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**Article**

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# Weibull parameters evaluation by different methods for windmills farms

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## Abstract

Electrical power generated from the wind's motion is one of the most common clean and renewable energy produced. The wind turbines used to convert wind mechanical power to electricity have to be placed at a site presenting favorable conditions. This work focuses on finding an accurate method for modeling the power generated by a wind farm using Weibull distribution. Experimental data collected at AL-Najaf site – Iraq – is used to determine the best theoretical method to hold in order to determine the Weibull parameters. The data was collected on different levels above the ground 10, 30, and 50 m. Four criteria were displayed to assess the wind data fitting procedures; these are Root Mean Square Error, Chi-Square, correlation coefficient, and coefficient of determination. The valid distribution model was determined according to specific conditions that gives the best results. The findings indicate that the Equivalent Energy Method is the best to calculate the value of the Weibull shape parameter and the Weibull scale parameter for the Weibull distribution curves at this site based on the goodness of fit tests.

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**Keywords:** Weibull parameters; Maximum likelihood method; Modified maximum likelihood method

## 1. Introduction

The demand for electricity is increasing and becoming indispensable for life. Renewable energy is still a hot topic for researchers for its unlimited opportunities and its ecofriendly character. This research focuses the estimation of the electric power generated by a planned wind turbine farm. There are many methods to calculate and estimate the power produced from wind at a specific location, but the accurate one vary depending on the parameters used in the process.

The proposal was made for a nested Maximum Likelihood Estimation (MLE) technique in which a space parameter was subdivided for the best fit parameters [1]. However, this method reveals only marginally stronger projections than that of the ordinary MLE technique [2]. In order to prevent incompatible alternatives, Lockhart

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et al. [3] added an alternate technique to the standard MLE technique, when the real form parameter is less than 1. The periodic MLE process generalizations are the Bayesian estimating methods and the MLE previously informed [4]

The theoretical calculations concepts are summarized below for each parameter used in this research;

Mean wind speed [5–8]

$$\bar{v} = \frac{1}{n} \sum_{i=1}^n v_i \quad (1)$$

It can be given by Weibull parameters as;

$$\bar{v} = c\Gamma\left(1 + \frac{1}{k}\right) \quad (2)$$

where  $n$  is the number of wind data, and  $v_i$  is the wind speed.

Maximum wind speed [9]

$$v_{max} = c \left(\frac{k+2}{k}\right)^{1/k} \quad (3)$$

Two parameters probability density function (PDF) [10]

$$f(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)^k\right) \quad (4)$$

where  $f(v) \geq 0$ ,  $v \geq 0$ ;  $k > 0$ ,  $c > 0$

$f(v)$  is the probability of observing wind speed.

$k$  is the Weibull shape parameter

$c$  is the Weibull scale parameter

Standard deviation of Weibull density function: [5–8]

$$\sigma = c \cdot \sqrt{\Gamma\left(1 + \frac{2}{k}\right) - \left(\Gamma\left(1 + \frac{1}{k}\right)\right)^2} \quad (5)$$

Coefficient of variation (COV %): [11]

$$COV (\%) = \frac{\sigma}{\bar{v}} = \frac{\sqrt{\Gamma\left(1 + \frac{2}{k}\right) - \left(\Gamma\left(1 + \frac{1}{k}\right)\right)^2}}{\Gamma\left(1 + \frac{1}{k}\right)} \times 100\% \quad (6)$$

Power law coefficient [12]

$$\alpha = \frac{\ln(v_2) - \ln v_1}{\ln(Z_2) - \ln Z_1} \quad (7)$$

Histogram Intervals: [13]

$$\bar{v} = \frac{1}{n} \sum_{i=1}^w m_i v_i \quad (8)$$

where  $m_i$  is the numbers of observations of a specific wind speed  $v_i$ .

$w$  is the numbers of different values of observed wind speed.

Wind Speed Frequency Distribution [14]

$$R_f = \frac{\text{frequency of given wind speed}}{\text{total period}} \quad (9)$$

## 2. Weibull factors estimation methods

The Weibull factors were estimated using six different methods.

1-Standard deviation method (STDm) [15–17]

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086} \quad (10)$$

$$c = \frac{\bar{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \quad (11)$$

2-Maximum Likelihood Method (MLM) [18–20]

Maximum likelihood estimation has been the most widely used method for estimating the parameters of the Weibull distribution.

Eq. (12) known as a function equation of Likelihood, the arbitrary sample is likely to be combined by  $n$  random variables, and depending on the unknown parameter given as:

$$L = \prod_{i=1}^n f_{vi}(v_i, \theta) \quad (12)$$

where  $v_1, v_2, \dots, v_n$  is supposed to be an arbitrary sample of size  $n$  of an infinitely variable  $f(v_i, \theta)$ , where  $\theta$  a parameter that is unknown.

The maximum likelihood estimator (MLE) of, say  $\hat{\theta}$ , is the value of  $\theta$  that maximizes  $L$  or, in the same way,  $L$ 's logarithm.

$$\frac{d \log L}{d\theta} = 0 \quad (13)$$

By applying MLE, Weibull parameters can be obtained. The likelihood function can be rewritten considering the Weibull Probability function (pdf) and can describe as;

$$L(v_1 v_2 \dots v_n, k, c) = \prod_{i=1}^n \frac{k}{c} \left(\frac{v_i}{c}\right)^{k-1} \exp\left(-\left(\frac{v_i}{c}\right)^k\right) \quad (14)$$

On taking the logarithms of both sides of Equation above, we obtain the estimating log-likelihood function:

$$\ln(L) = n \ln(k) - nk \ln(c) + (k-1) \sum_{i=1}^n \ln v_i - \sum_{i=1}^n \left(\frac{v_i}{c}\right)^k \quad (15)$$

Differentiating Equation above with respect to  $k$  and  $c$  in turn and equating to zero, we have

$$\frac{\partial \ln(L)}{\partial c} = -n \left(\frac{k}{c}\right) + \left(\frac{k}{c}\right) \sum_{i=1}^n \left(\frac{v_i}{c}\right)^k = 0 \quad (16)$$

$$\frac{\partial \ln(L)}{\partial k} = \left(\frac{n}{k}\right) + \sum_{i=1}^n \left(\frac{v_i}{c}\right)^k - \sum_{i=1}^n \left(\frac{v_i}{c}\right)^k \ln\left(\frac{v_i}{c}\right) = 0 \quad (17)$$

$$c = \left[ \frac{1}{n} \sum_{i=1}^n (v_i)^k \right]^{1/k} \quad (18)$$

If  $k$  is acquired,  $c$  can be determined.

Maximum Likelihood Method–Newton Raphson Method (MLM–NRM); [18,21,22]

$k$  in Eq. (18) can be solved by using NRM as follow;

$$f'(k) = -\left(\frac{n}{k^2}\right) - \sum_{i=1}^n \left(\frac{v_i}{c}\right)^k \ln^2\left(\frac{v_i}{c}\right) \quad (19)$$

Substituting Eq. (18) into Eq. (17) gives;

$$f'(k) = -\left\{ \left(\frac{n}{k}\right) + \sum_{i=1}^n \left[ \frac{(v_i)^k}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}} \right] \ln^2 \left[ \frac{(v_i)}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}^{1/k}} \right] \right\} \quad (20)$$

Therefore,  $k$  is obtained from the equation below by carefully choosing an initial value for  $k_i$  and iterating the process until it converges:

$$k_{i+1} = k_i - \frac{\left(\frac{n}{k}\right) + \sum_{i=1}^n \left[ \frac{(v_i)}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}^{\frac{1}{k}}} \right]}{\left\{ \left(\frac{n}{k}\right) + \sum_{i=1}^n \left[ \frac{(v_i)^k}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}} \right] \ln^2 \left[ \frac{(v_i)}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}^{\frac{1}{k}}} \right] \right\}} - \frac{\sum_{i=1}^n \left[ \frac{(v_i)^k}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}} \right] \ln \left[ \frac{(v_i)}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}^{\frac{1}{k}}} \right]}{\left\{ \left(\frac{n}{k}\right) + \sum_{i=1}^n \left[ \frac{(v_i)^k}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}} \right] \ln^2 \left[ \frac{(v_i)}{\left\{ \left(\frac{1}{n}\right) \sum_{i=1}^n (v_i)^k \right\}^{\frac{1}{k}}} \right] \right\}} \tag{21}$$

3-Maximum Likelihood Method using modified iterative method (MLE-MIM) [23–28]

Three-parameters Weibull distribution expression can be expressed as

$$f(v) = \frac{k}{c} \left(\frac{v-g}{c}\right)^{k-1} \exp\left(-\left(\frac{v-g}{c}\right)^k\right) \tag{22}$$

where,  $g$  = the location parameter, and  $g \leq v$ .

From Eq. (22)

$$-\frac{nk}{c} + \frac{k}{c} \sum_{i=1}^n \left(\frac{v_i - g}{c}\right)^k = 0 \tag{23}$$

By simplifying above gives:

$$c = \left[ \frac{1}{n} \sum_{i=1}^n (v_i - g)^k \right]^{1/k} \tag{24}$$

After some substitutions and arrangements, shape parameter is given by:

$$k = \left( \frac{\sum_{i=1}^n (v_i - g)^k \ln(v_i - g)}{\sum_{i=1}^n (v_i - g)} - \frac{\sum_{i=1}^n \ln(v_i - g)}{n} \right)^{-1} \tag{25}$$

4-Maximum Likelihood Method using iterative method (MLM-IM) [29,30]

From Eqs. (16) and (17), eliminating  $c$  between these two equations and simplifying the results yield

$$\frac{\sum_{i=1}^n v_i^k \ln(v_i)}{\sum_{i=1}^n v_i^k} - \frac{1}{k} - \frac{1}{n} \sum_{i=1}^n \ln(v_i) = 0 \tag{26}$$

After rearranging Eq. (26), it is possible to estimate the shape factor as follows,

$$k = \left( \frac{\sum_{i=1}^n v_i^k \ln(v_i)}{\sum_{i=1}^n v_i^k} - \frac{\sum_{i=1}^n \ln(v_i)}{n} \right)^{-1} \tag{27}$$

The above equation must be solved using iterative procedure, after which Eq. (18) is applied in order to estimate scale parameter. Care must be taken to apply Eq. (27) only to the nonzero wind speed data points.

5-Energy pattern factor method (EPFM) [18,26,31]

Energy pattern factor (EPF) or Cube Factor is the ratio between the total power available in the wind and the power corresponding to the cube of the mean wind speed,

$$E_{PF} = \frac{\text{Total amount of power available in the wind}}{\text{power calculated by mean cube speed}} \tag{28}$$

In terms of wind speed we have;

$$E_{PF} = \frac{\frac{1}{n} \sum_{i=1}^n v_i^3}{\left(\frac{1}{n} \sum_{i=1}^n v_i\right)^3} \tag{29}$$

Once the energy pattern factor for a regime is found from the wind data, an approximate solution for k is:

$$k = 3.957 E_{PF}^{-0.898} \tag{30}$$

6-Equivalent energy method (EEM) [11,30,32]

The probability of wind speed observation is higher or equal to a particular value, v, depending on the Weibull distribution. It is defined by

$$P(v) = \exp - \left(\frac{v}{c}\right)^k \tag{31}$$

P(v) represents the frequency of the observed wind speed in the interval  $(v - 1) \leq V < v$ .

The probability that the wind speeds are higher than v - 1 ( $v - 1 < v$ ) now is

$$P = P(v - 1) - P(v) \tag{32}$$

$$P(v) = \exp - \left(\frac{v - 1}{c}\right)^k - \exp - \left(\frac{v}{c}\right)^k \tag{33}$$

Statistically a stochastic variable Pv represented by the probability function P can be defined as:

$$Pv = P(v) + \varepsilon = \exp - \left(\frac{v - 1}{c}\right)^k - \exp - \left(\frac{v}{c}\right)^k + \varepsilon \tag{34}$$

where ε corresponds to the stochastic term.

The first hypothesis states that: “Energy density is a parameter which helps determining the Weibull distribution parameters for wind energy applications”. The associated deterministic factor part must correspond to the energy content equivalence conditions between the wind speeds observed in the Weibull distribution, the scale factor c can be indicated as the mean cube expression

$$c = \left(\frac{\bar{v}^3}{\Gamma(1 + \frac{3}{k})}\right)^{1/3} \tag{35}$$

Substituting Eq. (35) in Eq. (34) yields

$$Pv = e^{-\left(\frac{(v-1)\Gamma(1+\frac{3}{k})^{1/3}}{\bar{v}}\right)^k} - e^{-\left(\frac{v\Gamma(1+\frac{3}{k})^{1/3}}{\bar{v}}\right)^k} + \varepsilon \tag{36}$$

By using the least squares method for the following expression, the Weibull shape factor, k, can be assessed

$$\sum_{i=1}^{\acute{n}} \left[ P_{v_i} - e^{-\left(\frac{(v_i-1)\Gamma(1+\frac{3}{k})^{1/3}}{\bar{v}}\right)^k} + e^{-\left(\frac{v_i\Gamma(1+\frac{3}{k})^{1/3}}{\bar{v}}\right)^k} \right]^2 = \sum_{i=1}^{\acute{n}} (\varepsilon_i)^2 \tag{37}$$

- $P_{v_i}$  Wind speeds for the ith bin, probability,
- $\acute{n}$  The wind speed histogram number of bins,
- $v_i$  The ith bin’s highest wind speed value
- $\bar{v}^3$  the mean cube (observed).

The scale factor is calculated from Eq. (35) after k has been computed.

Four criteria are used to validate the accuracy of the predicted wind speed distribution derived from the Weibull probability density function;

1- Root mean square error (RMSE). The RMSE was used to assess the difference between both the estimated and the observed values. It is given by Eq. (38) [28,33]

$$RMSE = \left[ \frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2 \right]^{1/2} \quad (38)$$

where,

$y_i$  = is the  $i$ th actual wind distribution (measured data)

$x_i$  = is the predicted wind distribution from the Weibull.

$n$  = is the number of wind speed dataset (bins).

2-Chi-square ( $\chi^2$ ). It is used for the evaluation of the predicted wind distribution in relation to real wind distribution. For the Chi-square test “ $\chi^2$ ” the mathematical expression is described: [28,34]

$$\chi^2 = \sum_{i=1}^n \frac{(y_i - x_i)^2}{x_i} \quad (39)$$

3-Correlation coefficient (R), A statistical method is employed to ascertain the linear correlation between two datasets. The R mathematical equation is interpreted as [35]

$$R = \frac{\sum_{i=1}^n (y_i \cdot x_i) - \sum_{i=1}^n y_i \cdot \sum_{i=1}^n x_i}{\sqrt{\sum_{i=1}^n y_i^2 - \left(\sum_{i=1}^n y_i\right)^2} \cdot \sqrt{\sum_{i=1}^n x_i^2 - \left(\sum_{i=1}^n x_i\right)^2}} \quad (40)$$

4-The coefficient of determination ( $R^2$ ), The values of  $R^2$  measures the strength of the linear ratio of estimated and actual bins frequencies, it is described as [35]

$$R^2 = \frac{\sum_{i=1}^n (y_i - z_i)^2 - \sum_{i=1}^n (y_i - x_i)^2}{\sum_{i=1}^n (y_i - z_i)^2} \quad (41)$$

Z is the mean value of  $y_i$ .

In general, the more useful distribution function can be selected according to the lowest values of RMSE and highest values of R and  $R^2$

#### Methodology:

Weibull scale and shape parameters were evaluated by six methods:

Standard Deviation Method (STDM).

Maximum likelihood Estimation-Newton Raphson Method (MLE-NRM).

Maximum Likelihood Estimation-Modified Iterative Method (MLE-MIM).

Maximum likelihood Estimation-Iterative Method (MLE-IM).

Energy Pattern Factor Method (EPFM).

Equivalent energy method (EEM).

These methods (STDM), (EPFM), (MLE-NRM), (MLE-IM), (ML-EMIM), (EEM) were applied to data series recorded at Al-Najaf site at 10, 30, 50 m above ground level. The values of speed and direction were recorded every 10 min. Minimum, maximum values, mean wind speed, standard deviation and variance data were applied as statistics techniques. To decide the appropriateness of the supposed distributions for wind speed data, several analytical criteria have been established. Four criteria are displayed to evaluate the wind data fitting procedures; these are RMSE, Chi-Square ( $\chi^2$ ), correlation coefficient (R), and coefficient of determination  $R^2$ . The valid distributional model can be determined according to the highest values of R and  $R^2$  and lowest values of RMSE and  $\chi^2$ .

#### Description of wind data measurements

The wind data employed in this study were collected over the year 2016 at 10, 30, 50 m height above ground level, a time interval of 10 min. The mast was installed from renewable energy directorate — Ministry of Science and technology. Fig. 1 shows the picture of the installed mast.

### 3. Results and discussions

The data was collected by the metrological mast every 10 min at (10, 30, and 50) m height. The wind speed and directions vary with time nonlinearly. Therefore the average wind speed could not be easily calculated. The



Fig. 1. Met. Mast [36].

monthly mean wind speed were calculated with respect to Eq. (2). Table 1 illustrates the monthly mean wind speed, maximum speed, minimum speed, Standard deviation, and coefficient of variation (COV) at 10 m height. Tables 2 and 3 illustrate the same parameters as in Table 1 but at 30 m and 50 m height respectively.

Table 1. Mean monthly (m/s) statistics of wind speed (10 m a.g.l) for Al-Najaf station.

Wind	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
N (10 min)	4606	4176	4456	4321	4465	4321	4465	4465	4321	4465	4321	4465
V mean	3.83	4.08	4.32	3.75	4.72	4.95	4.95	4.06	4.2	3.29	4.22	3.41
V max	5.13	5.58	6.08	5.62	6.85	7.06	7.11	5.77	5.89	4.71	5.6	4.69
V min	2.46	2.58	2.63	2.01	2.74	2.91	2.96	2.34	2.5	1.96	2.75	2.21
$\sigma$ (m/s)	0.53	0.59	0.7	0.77	0.8	0.83	0.84	0.69	0.68	0.59	0.55	0.53
COV (%)	13.8	14.5	16.2	20.5	16.9	16.8	17.0	17.0	16.2	17.9	13.0	15.5

Table 2. Mean monthly (m/s) statistics of wind speed (30 m a.g.l) for Al-Najaf station.

Wind	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
N (10 min)	4606	4176	4456	4321	4465	4321	4465	4465	4321	4465	4321	4465
V mean	5.02	5.27	5.47	4.79	5.88	6.09	6.14	5.08	5.38	4.25	5.53	4.51
V max	6.18	6.58	7.07	6.51	7.82	8.02	8.13	6.65	6.91	5.57	6.66	5.6
V min	3.72	3.87	3.83	3.12	3.98	4.11	4.21	3.42	3.78	2.98	4.26	3.32
$\sigma$ (m/s)	0.49	0.54	0.66	0.72	0.79	0.79	0.81	0.66	0.63	0.56	0.46	0.46
COV (%)	9.8	10.2	12.1	15.0	13.4	13.0	13.2	13.0	11.7	13.2	8.3	10.2

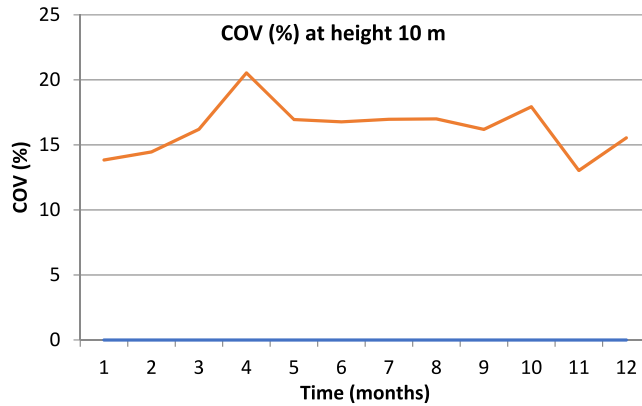
Figs. 2–4 illustrate the monthly coefficient of variation (COV) at 10, 30, and 50 m height. These figures show that the variation of COV is more important at low level (10 m), whereas at higher levels those variations are reduced. The reason behind this increase of stability is the lower effect of the obstacles on the wind's motion.

Table 4 illustrated the power law coefficient ( $\eta$ ) at 30 and 50 m height. The results show that power law varies from a month to the other, and it should be mentioned that ( $\eta$ ) was calculated with respect to experimental data.

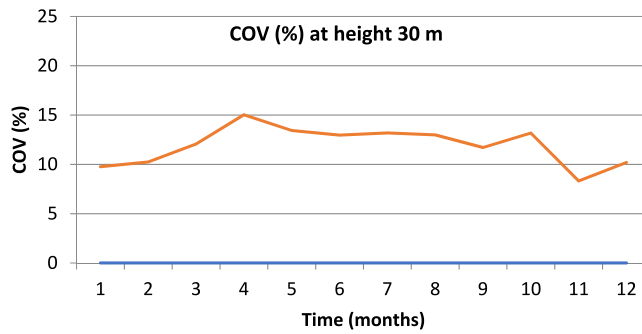


**Table 3.** Mean monthly (m/s) statistics of wind speed (50 m a.g.l) for Al-Najaf station.

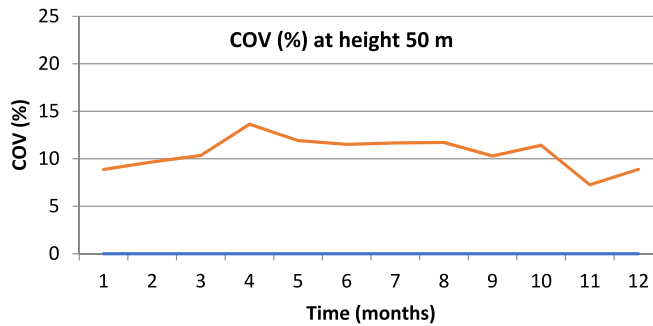
Wind	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
N (10 min)	4606	4176	4456	4321	4465	4321	4465	4465	4321	4465	4321	4465
V mean	5.52	5.69	6.09	5.28	6.38	6.51	6.69	5.46	5.83	4.64	5.92	4.95
V max	6.65	7.13	7.64	7.05	8.31	8.39	8.64	6.99	7.31	5.87	6.99	6.01
V min	4.29	4.35	4.5	3.64	4.52	4.62	4.81	3.88	4.31	3.39	4.75	3.84
$\sigma$ (m/s)	0.49	0.55	0.63	0.72	0.76	0.75	0.78	0.64	0.6	0.53	0.43	0.44
COV (%)	8.9	9.7	10.3	13.6	11.9	11.5	11.7	11.7	10.3	11.4	7.3	8.9



**Fig. 2.** Monthly mean COV of turbulence at 10 m height.



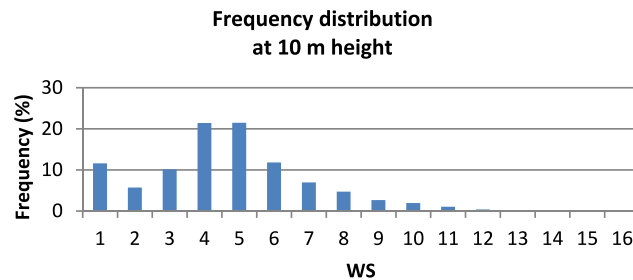
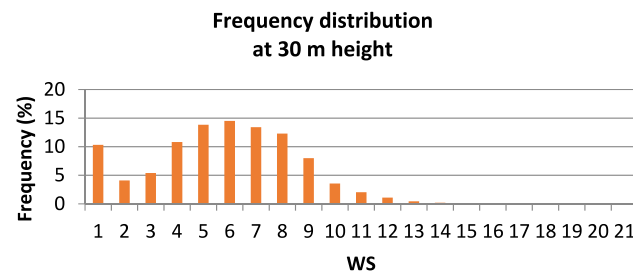
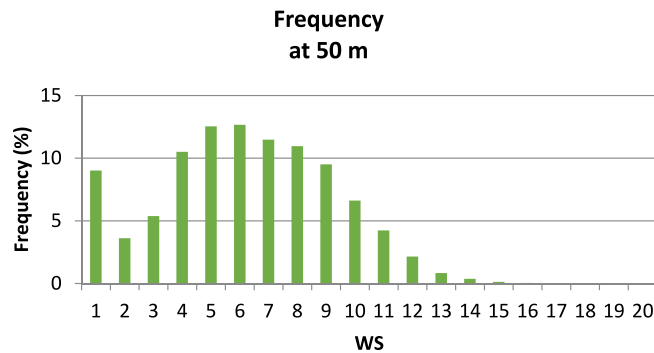
**Fig. 3.** Monthly mean turbulence COV at a height of 30 m.



**Fig. 4.** Monthly mean turbulence COV at a height of 50 m.

**Table 4.** Monthly wind speed, coefficient of power law ( $\eta$ ), at 30 and 50 m height.

ind	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
V mean (30 m)	5.02	5.27	5.47	4.79	5.88	6.09	6.14	5.08	5.38	4.25	5.53	4.51
V mean (50 m)	5.52	5.69	6.09	5.28	6.38	6.51	6.69	5.46	5.83	4.64	5.92	4.95
Power law coefficient ( $\eta$ )	0.18587	0.15011	0.21019	0.19066	0.15976	0.13056	0.16794	0.14122	0.15725	0.14027	0.13341	0.1504

**Fig. 5.** Frequency distribution for the selected site at 10 m height.**Fig. 6.** Frequency distribution for the selected site at 30 m height.**Fig. 7.** Frequency distribution for the selected site at 50 m height.

The frequency of wind speed values are calculated and presented in Fig. 5 for 10 m height. Figs. 6 and 7 illustrated the frequency of wind speed at 30 m and 50 m heights respectively.

The results showed, however, that the wind speed at values 4 and 5 m/s has approximately 20 percent of the highest frequency in Fig. 5, while in Fig. 6 the highest frequency at wind speed is 5, 6 and at 7 m/s (14 percent). In Fig. 7, the most frequent wind speeds of values 5 and 6 m/s are about 13%.

Tables 5–7 summarize how adequate are (SDDM), (MLE-NRM), (MLE-MIM), (MLE-IM), (EPFM), and (EEM) to the calculation of Weibull parameters  $c$  and  $k$  for Al-Najaf station at a height of 10 m, 30 m and 50 m heights respectively, as well as the statistical test efficiency criteria.

**Table 5.** Weibull distribution analysis at 10 m in height for Al-Najaf station.

Statistical methods	The Weibull parameters		Statistical test efficiency			
	c	k	RMSE	( $\chi^2$ )	R	R <sup>2</sup>
STDm	4.67	1.89	0.03485	0.177	0.75	0.56
MLE-NRM	4.47	1.5	0.042	0.209	0.64	0.4
MLE-MIM	4.62	1.77	0.03642	0.163	0.72	0.53
MLE-IM	4.62	1.77	0.03642	0.163	0.72	0.53
EPFM	4.68	2.11	0.03297	0.266	0.77	0.59
EEM	4.96	2.28	0.03213	0.137	0.78	0.62

Table 5 summarizes statistical fitness errors between the estimated probability distribution functions and the histogram of the measured data at 10 m height as a result of calculating the correctness of fit between the estimated probability distribution functions. It was shown that, in addition to the highest values of R and COD, EEM offers the best distribution model in the lowest RMME and  $\chi^2$  values.

**Table 6.** Weibull distribution analysis at 30 m in height for Al-Najaf station.

Statistical methods	The Weibull parameters		Statistical test efficiency			
	c	k	RMSE	( $\chi^2$ )	R	R <sup>2</sup>
STDm	5.96	2.04	0.02756	0.323	0.74	0.54
MLE-NRM	5.65	1.5	0.03467	0.267	0.58	0.34
MLE-MIM	5.88	1.87	0.02923	0.247	0.7	0.5
MLE-IM	5.88	1.87	0.02923	0.247	0.7	0.5
EPFM	5.96	2.32	0.0271	0.601	0.74	0.56
EEM	6.26	2.55	0.025	1.175	0.78	0.61

It is been shown in Table 6 that EEM offers the best distribution model in the lower RMSE values in addition to the highest R and COD values.

**Table 7.** Weibull distribution analysis at 50 m in height for Al-Najaf station.

Statistical methods	The Weibull parameters		Statistical test efficiency			
	c	k	RMSE	( $\chi^2$ )	R	R <sup>2</sup>
STDm	6.48	2.01	0.0192	0.261	0.83	0.69
MLE-NRM	6.64	2.3	0.01837	0.541	0.84	0.72
MLE-MIM	6.39	1.84	0.02045	0.195	0.81	0.66
MLE-IM	6.39	1.84	0.02045	0.195	0.81	0.66
EPFM	6.48	2.28	0.01946	0.499	0.83	0.68
EEM	6.69	2.31	0.01828	0.574	0.85	0.72

It is shown that EEM provides the best distribution model in the lowest RMSE values, in addition to the highest R and COD values.

The applied method for calculating the Weibull distribution parameters are compared with each other with respect to RMS and the ranking is illustrated in Table 8.

**Table 8.** Comparison of the Weibull distribution analysis for Al-Najaf Station at 10, 30, and 50 m height.

Statistical methods	10 m height RMSE	30 m height RMSE	50 m height RMSE	Rank at 10 m	Rank at 30 m	Rank at 50 m
STDm	0.03485	0.02756	0.0192	Fifth	Fifth	Fifth
MLE-NRM	0.042	0.03467	0.01837	Fourth	Fourth	Fourth
MLE-MIM	0.03642	0.02923	0.02045	Third	Third	Third
MLE-IM	0.03642	0.02923	0.02045	Third	Third	Third
EPFM	0.03297	0.0271	0.01946	Second	Second	Second
EEM	0.03213	0.025	0.01828	First	First	First

The comparison of the different methods with respect to power density are illustrated in Table 9.

**Table 9.** Calculated power density at different Weibull distribution analysis methods.

Statistical methods	10 m height Power density (W/m <sup>2</sup> )	30 m height Power density (W/m <sup>2</sup> )	50 m height Power density (W/m <sup>2</sup> )
STDM	88.51	168.98	219.81
MLE-NRM	109.49	172.2	221.38
MLE-MIM	92.95	178.3	232.3
MLE-IM	92.95	187.3	232.3
EPFM	97.29	150.75	196.2
EEM	88.4	163.26	213.58

#### 4. Conclusion

The evaluation and estimation of the finding of an exact method to model wind farm power generated by the Weibull distribution are the main goal of this work. In the present paper Weibull parameters were evaluated by different methods for Al-Najaf site — Iraq. The data series were recorded at 10, 30, and 50 m above the ground level at al-Najaf site. The application of two parameters, Weibull PDF, to estimate the wind potentially at a particular location provides a great result based on several researchers and IEC 61400-12 international standard, as well as other global recommendations. Six methods namely (STDM), (MLE-NRM), (MLE-MIM), (MLE-IM), (EPFM) and (EEM) are therefore tested to discover the best model to estimate Weibull parameters. It is necessary to note that any of the statistical four goodness of fit tests, i.e. RMSE, chi-square error ( $\chi^2$ ), correlation coefficient (R) and method variance or effectiveness assessment ( $R^2$ ), are sufficiently enough to rank the processes. However, analysis were carried out using them all to rank more accurately. The comparisons indicate that the EEM exceeds other energy assessment methods depending on the goodness of fit tests for Weibull distribution curve.

The findings indicate that the EEM is the best method to calculate k and c value in this site.

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