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ORIGINAL PAPER

Statistical analysis of wind energy potential using different estimation methods for Weibull parameters: a case study

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Abstract

Accurate estimation of wind speed distributions is a challenging task in wind power planning and operation. The selection of convenient functions for describing wind speed distribution is a crucial requisite. In this paper, remarkable bi-parameter Weibull function is presented to estimate the wind energy potential. Weibull parameters based on different six estimation methods, namely graphical, method of moment, energy pattern factor, mean standard deviation, power density methods, and genetic algorithm are evaluated. Besides, the goodness of fit of the estimation methods is investigated via mean absolute error, root mean square error, normalized mean absolute error, Chi-square error, and regression coefficient. To plainly identify the best matching estimation method, Net Fitness test is also presented. Catalca in the Marmara region in Istanbul, Republic of Turkey, is selected to be the underlying site. The experimental results show the effectiveness of the estimation methods in modeling wind distribution but with relatively small differences in terms of performance. However, the genetic algorithm and energy pattern factor accomplish the best and worst matching estimation methods, respectively.

Keywords Wind energy · Weibull distribution · Probability distribution function (PDF) · Cumulative distribution function (CDF) · Shape parameter · Scale parameter

1 Introduction

In ancient times, wind energy was used in windmills and water extraction; these days, the wind is exploited to produce clean energy and reduce the dependency on fossil fuels which have destructive effects on the environment as one of the most contributing causes of global warming. Due to the significant increase in energy demand and shortage of fossil fuels, the governments and the stakeholders have to search for alternative and renewable energy sources such as hydroelectric, biomass, wind, and solar energies. In the last few decades, wind energy occupied a privileged position and achieved a rapid growing among the different renewable sources. Wind energy technology continuously has been developed, which has led to its cost-effectiveness and high efficiency. Total global installed wind power capacity reached about 650 GW by the end of 2019 [1,2].

Hundreds of studies have been presented to analyze the wind potential and the feasibility of a considerable number of sites worldwide. Since the last decade, Turkey is one of the countries that has been trying to exploit wind energy, and this can be noticed by the gradual increasing of the installed capacity. For instance, an amount of 687 MW of wind power was installed during 2019 which raised the total of wind capacity in Turkey to 8056 MW [3]. Ozerdem et al. [4] presented the feasibility of wind farms in Izmir, and the study showed that Izmir is feasible for wind farms due to high wind potential and the generating cost was found to be about 2.68 US cent/kWh. Furthermore, Guseinoviene et al. introduced an analysis based on Weibull and Wavelet functions to estimate the wind speed in Mardin city and the mean wind speed was found to be 3.38 m/s at 10 m height [5]. Weibull distribution and the continuous Wavelet transform were compared, and the estimation via continuous Wavelet transform provided the optimal estimation.

In the study [6], two-parameter Weibull function based on Energy Pattern Factor (EPF), Graphical Method (GM), Method of Moments (MOM), and Mean Standard Devia-

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tion (MSD) methods was presented to assess the Weibull shape parameter (k) and the scale parameter (c) at different four locations in the north of Ethiopia. The results showed that GM introduced the best matching while EPF, MOM, and MSD introduced the worst matching. Besides, it was found that GM based on the cross-checks, energy potential, and cumulative distribution function (CDF) provided the best fitness of Weibull function. Sohoni et al. presented a comparative study of four sites for wind power assessment based on three distribution functions: Weibull, Rayleigh, and Gamma [7]. The study showed the best fitting with Weibull for the sites that have moderate mean speed, while Gamma for high and low mean wind speed sites. Furthermore, the less-skewed wind speed data were the best fitted by Weibull function, while highly skewed wind speed data were the best fitted by Gamma function. On the one hand, Rayleigh function was not suitable for any of the studied sites.

Seven methods, namely, GM, MOM, STD, maximum likelihood (ML), power density (PD), modified maximum likelihood (MML), and equivalent energy (EE) were presented to assess the Weibull parameters for wind power assessment for agricultural applications [8]. The analyzed results showed that MOM and ML gave the best values of k and c to fit the wind data. Moreover, numerical integration using Trapezoidal sums and Simpson's rules were utilized to compute the Capacity Factor (CF) and the total energy generated by a small-scale wind turbine. In the study [9], two-parameter Weibull function based on GM, ML, MML, MOM, PD, and Part Density Energy (PDE) methods were presented for 29 sites. The results showed that PDE and MOM provided the best fitting of the real wind data.

Bokde et al. [10] exploited the GM, ML, and MOM methods which were investigated extensively in [11–13] to assess the wind turbine power curves that generally provided by wind turbine manufacturers and designed according to International Electrotechnical Commission (IEC) standards [14]. Many wind turbines were considered such as Vestas V80/V164, Siemens 82/107, and Nordex N90. The trial-and-error method was used to detect the optimal values of k and c, and their ranges were assumed to be 3 to 5 and 8–10, respectively. Besides, a software package was provided to generate Weibull functions for fitting wind turbine power curves easily. In the study [15], three sites were selected in Australia to analyze the half-hourly collected wind speed data based on MOM, empirical method (EM), and PD to estimate the Weibull parameters. The accuracy of the introduced methods was investigated by Chi-square error. EM provided the best matching of the Weibull parameters.

Jowder [16] studied wind data for 3 years based on Weibull distribution function in the Kingdom of Bahrain and the study showed that the selected sites were appropriate for small-scale wind turbines at 30 m and large-scale wind turbines at 60 m. In [17], Weibull based on MSD, ML, GM, PD, and MML methods was introduced to analyze wind data for 1 year in the Zafarana area in Egypt. In addition, 1 day in summer and 1 day in winter (ten-minutely) collected data were analyzed. Further, the performance of the introduced methods were investigated via RMS error. The study recommended using MSD and ML methods in estimating the wind potential. In [18], five different areas all over the world for 96 months of wind data were analyzed using Weibull distribution function instead of measured data for approximating wind potential.

Chellali et al. [19] presented a time-frequency analysis for the collected wind data for 6 years at Hassi-Rmel in Algeria. The time-frequency analysis was compared to the Fourier analysis; however, the antecedent provided superior matching due to its ability to follow the spectrum variation concerning time. In addition, a techno-economical study for the selected site was taken into consideration and the simulation results showed that the site is entirely adequate for wind energy generation.

Wind energy potential based on Weibull function was analyzed at four zones in two locations for ten-minutely collected data at 10, 30, and 40 m heights for 1 year in Khorasan in Iran [20]. The wind roses were provided at 30 m height in order to detect the dominated wind directions. The obtained results showed that the four zones have the suitable conditions for power extraction. In like manner, 13 years of wind speed data at 11 sites were studied to estimate the wind power potential in Yazd in Iran [21]. The analysis showed that most of the selected sites have average annual wind speed less than 4.5 m/s. On the contrary, the city of Herat has the highest average annual wind speed equals to 5.05 m/s and 6.86 m/s at 10 and 40 m heights, respectively. An adaptive neuro-fuzzy inference system (ANFIS) was used to assess the wind speed at different heights from 10 to 100 m at several locations in Saudi Arabia and the mean absolute error between the estimated and measured wind data was 0.03 [22]. Akdag et al. [23] proposed a new method based on PD to estimate the Weibull parameters for four different sites in Turkey. The new PD method was compared to GM, ML, MOM, and the numerical method in [24]. The obtained results showed that PD method provided a slight improvement in Weibull parameter estimation comparing to the other methods.

Many distribution functions have been proposed in the literature to assess the wind speed data of hundreds sites around the world. Weibull [25–27], Rayleigh [28,29], Gamma [30], Burr [31], Loglogistic [32], Normal [33], truncated normal [33], and lognormal [34] probability density functions are the commonly-used functions to model wind speed measurements [35]. These functions have different degrees of complexity, fitness, and accuracy. Weibull, Gamma, and Rayleigh probability density functions (PDFs) are the widely used functions to assess the wind regimes; however, Weibull representation provided more accurate approximation than

Rayleigh representation in different sites [28]. Thus, the selection of suitable function to represent wind speed distribution is a crucial requisite during the design, management, and operation stages of a wind system.

In this paper, the Weibull parameters are estimated based on GM, MOM, EPF, MSD, PD, and Genetic Algorithms (GA) methods. In addition, to evaluate the performance and the accuracy of the estimation methods: mean absolute error (MAE), root-mean-square error (RMSE), normalized mean absolute error (NMAE), Chi-square error (χ^2), regression coefficient (R^2), and Net Fitness test are calculated and compared. Catalca is selected to be the underlying site.

The rest of the paper is organized as follows. Section 2 presents the estimation methods for Weibull parameters. Section 3 explains the process of wind speed extrapolation. Section 4 introduces the performance and accuracy measures. Wind power density and wind energy potential are analyzed in Sect. 5. The results and discussion obtained by these methods are presented in Sect. 6. Section 7 concludes the paper.

2 Weibull parameters estimation methods

Weibull distribution depends on two parameters (c) and (k), and generally gives more accurate and superior estimation than other distribution functions. The PDF of Weibull distribution is given by Eq. (1):

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \mathrm{e}^{-\left(\frac{v}{c}\right)^k} \tag{1}$$

where $f(v)$ is the probability of observing wind speed v, k is the dimensionless shape parameter, and c is the scale parameter (m/s). There are paramount characteristics of Weibull distribution such as its parameters are estimated at a specific height and it is possible to extrapolate these parameters for other heights [36]. The CDF can be expressed as in Eq. (2):

$$F(v) = 1 - \mathrm{e}^{-\left(\frac{v}{c}\right)^k} \tag{2}$$

Many methods have been proposed for determining the Weibull parameters such as GM, EPF, MOM, MSD, ML, MML, PD, Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), and Moth Flame Optimization (MFO) [37,38]. In what follows, a brief description of GM [4,5,16,17], MOM, EPF, MSD, PD, and GA [39] is given.

2.1 Graphical method

The graphical method, also known as the least squares regression (LSR) method, is derived from the CDF of Weibull distribution by taking lognormal for two times of Eq. (2).

$$\ln\left[-\ln\left[1 - F(v)\right]\right] = k \ln v - k \ln c \tag{3}$$

Comparing Eq. (3) with a linear equation $y = mx + b$, using the CDF of Weibull distribution, solve the Linear Least Squares (LLS) problem to obtain coefficients of a linear equation m and b [28]. Then, mathematically, the Weibull parameters can be obtained using the following equations:

$$k = m \tag{4}$$

$$c = \mathrm{e}^{\left(\frac{-b}{m}\right)} \tag{5}$$

Practically, the parameters k and c based on GM method can be computed using the following three steps: (i) using the measured wind speed data to obtain the cumulative frequency distribution by sorting wind speed data into bins, then compute the frequency distribution; (ii) calculate ($\ln(v_i)$, $\ln[-\ln(1 - F(v_i))]$) pairs; (iii) solve the LLS problem and estimate the k and c parameters using Eqs. (4) and (5), respectively.

2.2 Method of moment

MOM, also called as the approximated method, depends mainly on two components, namely the mean wind speed ($\overline{v}$) and the standard deviation (σ).

$$\overline{v} = \tfrac{1}{n}\textstyle\sum_{i=1}^{n} v_i \tag{6}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(v_i - \overline{v})} \tag{7}$$

Hence, Weibull parameters can be calculated as given by the following equations [16]:

$$k = \left(\tfrac{\sigma}{\overline{v}}\right)^{-1.086} \tag{8}$$

$$c = \frac{\overline{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{9}$$

where Γ is the Gamma function and is defined by the following integral [38]:

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t}\mathrm{d}t \tag{10}$$

This method also requires three steps such that: (i) compute $\overline{v}$ by using Eq. (6); (ii) calculate σ using Eq. (7); (iii) compute k and c using Eqs. (8) and (9), respectively.

2.3 Energy pattern factor method

The energy pattern factor is expressed as the ratio between the total available power in the wind and the power corresponding to the cube of average wind speed [40]. In other words, it is the ratio between the mean of cubic wind speed to the cube of mean wind speed as defined [38]:

$$E_{\mathrm{PF}}=\frac{\frac{1}{n}\sum_{i}^{n}v_{i}^{3}}{\left[\frac{1}{n}\sum_{i}^{n}v_{i}\right]^{3}} \tag{11}$$

Alternatively, the E_{PF} value can be computed as shown in Eq. (12) [6]:

$$E_{\mathrm{PF}}=\frac{1}{(\overline{v})^{3}}\left(\sum_{i=1}^{n}\frac{v_{i}^{3}}{n}\right)=\frac{\Gamma\left(1+\frac{3}{k}\right)}{\Gamma^{3}\left(1+\frac{1}{k}\right)} \tag{12}$$

where v_i is the wind speed for ith observation and n is the total number of wind speed observations. Once E_{PF} value is calculated, the Weibull shape and scale parameters can be estimated from the following formulas [38]:

$$k=3.957E_{\mathrm{PF}}^{-0.898} \tag{13}$$

$$c=\frac{\overline{v}}{0.89} \tag{14}$$

The superiority of this method originates from the simplicity of parameter computation in comparison with others. Variation of E_{PF} for a lot of wind speed measurement stations and various wind regimes were reported in [41]. The value of E_{PF} for polar regions is about 6; meanwhile, its values for continental and irregular, coastal, and trade wind regions are 2.7, [1.57, 1.92], and [1.22, 1.36], respectively [40]. This method requires four steps such that: (i) compute the mean of cube wind speed for the measured data as in the numerator of Eq. (11); (ii) compute the cube of mean wind speed for the measured data as in the denominator of Eq. (11); (iii) compute the energy pattern factor value as given in Eq. (11); (iv) compute the values of k and c using Eqs. (13) and (14), respectively.

2.4 Mean standard deviation method

The mean standard deviation method, also known as the EM, is mainly based on the mean wind speed of the measured data and the standard deviation. Weibull shape parameter can be obtained easily as same as in MOM in Sect. 2.2. On the other hand, the Weibull scale parameter can be estimated as in the following equation:

$$c=\frac{\overline{v}k^{2.6674}}{0.184+0.816k^{2.73855}} \tag{15}$$

Accordingly, MSD method requires three steps such that: (i) compute the mean wind speed of the measured data using Eq. (6); (ii) calculate the standard deviation of the measured data using Eq. (7); (iii) compute k and c using Eqs. (8) and (15), respectively.

2.5 Power density method

The power density method is proposed in [23] and it is recommended as an estimation method since it has a high accuracy, more straightforward formulation, and fewer computations. The wind power density based on Weibull distribution can be expressed as:

$$P_D=0.5\rho\int_{0}^{\infty}v^{3}f(v)\,\mathrm{d}v \tag{16}$$

In terms of summation, P_D can be calculated as shown in Eq. (17):

$$P_D=0.5\rho\sum_{i=1}^{n}v_{i}^{3}f(v_i) \tag{17}$$

where $f(v_i)$ is the frequency when the measured wind speed is v_i (m/s), ρ is air density of the region.

The Weibull parameters can be estimated as follows [42]:

$$k=1+\frac{3.69}{E_{\mathrm{PF}}^{2}} \tag{18}$$

$$c=\frac{\overline{v}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{19}$$

The PD method also requires three steps such that: (i) compute the mean of the measured wind speed using Eq. (6); (ii) calculate the E_{PF} value using Eq. (11); (iii) compute k and c values using Eqs. (18) and (19), respectively. Weibull parameters based on PD method have paramount characteristics that it does not require binning, solving the LLS problem or iterative procedure since it is based on the mean of the cube of wind speeds and mean wind speed [23].

The final k and c values are estimated based on a two-level process. In the lower level, k and c values are computed using the derived mathematical formulas for each estimation method. In the upper level, k and c are optimized based on generalized reduced gradient nonlinear (GRGN) method which minimizes the difference between the estimated power density and the real power density.

2.6 Genetic algorithms method

The selection of Weibull parameters can be interpreted as a nonlinear optimization task which yields to minimize the MAE between the measured wind speeds vector and the corresponding vector of Weibull-generated wind speeds with given k and c as shown mathematically in Eq. (20).

$$\begin{aligned}&\min\left\{\mathrm{MAE}\left(V_{\mathrm{m}},V_{\mathrm{w}}\right)\right\}\\&\quad 1\le k\le 10\\&\quad 0<c<\infty\end{aligned} \tag{20}$$

where V_m and V_w are the vectors of measured and Weibull-generated wind speed vectors, respectively. Equally important, V_w can be obtained artificially by using the inverse cumulative density function (ICDF) of Weibull distribution and can be expressed in the following equation:

$$V_w = c\left[-\ln(1-p)\frac{1}{k}\right] \tag{21}$$

where p is the cumulative probability density of the measured wind speed vector, uniformly distributed in [0, 1]. The former vector can be easily computed by finding out the probability that wind speed is equal or lower than v_i, i=1,2, …,N where v_i is the ith measured wind speed, and N is the number of the measured wind speeds.

In order to solve the optimization problem mentioned above, evolutionary algorithms (EA) can be utilized. EAs are a set of metaheuristic algorithms that perform well in nonlinear optimization problems and are deemed to be a rapidly growing area of artificial intelligence [43–46]. One of the widely used EAs is GA, a search algorithm based on the principles of natural selection and genetics [47]. In GA, a population of chromosomes indicates candidate solutions to the problem is created. Regarding the problem of Weibull parameter selection, each chromosome consists of two integer values represented the values of k and c parameters. The initial population of chromosomes is created randomly within certain lower and upper bounds of parameters. After that, the first iteration is started and the fitness score value of each chromosome is computed using Eq. (20). Then, the population grows by searching the optimal solution using genetic operators, i.e., selection, crossover, and mutation. It continues in the same manner until one of the stopping conditions is satisfied. We used two stopping conditions; the first occurs when the maximum number of iterations is reached, whereas the second condition happens when the increment of the best fitness score is less than a predefined threshold (ϵ). Figure 1 depicts flowchart of the GA method for Weibull parameters selection. Table 1 presents the values of GA operation parameters, which are selected by performing a grid search for each parameter in its predefined domain.

Table 1 The values of GA main operation parameters

GA parameter	Selected value
Number of variables	2
Lower bound	1 for k and 0 for c
Upper bound	10 for k and ∞ for c
Population size	50
Maximum number of iterations	200
Stopping threshold (ϵ)	1×10^{-6}
Crossover rate	0.1
Mutation rate	0.01

Table 2 shows the computation time in seconds which is elapsed for the estimation methods to select the optimal parameters of Weibull distribution over all datasets. Primarily, the higher computation overhead of method, the higher computation time it will consume. However, the trade-off between computation time and efficiency of the methods is indispensably required.

3 Extrapolation of wind speed

Wind data from meteorology stations is always taken at a standard height of 10 m, then it can be extrapolated at different heights. The following formula [21] can obtain the speed

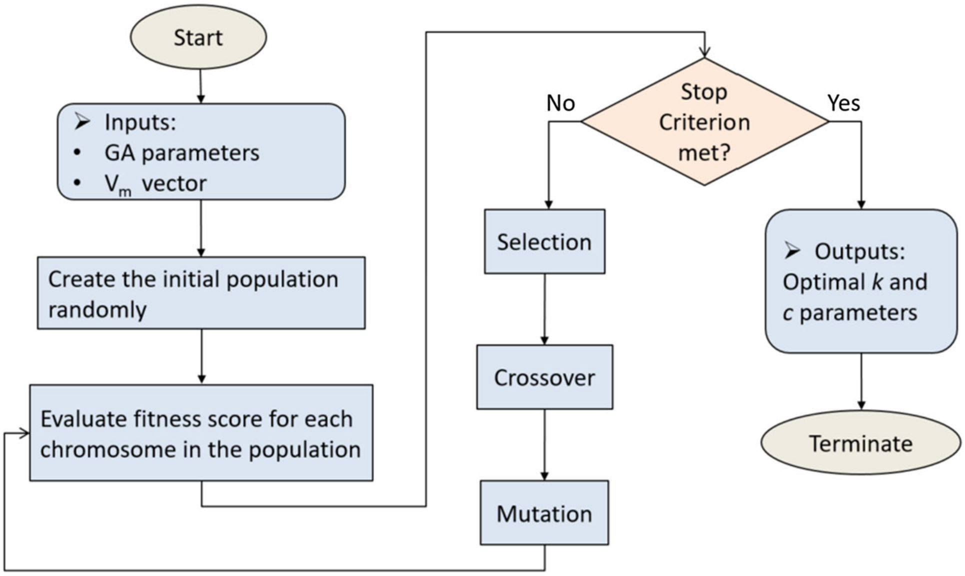


Fig. 1 Flowchart of GA method for Weibull parameters selection

Table 2 The computation time of the estimation methods (s)

Dataset	Method	Height (m)		
		30	60	80
2008	GM	**0.141**	0.235	**0.407**
	MOM	0.145	**0.201**	0.581
	EPF	0.325	0.467	0.662
	MSD	0.166	0.210	0.567
	PD	0.155	0.290	0.541
	GA	4.154	4.509	4.673
2009	GM	**1.325**	1.762	1.825
	MOM	1.461	**1.671**	**1.773**
	EPF	2.562	2.721	2.845
	MSD	1.822	1.933	2.025
	PD	4.352	4.410	4.562
	GA	4.099	4.133	4.648
2010	GM	**1.526**	1.832	1.964
	MOM	1.622	**1.752**	**1.925**
	EPF	2.731	2.862	3.323
	MSD	2.242	2.662	2.866
	PD	4.561	4.722	4.884
	GA	5.414	5.254	4.988

The bold values indicate the smallest time for each dataset, whereas the underline values indicate the smallest time over all datasets

at any height:

$$\frac{V_2}{V_1} = \left(\frac{h_2}{h_1}\right)^{\alpha} \tag{22}$$

where V_1 is the actual wind speed measured at the height of h_1, V_2 is the wind speed required at the extrapolated height h_2, and α is the roughness coefficient, also known as wind shear coefficient, varies according to the characteristic of the surface, atmospheric stability, wind speed, and height interval [48]. Different values of the roughness coefficient can be found in Table 3 [21]. Moreover, the value of α can also be obtained from the following equation [41,49,50] if wind speeds at two different heights are available:

$$\alpha = \frac{\ln(v_2) - \ln(v_1)}{\ln(h_2) - \ln(h_1)} \tag{23}$$

where v_1 and v_2 (m/s) are the wind speeds at heights of h_1 and h_2 (m), respectively.

Otherwise, the value of α can be calculated based on the roughness length (z_o) of the underlying site using Eq. (24) [51].

$$\alpha = \left(\frac{z_o}{h_1}\right)^{0.2} \left[1 - 0.55 \log(v_1)\right] \tag{24}$$

Table 3 Roughness value and gradient elevation for different surfaces

Surface characteristic	α
Sea and icy land	[0.10, 0.11]
Villages with scattered trees	[0.13, 0.15]
Heavily forested land	[0.22, 0.25]
Small cities	[0.25, 0.30]
Big cities and tall building	[0.36, 0.40]

where z_o is equal to 0.0095 m for the underlaying site [52] and the value of h_1 is equal to 10 m.

In this study, the value of α is equal to 0.143 which is computed using Eq. (24). Afterwards, the value of α is verified by using Eq. (23) at heights 10 and 30 m.

4 Statistical accuracy measures

Different statistical criteria were introduced in the literature to detect the best method for matching real data. For each dataset and estimation method, six of the most common error criteria are utilized in this paper. The extent of error approaching zero measures the grade of the goodness of fit (GOF). Statistical accuracy analysis, such as the Chi-square error, which strongly depends on the number of the data point, is also used in this paper since all datasets are for the same site. The list of used error measures and their definitions and formulas is as follows:

- Mean absolute error is an arithmetic average between the measured wind speed vector (x) and the predicted wind speed vector (y) which is generated by Weibull distribution as in Eq. (25) [53].

  $$\text{MAE} = \frac{\sum_{i=1}^{N} \mid y_i - x_i \mid}{N} \tag{25}$$

  where N is the length of both x and y vectors.
- Root Mean Square Error is the square root of the second sample moment of the differences between predicted wind speeds and measured wind speeds [54]. It is also known as the quadratic mean of these differences and given in the following formula.

  $$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i - x_i)^2}{N}} \tag{26}$$

- Normalized mean absolute error is the absolute error normalized over the data which allows the error to be compared across data with different scales. In other words, NMAE is the absolute error normalized over the actual value, computed for every data point, and then averaged.

$$\mathrm{NMAE} = \frac{\sum_{i=1}^{N} \left| \frac{y_i - x_i}{x_i} \right|}{N} \tag{27}$$

- Chi-square Error is used extensively in the GOF tests to determine whether the measured wind speeds follow the distribution of the predicted wind speeds by Weibull distribution [55]. Mathematically, Chi-square error can be calculated using Eq. (28).

$$\chi^2 = \sum_{i=1}^{N} \frac{(x_i - y_i)^2}{y_i} \tag{28}$$

- Regression coefficient presents the linear relationship between the predicted wind speeds from the Weibull distribution and the measured data, as shown in Eq. (29). The ideal value of the regression coefficient equals 1.

$$R^2 = \frac{\sum_{i=1}^{N} (x_i - z_i)^2 - \sum_{i=1}^{N} (x_i - y_i)^2}{\sum_{i=1}^{N} (x_i - z_i)^2} \tag{29}$$

where z_i is the mean of the ith wind speed from the measured data.

- Net fitness is used to average the aforementioned measures in a fair-and-square manner. It is worthy to say that all measures have the same importance in the numerator, that is, the weight for each measure is 1. Furthermore, the major goal of using such an average measure is ranking the estimation methods based on their overall performance. The general formula of net fitness is given as follows [56].

$$\text{Net Fitness} = \frac{\sum_{i=1}^{n} | \mathrm{MAE}_i | + \sum_{i=1}^{n} | \mathrm{RMSE}_i | + \sum_{i=1}^{n} | \mathrm{NMAE}_i | + \sum_{i=1}^{n} | \chi_i^2 | + \sum_{i=1}^{n} (1 - R_i^2)}{5n} \tag{30}$$

where n is the total number of error entries, and in this study it is equal to 1 since Net Fitness is computed at each height separately.

5 Wind energy potential

The kinetic energy stored in the wind stream can be transformed into electrical energy by wind turbines. The performance of wind turbine is mainly related to the type and shape of wind distribution in that site. A good matching model of the power curve is a paramount tool in predicting wind power.

Table 4 The annual mean wind speed (m/s) at Catalca site

Dataset	Height (m)		
	30	60	80
2008	6.91	7.25	7.88
2009	7.65	7.66	8.74
2010	7.97	8.00	9.12

The output power of a wind turbine is generally based on cut-in, rated, and cutoff wind speeds. The wind energy based on the measured wind data can be expressed as the following Eq. [38]:

$$E_\mathrm{m} = 0.5 \rho \overline{v^3} T \tag{31}$$

where $\overline{v^3}$ is the mean of wind speed cubes. The equivalent theoretical wind energy based on the Weibull probability functions can be obtained using Eq. (32).

$$E_\mathrm{w} = 0.5 \rho c^3 \tau \left(1 + \frac{3}{k}\right) T \tag{32}$$

where the air density ρ is assumed to be equal to 1.225 kg/m^3, and T is the time factor. The monthly and annual values of T are 730 and 8760 h, respectively.

The average wind speed is a prefatory indication of the appropriateness of the wind energy potential of the site. Sites with mean wind speed higher than 6.7 m/s at 10 m height are considered an exceptional location for wind energy generation [57]. Table 4 provides the annual mean wind speed values at different heights in the Catalca site. Obviously, these values in Table 4 reflects a good indication of wind potential when compared with corresponding values in Table 5 [21].

The annual average power densities were (400.31, 540.08, 611.02), (463.41, 546.84, 622.42), and (590.16, 806.18, 917.61) W/m^2 at heights 30, 60 and 80 m for 2008, 2009, and 2010 datasets, respectively. The average power densities obtained from the actual analysis at the selected site can be classified in fifth and sixth classes which proves the site suitability for wind power generation, as illustrated in Table 6 [20,57,58].

6 Results and discussion

In order to test and compare, the performance of the estimation methods introduced in this study, the hourly wind data

Table 5 Potential value for Annual mean wind speed

Annual mean wind speed at height				Indication
10 m	30 m	60 m	80 m	
Less than 4.5 m/s	Less than 5.3 m/s	Less than 5.9 m/s	Less than 6.15 m/s	Poor
4.5–5.4 m/s	5.3–6.4 m/s	5.9–7.1 m/s	6.15–7.4 m/s	Marginal
5.4–6.7 m/s	6.4–7.9 m/s	7.1–8.8 m/s	7.4–9.15 m/s	Good-very good
Greater than 6.7 m/s	7.9 m/s	8.8 m/s	9.15 m/s	Exceptional

Table 6 Annual average power density classes [58]

Wind resource category	Wind class	Wind speed (m/s)	Wind power density ($\mathrm{W/m^2}$)
Poor	1	3.5–5.6	50–200
Marginal	2	5.6–6.4	200–300
Moderate	3	6.4–7	300–400
Good	4	7–7.5	400–500
Excellent	5	7.5–8	500–600
Excellent	6	8–8.8	600–800
Excellent	7	Above 8.8	Above 800

Table 7 The characteristics of the Catalca site

Site name	Country	Latitude (°)N	Longitude (°)E	Altitude (m)	Data
Catalca	Turkey	$41°8.5944'$	$28°27.6924'$	88	2008–2010

for 3 years are utilized. Table 7 presents the main characteristics of the Catalca site. The wind speed measurements are collected at 10 m above the ground level, then they are extrapolated to 30, 60, and 80 m heights, respectively.

The Weibull parameters values are remarkable indicators that reflect the characteristics and potentiality of wind stream at a specific site. The Weibull shape parameter describes the characteristics of wind shape in such a way that lower values of k, i.e., 1.5–2.3, correspond to broader distributions of wind speed, which means that wind wave distribution varies over a wide range of speeds. In contrast, higher values of k, i.e., 2.5–3.5, correspond to narrower distributions of wind speed, which means that wind wave distribution stays within a narrow range of speeds [59]. For instance, the value of k in gusty environments approaches 1.5, whereas it can reach 3 or 4 in tropical environments. In many wind estimation studies, the typical value of k varies between 1.9 and 2.5. Furthermore, wind distributions with a value of k closer to 2 indicate that wind wave is steady and uniform [60].

On the other hand, the Weibull scale parameter describes the potentiality of wind stream at a specific site where lower values of c refer to low potential of wind and vice versa for higher values of c. Regarding Table 8, the monthly and annual Weibull parameters for 2008 at heights of 30, 60, and 80 m are calculated based on the six estimation methods. For all months except September and November, the k values vary within the range of [1.9, 2.4], which means that the wind wave is steady and uniform. While, in September, the k values are small and varied between 1.1 and 1.5, which indicates that wind wave distribution varies over a wide range of speeds. For November, the k values are approximately 2.8, which indicates that wind wave distribution varies over a narrow range of speeds.

The annual value of k for all heights approaches 2, which means that the wind wave is regular and uniform. Regarding the scale parameter, it varies between 5.8 and 13.1, such that the lowest values are in June, whereas the highest are in October. Thus, these values indicate that the lowest wind potential can be generated in June while the highest in October. The annual c value, which varies between 7.66 and 8.99, shows the appropriateness of the site for wind power generation. Investigating Tables 9 and 10, the k values for all months in 2009 and 2010 datasets except for September and November vary within the range of 1.84 and 2.5. The maximum value of k was in October (2.83).

The c values for all months in 2009 and 2010 datasets vary within the range of 5.85 and 13.67. By comparing Tables 8, 9 and 10, it can be noticed that the annual value of k approaches 2 for all datasets at all heights, while the value of c approaches 7.8, 8.2 and 8.9 at the height of 30 m for datasets 2008, 2009 and 2010, respectively. At the height of 60 m, the value of c reaches 8.6 for both 2008 and 2009 datasets while reaches 9.8 for the 2010 dataset. Finally, at the height of 80 m, the value of c approaches 8.9 for 2008 and 2009 datasets, while approaches 10.2 for the 2010 dataset. This can be explained

Table 8 Comparison between Weibull parameters calculated using GM, MOM, EPF, MSD, PD and GA methods for 2008

Months	Height (m)	Methods											
		GM		MOM		EPF		MSD		PD		GA	
		k	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*
Jan	30	1.962	7.603	1.962	7.832	2.176	7.574	1.974	7.833	1.974	7.605	1.971	7.556
	60	2.110	8.669	2.163	9.896	2.321	8.617	2.175	9.896	2.125	8.659	2.033	8.449
	80	2.107	9.033	2.163	9.294	2.321	8.978	2.175	9.294	2.125	9.023	2.033	8.803
Feb	30	1.918	8.576	1.953	8.837	2.143	8.548	1.966	8.838	1.941	8.578	1.940	8.432
	60	1.882	9.484	1.953	10.856	2.145	9.464	1.966	10.858	1.943	9.498	1.937	9.340
	80	1.845	9.875	1.953	10.195	2.145	9.861	1.966	10.197	1.943	9.897	1.937	9.733
Mar	30	2.057	7.568	2.096	7.797	2.269	7.533	2.108	7.797	2.070	7.569	2.025	7.417
	60	2.057	8.359	2.096	9.552	2.269	8.318	2.108	9.553	2.070	8.357	2.026	8.192
	80	2.054	8.710	2.096	8.971	2.269	8.667	2.108	8.971	2.070	8.708	2.030	8.547
Apr	30	2.123	7.478	2.330	7.442	2.162	7.703	2.174	7.703	2.134	7.479	2.114	7.396
	60	2.116	8.251	2.162	9.438	2.330	8.217	2.174	9.438	2.134	8.258	2.114	8.166
	80	2.115	8.598	2.162	8.863	2.330	8.562	2.174	8.863	2.134	8.605	2.114	8.509
May	30	1.993	6.659	2.116	6.864	2.207	6.631	2.128	6.864	2.005	6.660	2.431	6.358
	60	1.987	7.350	2.116	8.409	2.207	7.322	2.128	8.410	2.005	7.354	2.431	7.021
	80	1.987	7.659	2.116	7.897	2.207	7.630	2.128	7.898	2.005	7.663	2.431	7.316
Jun	30	2.256	5.848	2.444	5.820	2.321	6.021	2.331	6.021	2.262	5.848	2.351	5.694
	60	2.250	6.452	2.321	7.377	2.444	6.426	2.331	7.377	2.262	6.457	2.351	6.287
	80	2.250	6.723	2.321	6.928	2.444	6.696	2.331	6.928	2.262	6.728	2.351	6.551
Jul	30	2.327	8.451	2.353	8.704	2.502	8.414	2.363	8.703	2.329	8.451	2.238	8.257
	60	2.326	9.333	2.353	10.664	2.502	9.291	2.363	10.663	2.329	9.332	2.238	9.118
	80	2.323	9.725	2.353	10.014	2.502	9.681	2.363	10.013	2.329	9.724	2.238	9.501
Aug	30	2.205	7.723	2.231	7.954	2.402	7.685	2.242	7.954	2.214	7.723	2.251	7.623
	60	2.213	8.538	2.231	9.745	2.402	8.486	2.242	9.745	2.214	8.527	2.251	8.418
	80	2.212	8.896	2.231	9.152	2.402	8.842	2.242	9.151	2.214	8.885	2.251	8.771
Sep	30	1.103	7.557	1.469	8.291	1.549	8.186	1.483	8.301	1.457	8.040	1.370	7.814
	60	1.230	8.595	1.469	10.158	1.549	9.039	1.483	10.170	1.457	8.878	1.369	8.618
	80	1.291	9.053	1.469	9.539	1.549	9.418	1.483	9.551	1.457	9.251	1.370	8.990
Oct	30	2.301	10.376	2.349	10.685	2.493	10.329	2.359	10.684	2.318	10.375	2.380	10.221
	60	2.241	11.465	2.349	13.091	2.493	11.405	2.359	13.090	2.318	11.456	2.380	11.286
	80	2.159	11.948	2.349	12.293	2.493	11.884	2.359	12.293	2.318	11.938	2.380	11.759
Nov	30	2.819	7.626	2.886	7.847	2.851	7.631	2.891	7.846	2.778	7.630	2.828	7.533
	60	2.870	8.414	2.886	9.614	2.851	8.427	2.891	9.613	2.778	8.425	2.828	8.318
	80	2.870	8.768	2.886	9.029	2.851	8.780	2.891	9.028	2.778	8.779	2.828	8.667
Dec	30	1.913	7.343	1.974	7.570	2.125	7.320	1.986	7.571	1.924	7.345	1.849	7.144
	60	1.907	8.108	1.974	9.274	2.125	8.083	1.986	9.275	1.924	8.110	1.849	7.888
	80	1.902	8.448	1.974	8.709	2.125	8.422	1.986	8.711	1.924	8.450	1.849	8.220
Annual	30	1.971	7.854	1.986	7.791	1.999	7.792	1.999	7.792	1.937	7.787	1.915	7.663
	60	1.925	8.620	2.002	8.628	2.150	8.591	2.014	8.629	1.948	8.623	1.917	8.470
	80	1.915	8.981	2.002	8.990	2.150	8.952	2.014	8.991	1.948	8.985	1.917	8.826

Table 9 Comparison between Weibull parameters calculated using GM, MOM, EPF, MSD, PD and GA methods for 2009

Months	Height (m)	Methods											
		GM		MOM		EPF		MSD		PD		GA	
		k	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*
Jan	30	1.960	7.983	1.962	7.832	2.176	7.953	1.974	7.833	1.974	7.605	1.971	7.934
	60	1.956	8.436	2.163	9.896	2.176	8.404	2.175	9.896	1.974	8.397	1.971	8.384
	80	1.949	8.807	2.163	10.333	2.176	8.775	2.175	10.333	2.125	9.023	1.971	8.754
Feb	30	1.906	9.003	1.953	8.837	2.143	8.975	1.966	8.838	1.941	8.578	1.940	8.853
	60	1.879	9.509	1.953	10.856	2.143	9.484	1.966	10.858	1.941	9.472	1.940	9.355
	80	1.837	9.920	1.953	11.335	2.143	9.902	1.966	11.337	1.943	9.897	1.939	9.768
Mar	30	2.057	7.947	2.096	7.797	2.269	7.910	2.108	7.797	2.070	7.569	2.026	7.788
	60	2.055	8.397	2.096	9.552	2.269	8.358	2.108	9.553	2.070	8.357	2.026	8.230
	80	2.052	8.768	2.096	9.974	2.269	8.727	2.108	9.974	2.070	8.708	2.027	8.598
Apr	30	2.122	7.852	2.162	7.703	2.330	7.814	2.174	7.703	2.134	7.479	2.114	7.765
	60	2.122	8.298	2.162	9.438	2.330	8.257	2.174	9.438	2.134	8.258	2.114	8.206
	80	2.120	8.664	2.162	9.854	2.330	8.621	2.174	9.854	2.134	8.605	2.114	8.568
May	30	1.993	6.992	2.116	6.864	2.207	6.963	2.128	6.864	2.005	6.660	2.431	6.676
	60	1.993	7.389	2.116	8.409	2.207	7.358	2.128	8.410	2.005	7.354	2.431	7.055
	80	1.992	7.715	2.116	8.780	2.207	7.682	2.128	8.781	2.005	7.663	2.431	7.366
Jun	30	2.256	6.140	2.321	6.021	2.444	6.111	2.331	6.021	2.262	5.848	2.351	5.978
	60	2.256	6.488	2.321	7.377	2.444	6.457	2.331	7.377	2.262	6.457	2.351	6.317
	80	2.256	6.775	2.321	7.703	2.444	6.742	2.331	7.702	2.262	6.728	2.351	6.596
Jul	30	2.327	8.874	2.353	8.704	2.502	8.835	2.363	8.703	2.329	8.451	2.238	8.670
	60	2.325	9.378	2.353	10.664	2.502	9.336	2.363	10.663	2.329	9.332	2.238	9.162
	80	2.323	9.791	2.353	11.134	2.502	9.747	2.363	11.133	2.329	9.724	2.238	9.566
Aug	30	2.205	8.109	2.231	7.954	2.402	8.069	2.242	7.954	2.214	7.723	2.251	8.004
	60	2.204	8.569	2.231	9.745	2.402	8.527	2.242	9.745	2.214	8.527	2.251	8.459
	80	2.203	8.947	2.231	10.175	2.402	8.903	2.242	10.174	2.214	8.885	2.251	8.832
Sep	30	1.163	8.064	1.469	8.291	1.549	8.595	1.483	8.301	1.457	8.040	1.370	8.203
	60	1.239	8.661	1.469	10.158	1.549	9.083	1.483	10.170	1.457	8.878	1.370	8.668
	80	1.304	9.144	1.469	10.606	1.549	9.483	1.483	10.618	1.457	9.251	1.370	9.052
Oct	30	2.281	10.896	2.349	10.685	2.493	10.845	2.359	10.684	2.318	10.375	2.380	10.732
	60	2.230	11.516	2.349	13.091	2.493	11.460	2.359	13.090	2.318	11.456	2.380	11.340
	80	1.848	11.989	2.349	13.668	2.493	11.966	2.359	13.667	2.318	11.938	2.380	11.840
Nov	30	2.870	8.001	2.886	7.847	2.851	8.013	2.891	7.846	2.778	7.630	2.828	7.909
	60	2.870	8.455	2.886	9.614	2.851	8.468	2.891	9.613	2.726	7.738	2.828	8.358
	80	2.870	8.828	2.886	10.038	2.851	8.841	2.891	10.037	2.778	8.779	2.828	8.727
Dec	30	1.911	7.710	1.974	7.570	2.125	7.686	1.986	7.571	1.924	7.345	1.849	7.501
	60	1.907	8.147	1.974	9.274	2.125	8.122	1.986	9.275	1.924	7.345	1.849	7.927
	80	1.901	8.506	1.974	9.683	2.125	8.480	1.986	9.684	1.924	8.450	1.849	8.276
Annual	30	1.995	8.182	1.986	8.181	2.138	8.147	1.999	8.182	1.937	8.176	1.914	8.046
	60	1.912	8.637	1.986	8.645	2.138	8.610	1.999	8.646	1.937	8.640	1.913	8.500
	80	1.912	9.018	1.986	9.026	2.138	8.989	1.999	9.027	1.937	9.021	1.914	8.876

Table 10 Comparison between Weibull parameters calculated using GM, MOM, EPF, MSD, PD and GA methods for 2010

Months	Height (m)	Methods											
		GM		MOM		EPF		MSD		PD		GA	
		k	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*	*c*
Jan	30	2.108	8.918	2.163	8.919	2.321	8.875	2.175	8.919	1.974	7.605	2.033	8.702
	60	2.108	8.918	2.163	9.896	2.321	9.847	2.175	9.896	2.125	8.659	2.033	9.656
	80	2.108	8.918	2.163	10.333	2.321	10.282	2.175	10.333	2.125	8.659	2.033	10.081
Feb	30	1.858	9.769	1.953	9.784	2.145	9.748	1.966	9.786	1.941	8.578	1.937	9.621
	60	1.858	9.769	1.953	10.856	2.145	10.816	1.966	10.858	1.943	9.498	1.937	10.675
	80	1.858	9.769	1.953	11.335	2.145	11.292	1.966	11.337	1.943	9.498	1.937	11.145
Mar	30	2.053	8.607	2.096	8.609	2.269	8.567	2.108	8.609	2.070	7.569	2.028	8.442
	60	2.053	8.607	2.096	9.552	2.269	9.506	2.108	9.553	2.070	8.357	2.026	9.362
	80	2.053	8.607	2.096	9.974	2.269	9.925	2.108	9.974	2.070	8.357	2.026	9.775
Apr	30	2.121	8.505	2.162	8.506	2.330	8.464	2.174	8.506	2.134	7.479	2.114	8.411
	60	2.121	8.505	2.162	9.438	2.330	9.391	2.174	9.438	2.134	8.258	2.114	9.333
	80	2.121	8.505	2.162	9.854	2.330	9.805	2.174	9.854	2.134	8.258	2.114	9.744
May	30	1.993	7.574	2.116	7.579	2.207	7.542	2.128	7.579	2.005	6.660	2.431	7.231
	60	1.993	7.574	2.116	8.409	2.207	8.368	2.128	8.410	2.005	7.354	2.431	8.024
	80	1.993	7.574	2.116	8.780	2.207	8.737	2.128	8.781	2.005	7.354	2.431	8.377
Jun	30	2.256	6.651	2.321	6.649	2.444	6.619	2.331	6.648	2.262	5.848	2.351	6.475
	60	2.256	6.651	2.321	7.377	2.444	7.344	2.331	7.377	2.262	6.457	2.351	7.185
	80	2.256	6.651	2.321	7.703	2.444	7.668	2.331	7.702	2.262	6.457	2.351	7.502
Jul	30	2.324	9.612	2.353	9.611	2.502	9.569	2.363	9.610	2.329	8.451	2.238	9.391
	60	2.324	9.612	2.353	10.664	2.502	10.618	2.363	10.663	2.329	9.332	2.238	10.420
	80	2.324	9.612	2.353	11.134	2.502	11.086	2.363	11.133	2.329	9.332	2.238	10.880
Aug	30	2.203	8.783	2.231	8.783	2.402	8.740	2.242	8.782	2.214	7.723	2.251	8.670
	60	2.203	8.783	2.231	9.745	2.402	9.698	2.242	9.745	2.214	8.527	2.251	9.620
	80	2.203	8.783	2.231	10.175	2.402	10.125	2.242	10.174	2.214	8.527	2.251	10.044
Sep	30	1.275	8.936	1.469	9.155	1.549	9.310	1.483	9.166	1.457	8.040	1.370	8.887
	60	1.275	8.936	1.469	10.158	1.549	10.330	1.483	10.170	1.457	8.878	1.370	9.860
	80	1.275	8.936	1.469	10.606	1.549	10.785	1.483	10.618	1.457	8.878	1.370	10.295
Oct	30	2.185	11.805	2.349	11.798	2.493	11.747	2.359	11.797	2.318	10.375	2.380	11.624
	60	2.185	11.805	2.349	13.091	2.493	13.034	2.359	13.090	2.318	11.456	2.380	12.898
	80	2.185	11.805	2.349	13.668	2.493	13.609	2.359	13.667	2.318	11.456	2.380	13.466
Nov	30	2.870	8.667	2.886	8.665	2.851	8.679	2.891	8.664	2.778	7.630	2.828	8.567
	60	2.870	8.667	2.886	9.614	2.851	9.630	2.891	9.613	2.778	8.425	2.828	9.506
	80	2.870	8.667	2.886	10.038	2.851	10.055	2.891	10.037	2.778	8.425	2.828	9.925
Dec	30	1.904	8.350	1.974	8.358	2.125	8.325	1.986	8.360	1.924	7.345	1.849	8.125
	60	1.904	8.350	1.974	9.274	2.125	9.237	1.986	9.275	1.924	8.110	1.849	9.015
	80	1.904	8.350	1.974	9.683	2.125	9.645	1.986	9.684	1.924	8.110	1.849	9.413
Annual	30	1.482	8.020	2.002	8.887	2.150	8.849	2.014	8.888	1.948	8.881	1.917	8.724
	60	1.165	8.082	2.014	9.861	2.150	9.818	2.014	9.861	1.948	9.855	1.917	9.680
	80	1.165	8.082	2.002	10.295	2.150	10.251	2.014	10.296	1.948	10.289	1.917	10.107

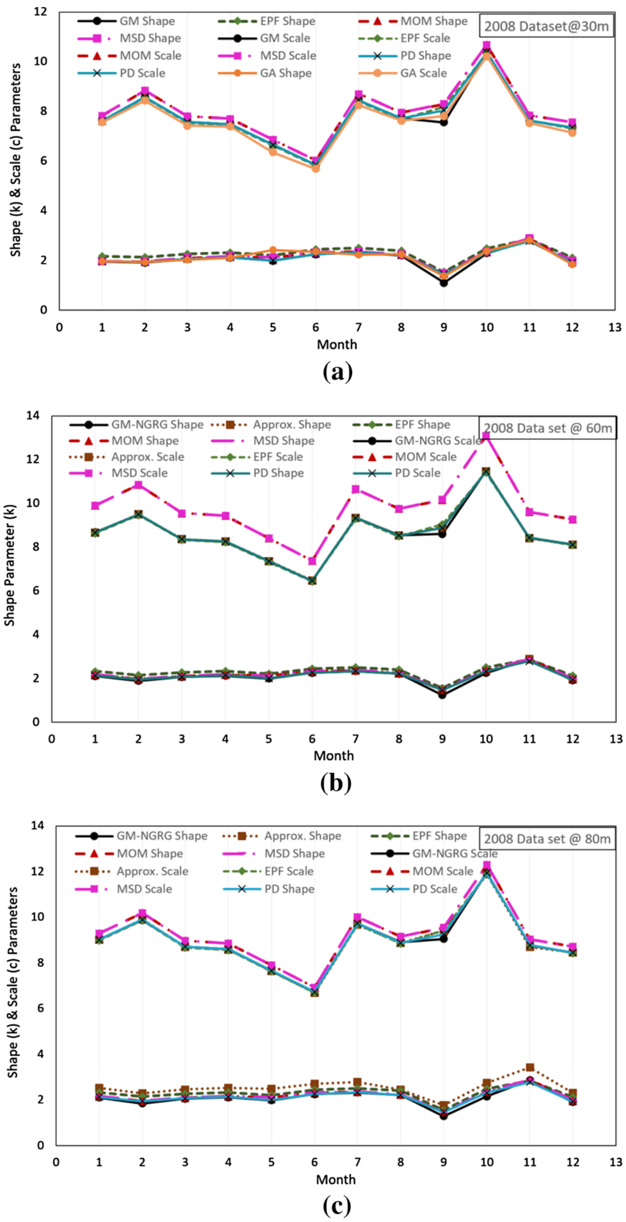


Fig. 2 Weibull shape and scale parameters for: **a** 2008 dataset at 30 m, **b** 2009 dataset at 60 m and **c** 2010 dataset at 80 m

by the fact that the wind potential proportionally increases as the wind tower height does.

Figure 2a–c illustrates the profile of Weibull parameters for the datasets 2008, 2009, and 2010 at 30, 60, and 80 m heights, respectively. Comparing the Weibull scale pattern with the monthly mean wind speeds pattern in reference [25], which analyzed the same datasets, it can be noticed that both patterns are matched. Based on this result, the Weibull scale parameter can be predicted by calculating the monthly mean wind speeds and vice versa. Figures 3 and 4 depict the Weibull PDF and CDF curves, respectively, of the measured data and the estimated data. It is recommended to draw the PDF and CDF curves using the full-length wind speed vectors rather than binned-data [61]. This due to the fact that using wide interval of wind speeds likely leads to bad matching.

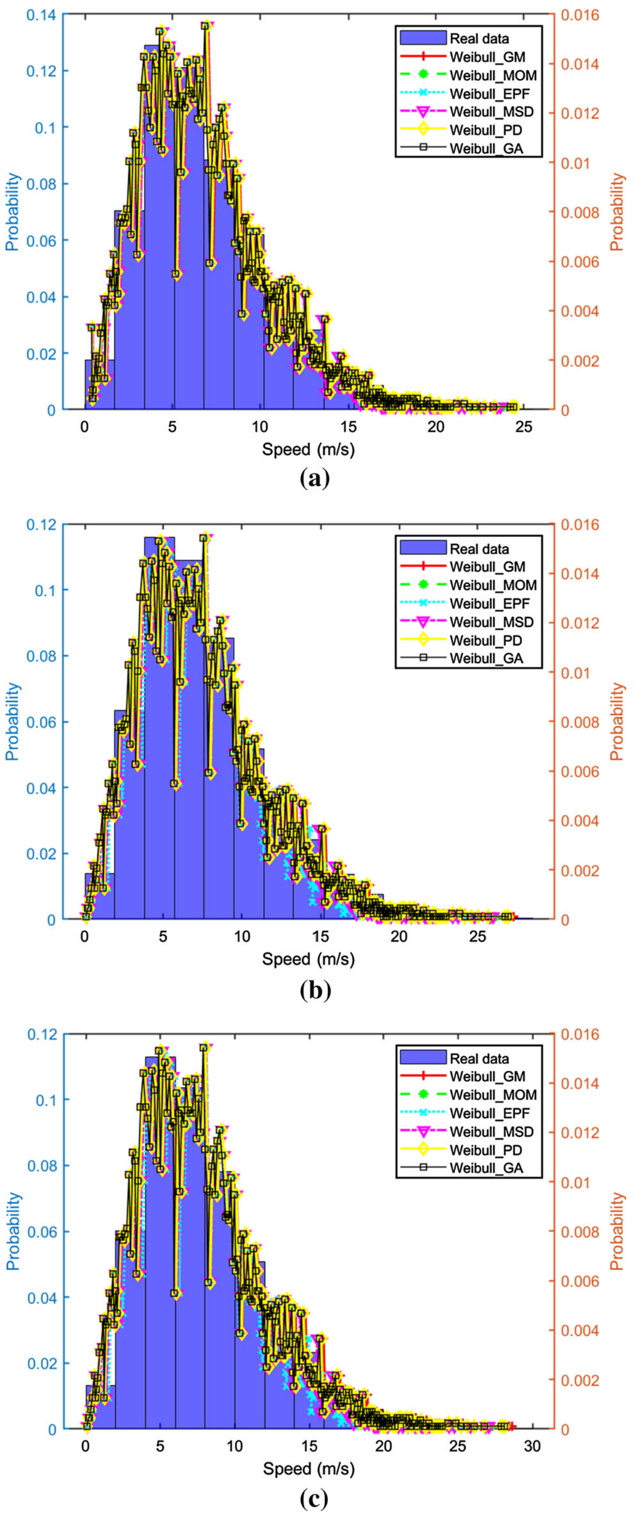
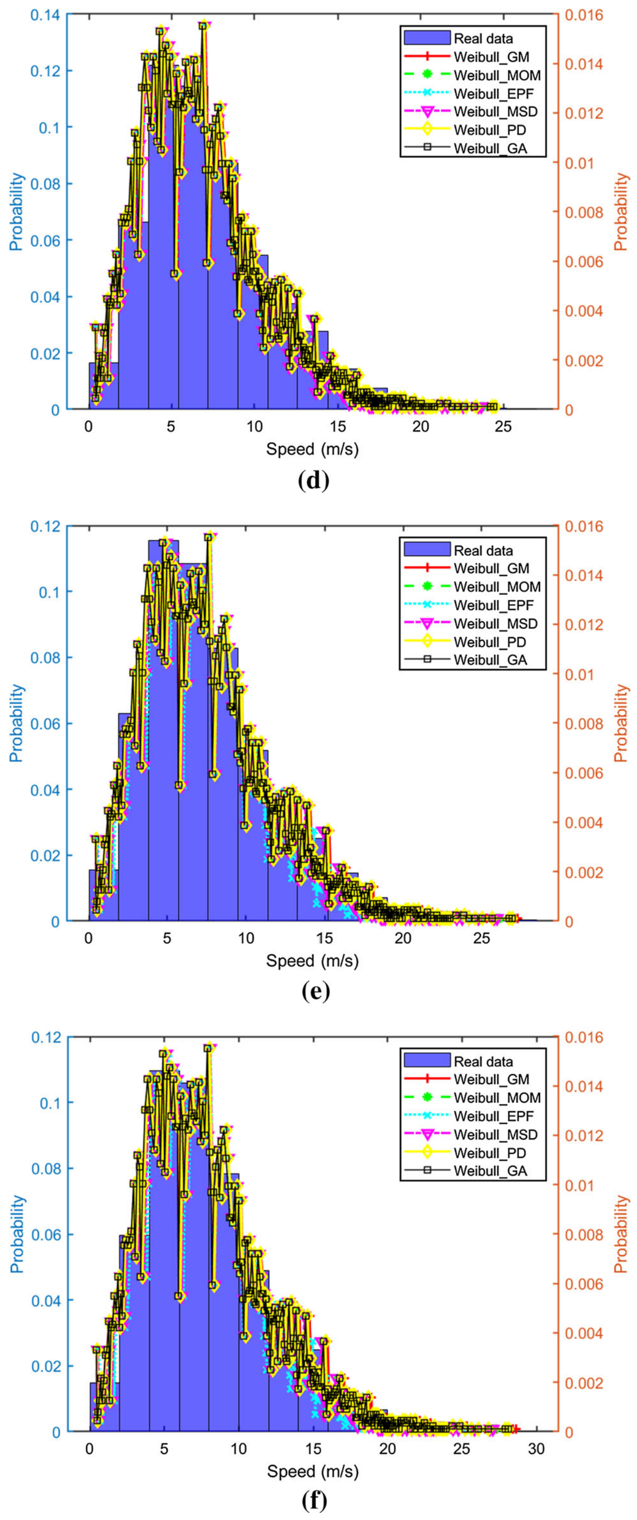


Fig. 3 The PDF curves of used methods for: **a** 2008 at 30 m, **b** 2008 at 60 m, **c** 2008 at 80 m. **d** 2009 at 30 m, **e** 2009 at 60 m, **f** 2009 at 80 m. **g** 2010 at 30 m, **h** 2010 at 60 m, and **i** 2010 at 80 m

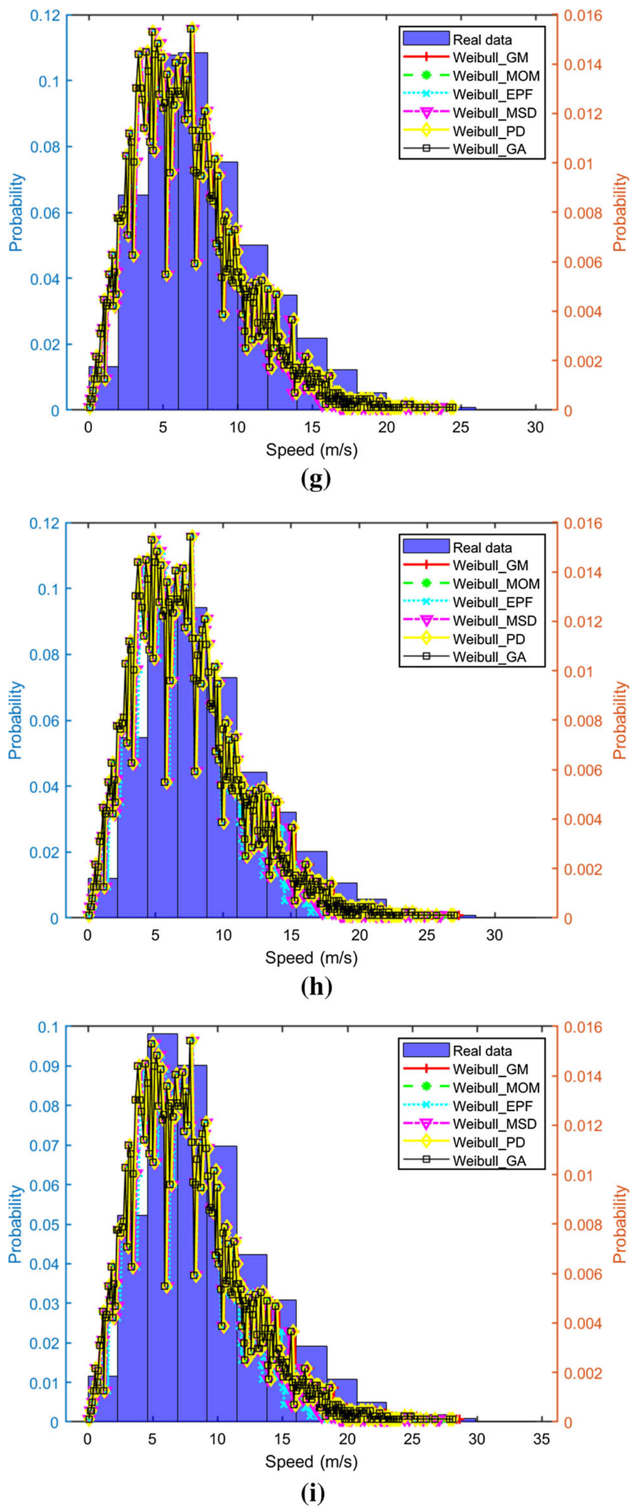


(d)

(e)

(f)

Fig. 3 continued



(g)

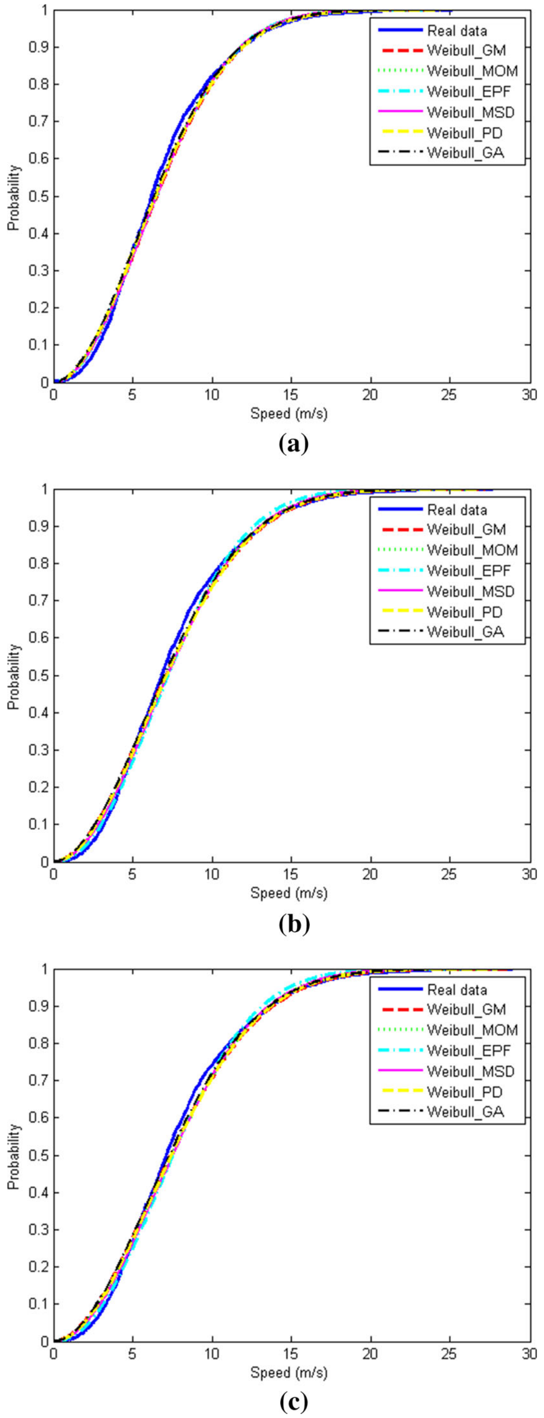
(h)

(i)

Fig. 3 continued

Unlike 2008 and 2009, the PDF and CDF curves of the 2010 dataset considerably deviate from the real data curve. This can be attributed to significant fluctuating in wind speeds.

The performance of the six introduced estimation methods are subjected to various statistical tests and error criteria to evaluate their accuracy. Tables 11, 12 and 13 present the results of 2008, 2009 and 2010 datasets, respectively. Furthermore, the bold values represent the best results among the same height, whereas the underlined values are the best over the particular dataset. It is worth noting that the results

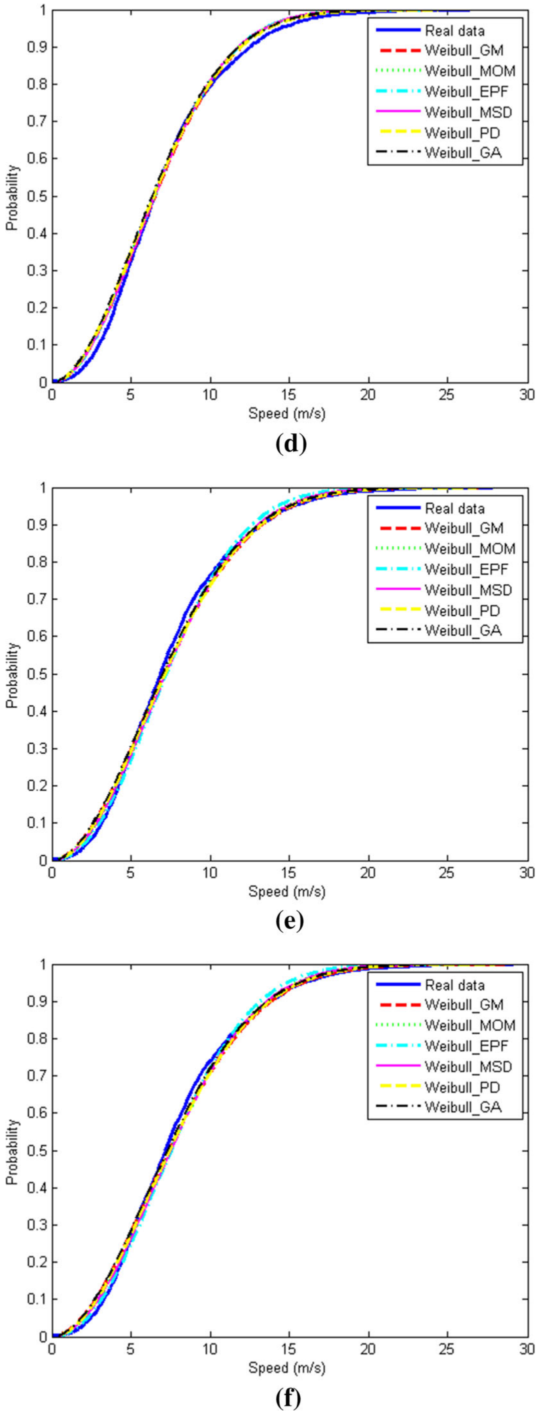


(a)

(b)

(c)

Fig. 4 The CDF curves of used methods for: **a** 2008 at 30 m, **b** 2008 at 60 m, **c** 2008 at 80 m. **d** 2009 at 30 m, **e** 2009 at 60 m, **f** 2009 at 80 m. **g** 2010 at 30 m, **h** 2010 at 60 m, and **i** 2010 at 80 m



(d)

(e)

(f)

Fig. 4 continued

at different heights are not independent, as the data used only depends on the wind extrapolation.

Basically, the mean wind speed apparently increases as much as the height of wind tower increases, whereas, the standard deviation slightly increases. In statistics, skewness refers to the degree of asymmetry from the mean of data distribution. Indeed, the skewness of the Weibull distribution function mainly depends on the value of the shape parameter [62]. The distribution of the measured wind speed is positively skewed with values between 0.993 and 1.012. Kurtosis measures the peak of a frequency distribution [63]. In other words, a variable υ has positive (negative) kurtosis if its PDF is more sharply peaked (broadly peaked) and has longer (shorter) tails than a Gaussian distribution with the same

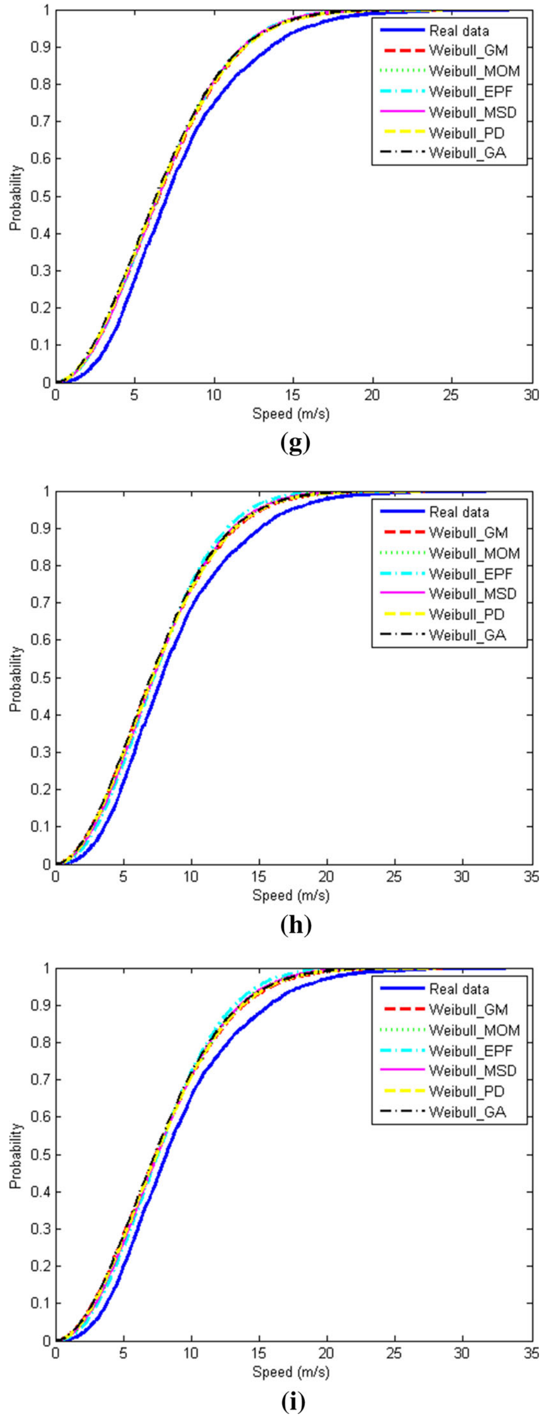


Fig. 4 continued

mean and standard deviation [64]. Throughout the underlying site, the kurtosis is positive, taking values in excess of 1.

Beyond doubt, the estimation method achieves the optimal matching when the difference of the measured value and the estimated value approaches zero. In this study, MAE, RMSE, NMAE, and R^2 are computed based on full-length wind speed vectors, meanwhile, χ^2 is computed with wind speed data put into bins since Chi-square test can be used only for discrete distribution. Tables 11, 12, and 13 summary the GOF results of the estimation methods for 2008, 2009, and 2010 datasets, respectively. GA and GM in terms of MAE, RMSE and R^2 tests achieve the first and second best method, respectively. However, in terms of NMAE and χ^2 tests, EPF outperforms the other methods. To clearly specify the accuracy and performance of the best estimation method, the rank is evaluated on the basis of the Net Fitness test. Methods are ranked according to five GOF criteria. The rankings are done by considering maximum of R^2, minimum of MAE, RMSE, NMAE, and χ^2. From aggregate results point of view, the top-down rank of estimation methods are GA, PD, GM, MOM, MSD, and EPF. GA is the best method for five cases, fourth best method for one case, fifth best method for one case and worst for two cases. On the other hand, EPF is second good method for two cases, third good method for one case, fourth good method for one case, fifth good method for one case, and worst for four cases. Table 14 presents overall performance of the estimation methods. According to Table 14 none of the methods ranked as the best for all cases. However, some of the methods may perform better than others. It can be concluded that there is not a single, universally accepted, best method to estimate Weibull distribution parameters [40].

Even though GM is simple and easy to use, one of its major drawbacks is biasing, i.e., the average of the predicted wind speeds differs from the corresponding actual mean wind speeds. In other words, GM method shows a higher deviation, this is due to higher discrepancy in shape and scale factor [65]. Regarding 2010 dataset, there is an inconsistency in wind speed pattern where wind speeds are varying intensively. Not only the GM but also all the other estimation methods are affected as shown in Figs. 3, 4, and 5 as well as Tables 11, 12, and 13. MOM is quite simple and yields consistent estimations, notwithstanding it is often biased and not necessarily sufficient, because it sometimes fails to take into consideration all relevant information in the sample.

Notably, GA metaheuristic method is superior to numerical estimation methods. This due to operating mechanism of the entire optimization process. The numerical methods depend on GRGN which is a single solution-based optimization technique, that is, it starts with a single random solution and improves over predefined generations. As a result, there is no information sharing and there arises many issues like local optima, deceptiveness and premature convergence with a single solution [37]. On other hand, GA is a population-based algorithm that starts with random solutions and improves as the iterations are increased. The main advantage of such population-based optimization is that there exists information exchange among the solutions of candidates. In this way, they can handle the local optima, bias of search space and premature convergence easier [37]. Nevertheless GA have overcome the limitations of numerical estimation

Table 11 Statistical accuracy analysis for 2008 dataset

Height (m)	Methods	Mean	SDV	Skewness	Kurtosis	MAE	RMSE	NMAE	χ^2	R^2	Net Fitness	Rank
30	GM	6.906	3.650	0.993	1.202	0.2899	0.3479	0.0559	0.0818	0.9909	0.1569	6
	MOM					0.2725	0.3380	0.0524	0.0755	0.9914	0.1494	4
	EPF					0.2760	0.3457	**0.0517**	**0.0519**	0.9910	0.1469	2
	MSD					0.2760	0.3457	**0.0517**	0.0755	0.9910	0.1516	5
	PD					0.2663	0.3216	0.0559	0.0917	0.9922	0.1487	3
	GA					**0.2409**	**0.3054**	0.0555	0.1016	**0.9930**	0.1421	1
60	GM	7.646	4.013	1.012	1.216	0.3105	0.3690	0.0616	0.1198	0.9915	0.1739	3
	MOM					0.3154	0.3901	0.0556	0.1049	0.9905	0.1751	4
	EPF					0.3736	0.5404	**0.0513**	**0.0911**	0.9819	0.2149	6
	MSD					0.3192	0.3981	0.0550	0.1049	0.9902	0.1774	5
	PD					0.3063	0.3692	0.0592	0.1151	0.9915	0.1716	2
	GA					**0.2746**	**0.3491**	0.0593	0.1125	**0.9924**	0.1606	1
80	GM	7.967	4.182	1.012	1.216	0.3273	0.3864	0.0628	0.0974	0.9915	0.1765	4
	MOM					0.3286	0.4065	0.0556	0.0741	0.9906	0.1748	3
	EPF					0.3893	0.5631	**0.0513**	**0.0548**	0.9819	0.2153	6
	MSD					0.3325	0.4148	0.0550	0.0741	0.9902	0.1772	5
	PD					0.3191	0.3846	0.0592	0.0885	0.9915	0.1720	2
	GA					**0.2862**	**0.3638**	0.0593	0.0992	**0.9924**	0.1632	1

Table 12 Statistical accuracy analysis for 2009 dataset

Height (m)	Methods	Mean	SDV	Skewness	Kurtosis	MAE	RMSE	NMAE	χ^2	R^2	Net Fitness	Rank
30	GM	7.251	3.833	0.993	1.202	**0.2855**	**0.4347**	**0.0544**	0.0762	**0.9871**	0.1727	1
	MOM					0.3133	0.4923	0.0565	0.0754	0.9835	0.1908	4
	EPF					0.3140	0.5057	0.0550	**0.0523**	0.9826	0.1889	3
	MSD					0.3140	0.5057	0.0550	0.0754	0.9826	0.1935	5
	PD					0.3115	0.4465	0.0624	0.0911	0.9864	0.1850	2
	GA					0.4001	0.5203	0.0773	0.1008	0.9816	0.2234	6
60	GM	7.663	4.050	0.993	1.202	0.2900	0.3511	0.0566	0.0890	0.9925	0.1588	3
	MOM					0.3033	0.3844	0.0512	0.0678	0.9910	0.1631	4
	EPF					0.3650	0.5524	**0.0475**	**0.0467**	0.9814	0.2060	6
	MSD					0.3075	0.3940	0.0506	0.0678	0.9905	0.1659	5
	PD					0.2903	0.3549	0.0546	0.0822	0.9923	0.1579	2
	GA					**0.2685**	**0.3433**	0.0558	0.0909	**0.9928**	0.1532	1
80	GM	8.0	4.229	0.993	1.202	0.2980	0.3624	0.0572	0.0961	**0.9927**	0.1642	3
	MOM					0.3133	0.4008	0.0508	0.0752	0.9910	0.1698	4
	EPF					0.3779	0.5812	**0.0469**	**0.0541**	0.9811	0.2158	6
	MSD					0.3178	0.4114	0.0503	0.0752	0.9905	0.1728	5
	PD					0.2988	0.3676	0.0542	0.0894	0.9924	0.1635	2
	GA					**0.2815**	**0.3619**	0.0562	0.0978	**0.9927**	0.1609	1

Table 13 Statistical accuracy analysis for 2010 dataset

Height (m)	Methods	Mean	SDV	Skewness	Kurtosis	MAE	RMSE	NMAE	χ^2	R^2	Net Fitness	Rank
30	GM	7.875	4.134	1.012	1.216	**0.8571**	**1.0315**	**0.1258**	0.3808	**0.9377**	0.4915	5
	MOM					0.9148	1.1061	0.1312	0.0677	0.9284	0.4583	3
	EPF					0.9150	1.1184	0.1298	**0.0475**	0.9268	0.4568	2
	MSD					0.9150	1.1184	0.1298	0.0677	0.9268	0.4608	4
	PD					0.9134	1.0610	0.1367	0.0828	0.9341	0.4520	1
	GA					1.0216	1.1587	0.1527	0.0941	0.9214	0.5011	6
60	GM	8.738	4.586	1.012	1.216	**1.0300**	**1.1835**	0.1400	0.7547	**0.9334**	0.6350	6
	MOM					1.0314	1.2610	0.1312	0.0646	0.9244	0.5128	2
	EPF					1.0725	1.4615	**0.1200**	**0.0477**	0.8985	0.5606	4
	MSD					1.0316	1.2736	0.1299	0.0646	0.9229	0.5154	3
	PD					1.0302	1.2056	0.1373	0.0774	0.9309	0.5039	1
	GA					1.1631	1.3193	0.1558	0.0860	0.9172	0.5614	5
80	GM	9.124	4.789	1.012	1.216	**1.0911**	**1.2429**	0.1429	0.7733	**0.9326**	0.6635	6
	MOM					1.0934	1.3340	0.1330	0.0642	0.9224	0.5405	2
	EPF					1.1357	1.5420	**0.1217**	**0.0485**	0.8963	0.5903	5
	MSD					1.0936	1.3472	0.1317	0.0642	0.9208	0.5432	3
	PD					1.0920	1.2762	0.1391	0.0762	0.9290	0.5309	1
	GA					1.2300	1.3945	0.1575	0.0842	0.9152	0.5902	4

Table 14 Ranking of the estimation methods

Estimation methods	Rank					
	1st	2nd	3rd	4th	5th	6th
GM	1	–	3	1	1	3
MOM	–	2	2	5	–	–
EPF	–	2	1	1	1	4
MSD	–	–	2	1	6	–
PD	3	5	1	–	–	–
GA	5	–	–	1	1	2
Best	GA	PD	GM	MOM	MSD	EPF

methods, but it deemed to be slower due to its computational complexity which is equal to $O(g(nm + nm + n))$ where g is the number of generations, n is the population size, and m is the size of the individuals. However, the computation time of GA as shown in Table 2 is still acceptable taking into account the penalty of computation overhead.

In order to interpret the results of Tables 11, 12, and 13 visually, the values of MAE for the estimation methods are drawn in Fig. 5. Further, Fig. 6 illustrates the scatter graphs of the estimation methods for all datasets. In each sub-graph of Fig. 6, the blue 45-degree line represents the measured wind speeds where other lines represent the deviations of the estimation methods from the real data. By scrutinizing Fig. 6, all six estimation methods almost fitted the measured data.

Many remarkable findings can be inferred from this study as follows:

- One of the most salient findings is that suitability of the estimation method may depend on various factors such as data size, data shape, and selected goodness of fit measures.
- The second important finding is that the distribution pattern of wind regime can differ from one site to another; therefore, to make a good decision which the estimation method to evaluate the Weibull parameters is the best, different estimation methods should be used.
- The third important finding is the used estimation method, For example, an estimation method could achieve the best matching at a particular site, but does not at another site. Besides, an estimation method can accomplish the best matching at particular height but does not for another height at the same site.
- The fourth important finding is the data size, since the distribution pattern of wind regime can differ from year to year at the same site. Hence, to decide the estimation method with the best effectiveness, it should be tested over wide range of years.
- The fifth important finding is the used error measures. For instance, a certain error measure may achieve the best for a particular estimation method; but the worst for another. Thus, it is necessary to apply different error measures. Then, to determine the top-rank estimation method accurately, the Net Fitness computation is required.

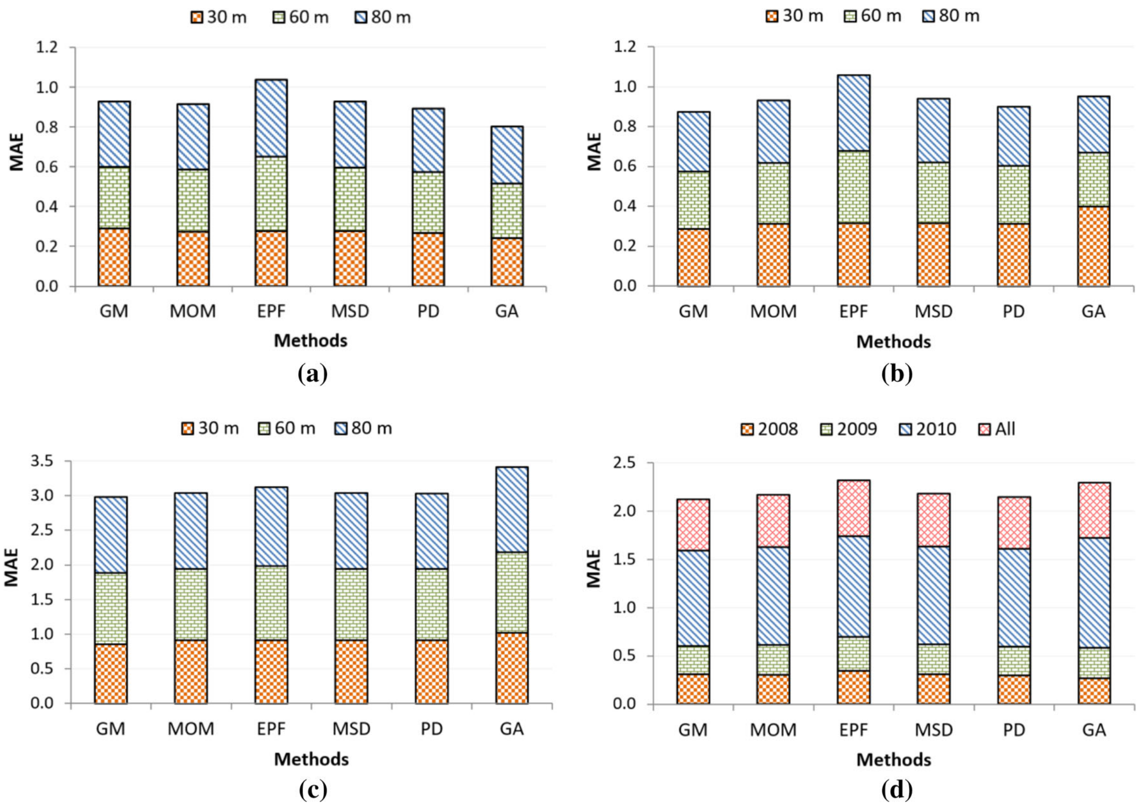
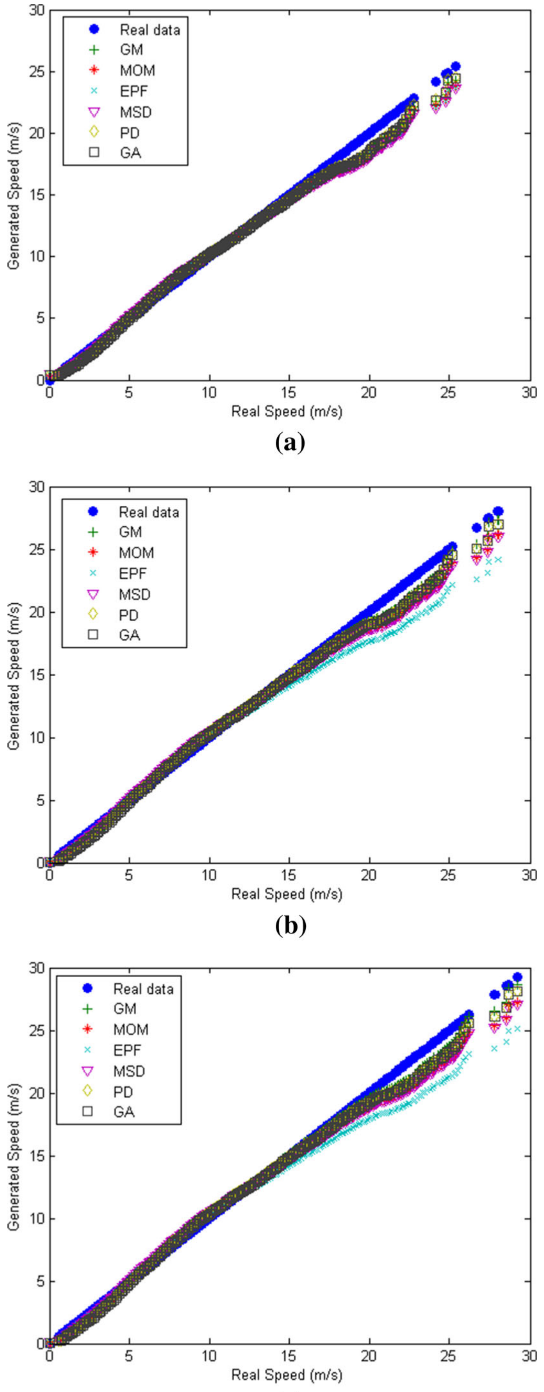


Fig. 5 The MAE charts of used methods for: **a** 2008 dataset, **b** 2009 dataset, **c** 2010 dataset, and **d** the average

- The sixth important finding is the Weibull scale parameter pattern can be used as indicator for monthly mean wind speeds pattern and vice versa.

7 Conclusion

Weibull is one of the most widely-used distribution functions to describe the wind pattern regime. Estimation of Weibull parameters is a significant factor for wind energy analyses, so they should be modeled accurately. In this paper, efficient, practical, and empirical six estimation methods: GM, MOM, EPF, MSD, PD, and GA, to estimate Weibull distribution parameters are presented. The performance and accuracy of the estimation methods are tested and compared using MAE, RMSE, NMAE, χ^2, and R^2 error criteria. Furthermore, the Net Fitness test is also computed to specify the top-rank estimation methods over all datasets. Wind data for 3 years at the Catalca site in the Marmara region in Istanbul, Republic of Turkey, are used to carry out this study. Comparison results show that GA and GM in terms of MAE, RMSE and R^2 tests achieve the first and second best method, respectively. However, in terms of NMAE and χ^2 tests, EPF outperforms the other methods. Besides, based on the Net Fitness test, the GA method achieves the best matching, whereas the EPF provides the worst matching. One of the most important findings of this paper is that suitability of the estimation methods depends on various factors such as data size, data shape, and selected goodness of fit measures. Therefore, various estimation methods based on sufficient size of wind data along with using various GOF measures are required to accurately decide the most appropriate estimation method.



(a)

(b)

(c)

Fig. 6 The scatter graphs of the used methods on 2008 at: **a** 30 m, **b** 60 m, and **c** 80 m. The scatter graphs of the used methods on 2009 dataset at: **a** 30 m, **b** 60 m, and **c** 80 m. The scatter graphs of the used methods on 2010 at: **a** 30 m, **b** 60 m, and **c** 80 m

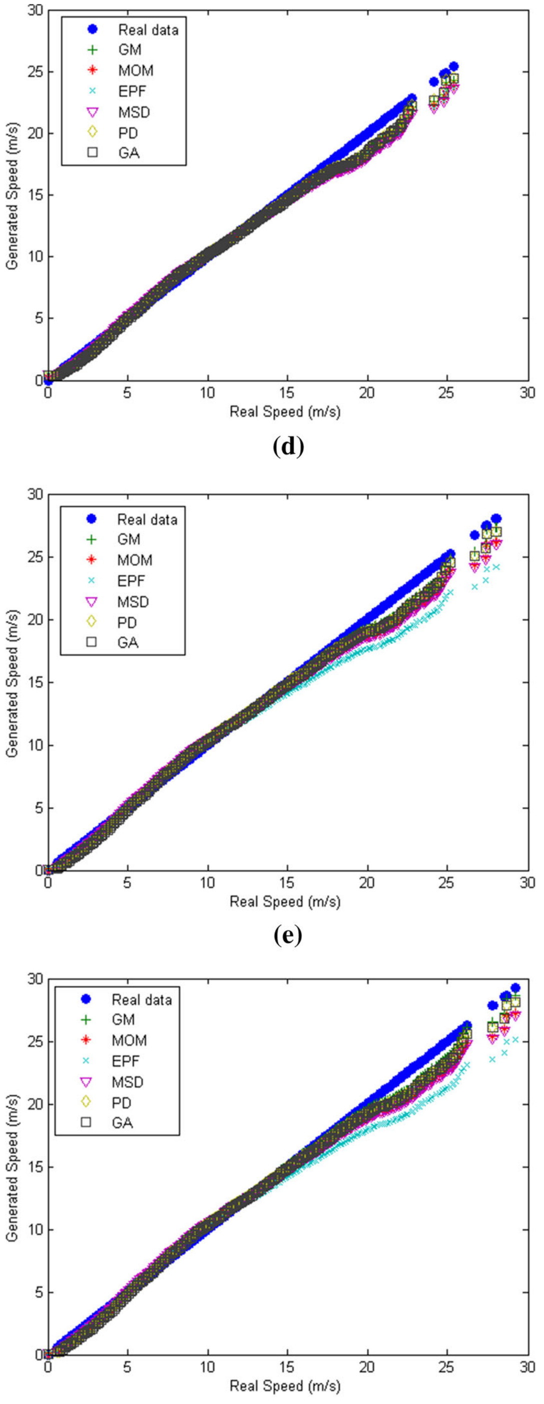


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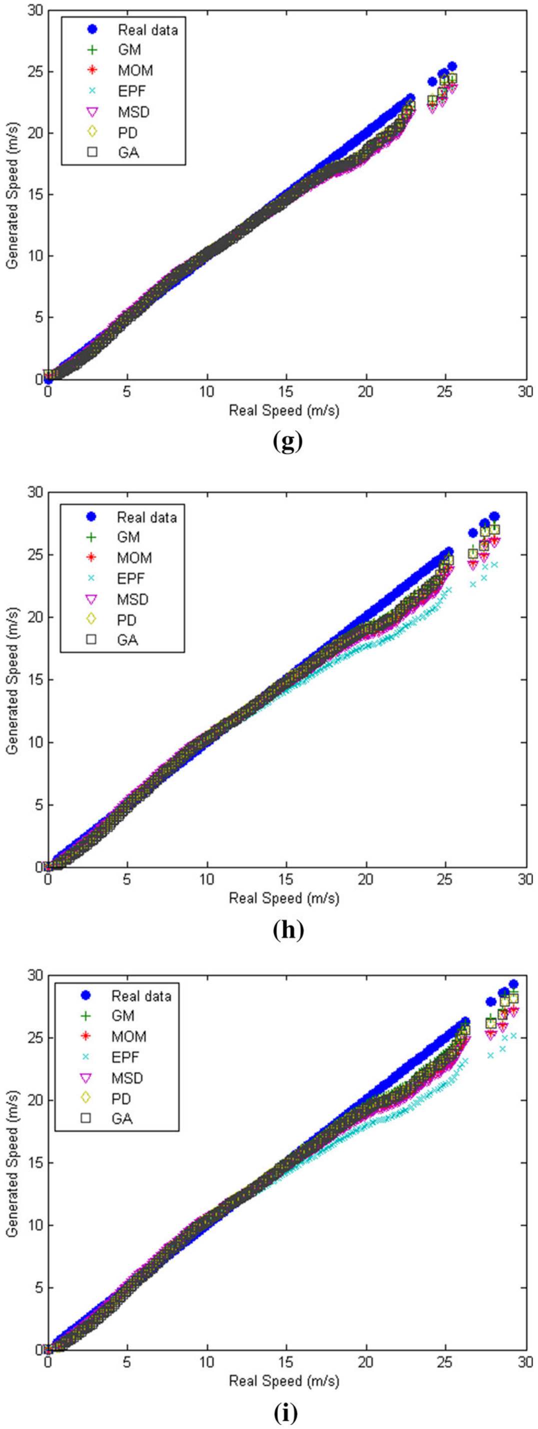
Fig. 6 continued



(g)

(h)

(i)

Fig. 6 continued

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Declarations

Conflict of interest The authors declare that there are no conflicts of interest regarding the publication of this paper.

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