963461	0.338267	1.705121	0.167077
	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
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
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
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
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
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
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
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
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
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
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
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
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

study. For this purpose, eleven years of daily wind speed data (2008–2018) at Eastern Jerusalem have been studied. The selected methods are EM, MoM, EPFM, MLM and MMLM. The results reveal that the EPFM does not yield acceptable adjustment errors of the distribution histogram of wind speeds, whereas the EM and the MoM are the best estimated methods for getting accurate and

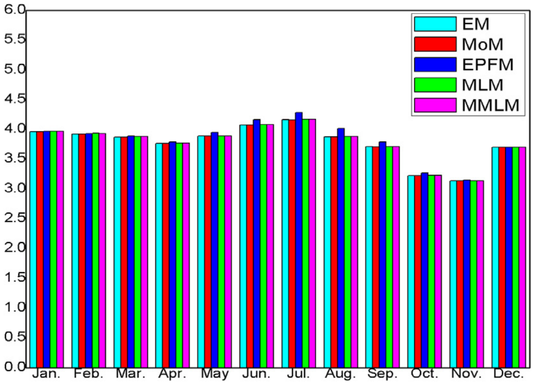


Fig. 5. Plot of the scale parameter of the Weibull distribution obtained by the five methods for each month.

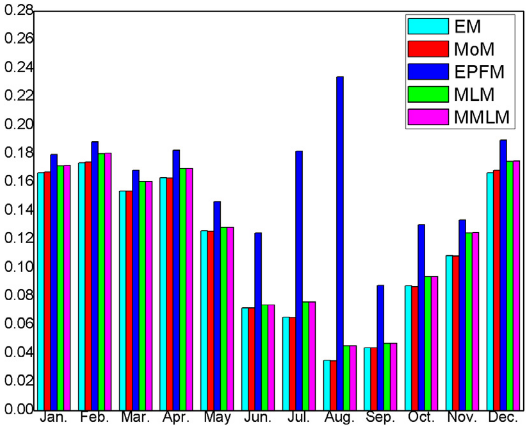


Fig. 6. Plot of the chi-square of the Weibull distribution obtained by the five methods for each month.

reliable results in estimating the Weibull parameters in the study site. This is due to the fact that both the EM and the MoM depend on the SD of the wind speed data. These findings are similar to studies done by other researchers at higher altitudes. For future work, an extension to other locations in the Palestinian territories will be conducted with employing other statistical models to improve the goodness-of-fit of the wind speed distribution function. Another research line is to study the wind power density to analyze the average annual wind power available per square meter of the study site.

CRediT authorship contribution statement

Husain R. Alsamamra: Witting the first draft, Methodology, Analysis, Results and discussion. **Saeed Salah:** Methodology, Programing, Discussions, Reviewing. **Jawad A.H. Shoqeir:** Resources, Writing – reviewing & editing. **Ali J. Manasra:** Data analysis, Editing, Discussion.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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