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Energy output estimation for small-scale wind power generators using Weibull-representative wind data

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Abstract

Estimation of energy output for small-scale wind power generators is the subject of this article. Monthly wind energy production is estimated using the Weibull-representative wind data for a total of 96 months, from 5 different locations in the world. The Weibull parameters are determined based on the wind distribution statistics calculated from the measured data, using the gamma function. The wind data in relative frequency format is obtained from these calculated Weibull parameters. The wind speed data in time-series format and the Weibull-representative wind speed data are used to calculate the wind energy output of a specific wind turbine. The monthly energy outputs calculated from the time-series and the Weibull-representative data are compared. It is shown that the Weibull-representative data estimate the wind energy output very accurately. The overall error in estimation of monthly energy outputs for the total 96 months is 2.79%.

Keywords: Estimation of wind energy; Weibull wind speed distribution model; Weibull-representative data

1. Introduction

Large-scale wind turbines have already proved themselves as cost competitive electricity generators in locations where wind resource is good enough. Improved turbine designs and plant utilisation have contributed to a decline in large-scale wind

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energy generation costs from 35 cents per kWh in 1980 to less than 5 cents per kWh in 1997 in favourable locations [1]. At this price, wind energy has become one of the least-cost power sources. Wind electricity by medium-scale wind turbines is preferable in remote locations and in small islands for being socially valuable and economically competitive. For example, as the Aegean Archipelago has excellent wind potential, the Greek State is strongly subsidising private investments in the area of wind energy applications. Kaldellis and Gavras [2] state that the mean electricity production cost of autonomous power stations, used to fulfil the electricity demands for most of the Aegean Sea islands, is extremely high, three times higher than the corresponding marginal cost of Greek Power Production Company (PPC). After a complete cost-benefit method and an extensive sensitivity analysis, they conclude that the vast majority of wind energy applications in Greece is one of the most promising investments in the energy production sector. Besides, wind power stations can fulfil the energy requirements for almost all islands of the Aegean Archipelago. The most appropriate wind farm in Greece includes about 10 wind turbines in the range of 300–500 kW each, according to Kaldellis and Gavras's experience.

Small-scale wind turbines (as small as 50 W nominal power) produce more costly electricity than large and medium-scale wind turbines, especially in poor wind sites and in autonomous applications that require a high level of reliability. However, when sized properly and used at optimal working conditions, small-scale wind turbines could be a reliable energy source and produce socio-economically valuable energy not only in developing countries but also in autonomous applications in locations that are far away from the grid power in developed countries. Small-scale wind turbines are in fact becoming an increasingly promising way to supply electricity in developing countries. Lew [3] states that the number of people in China who do not have access to the national electricity grid is approximately 72 million. By 1995, a total of 150 000 small-scale (typically 50–300 W) wind turbines had already been disseminated within a national program in China. Today, approximately 140 000 small wind turbines are located only in Imar, an autonomous region in northern China, contributing over 17 MW to installed capacity. It is also worth noting that China produces more wind turbines than any other country in the world and now has 40 manufacturers of small-scale wind turbines. The future of this continuing growth of small-scale wind turbines largely depends on the cost: namely, initial cost per W power and the unit-cost per kWh they produce. If an autonomous wind system is to supply reliable electricity at a reasonable cost in a given location, an accurate wind potential and wind energy assessment have to be carried out beforehand. It is however the lack of such assessment tools, providing an accurate and a simple assessment of wind speed and wind energy output, especially for small-scale systems, that prevents small-scale wind generators from becoming techno-economically successful in operation. Daoo et al. [4] relate the finding of a study in which it is shown that only about 40% of all installed wind mills in India were located in areas having sufficient wind speed for movement of the wind mills. This poor judgement of the wind potential and of the energy output leads to either over or under-sizing of such autonomous wind energy systems. This means a poorly designed system in terms of techno-economics. Therefore over or under-sized systems, which are mostly due to the misjudgement of the resource, should be avoided if such renewable energy systems are to become an alternative way for providing electricity. This is exceptionally crucial for developing countries where millions of people do not have access to conventional electricity services.

2. Existing energy estimation models

Energy output estimation for wind turbines of different power range has been the subject of a number of papers. Biswas et al. [5] present a simplified statistical technique, as a function of 12 input variables, for computing the annual energy output of electricity generating large-scale wind turbines. The computed performance parameters are the ratio of average power output to maximum power, the annual energy produced assuming 100% availability of the wind turbines, and the value of the cut-in wind speed obtained theoretically. Biswas et al. compared the predicted and the measured values for two turbines with the rated outputs of 224 and 56 kW. The measured values of the annual energy outputs are used as a base value, and the theoretically predicted values for the same are compared to the measured values, and are found to exhibit a variation of 6.55% and 6.78%, respectively. To calculate the available wind power, Kainkwa [6] suggests a formula,

$$P_{\mathrm{a}} = \tfrac{1}{2}\rho[\bar{V}^3 + 3\bar{V}\sigma^2], \tag{1}$$

where ρ is the density of air at the site under consideration, $\bar{V}$ is the mean wind speed and σ^2 is the variance of wind speed. The monthly mean wind speeds and the corresponding monthly mean wind power calculated using the formula given above are presented for two different sites in Tanzania. Feretic et al. [7] use a similar method to that of Kainkwa to calculate the annual-average electricity production for a feasibility analysis of wind energy utilisation in Croatia. Neither author however compares the estimated wind power to the measured or the calculated power using measured hour-by-hour wind speed data.

The estimation of wind speed and wind energy for short-term has also been dealt by researchers. For example, Alexiadis et al. [8] applied artificial neural network models for short-term forecasting (following 10 min or 1 h) of wind speed and related electrical power. An empirical model with a total of 5 parameters is given as the estimator. The corresponding improvements on the wind speed and wind power are presented for different values of these parameters. Although an improvement of up to 74% in energy estimate is reported, the deviation of estimate from the actual wind energy is not known. Landberg [9] describes a model also for short-term prediction (0 to 36 h ahead) of the power produced by wind farms connected to the electrical grid. Sfetsos [10] presents a comparison of various forecasting techniques using time-series analysis on mean hourly wind speed data. In addition to the traditional linear models and the commonly used feed forward and recurrent neural networks, other approaches are also examined including the Adaptive Neuro-Fuzzy Inference Systems and Neural Logic Networks. Even though they do not give a direct measure of the energy output, they can ultimately be used to estimate the wind energy output. One drawback, however, associated with such models is their complexity. The literature survey reveals the followings. Energy estimation models for small-scale wind turbines almost do not exist. The existing models do not give a full account of the quality of the technique because they give no comparison with the energy outputs calculated from the measured data. The models that generate hourly wind speed data are too complex to be used by non-expert people. Some of the techniques presented are for a short-term, which is unable to assess the long-term energy potential of a probable wind site.

The present article addresses the estimation of wind energy output from small-scale wind energy systems. The energy output is estimated on a monthly basis based on the Weibull-representative wind data for a total of 96 months, from 5 different locations in the world. Geographic, climatic, topographic information about the locations and descriptions of the wind speed data analysed in the present article are presented in Table 1. Note in Table 1 that the hourly mean wind data are mostly the average of wind speed measurements at lower resolutions of 5–30 s, by 3-cup anemometers. In only one location (Ankara), the data were continuously recorded and averaged over 1 h by a R. Fuess type of anemograph in a synoptical station. The Weibull parameters are determined based on the wind distribution statistics calculated from these measured hourly time-series data. The Weibull-representative wind data is obtained in frequency distribution format from these calculated Weibull parameters. Finally, the measured hourly time-series data and the Weibull-representative data are used to calculate monthly wind energy outputs for a specific wind turbine.

3. Wind speed distribution parameters for selected locations

Different wind speed distribution models are used to fit the wind speed distribution over a time period, such as the Weibull, the Rayleigh and the Lognormal. The 2-parameter Weibull function is accepted as the best among the models given because one can adjust the parameters to suit a period of time, usually 1 month or 1 year. It has been used widely both in wind speed and wind energy analysis. The Weibull function has been employed almost unanimously by researchers involved in wind speed analysis for many years. Furthermore, since the Weibull probability density function leads to a Weibull model for the distribution of the cube of the wind speed, it has also extensively been used in wind power analysis for many decades [11–13].

Obtaining the wind speed distribution parameters is illustrated next for a sample month of January, which were collected from Tal-y-Bont (TyB) site in Cardiff, in 1996. In wind speed analysis, the data are usually in time-series format (ungrouped observation), where the preferred resolution of the series is 1 h. Each month then contains $24 \times d$ data point, where d is the number of days in a particular month.

Table 1
Geographic, climatic, topographic information about the locations and descriptions of the wind speed data analysed in the present article

	Cardiff	Canberra	Davos	Athens	Ankara
Lat.	51.30N	35.18S	46.48N	38.00N	39.55N
Lon.	3.13W	149.08E	9.50E	23.44E	32.50E
Climate	Mild and variable in general, but can be very warm in the summer	Has an average annual rainfall of 630 mm	Temperature (year average) 2.8°C	Warm summers are cooled by a system of seasonal breezes	Typical continental
	Afternoon breezes are typical from the sea	Strong winds are frequent, mainly from the west and north-west	Rain (year average) 1007 mm (40% snow)	From June to August rainfall is rare	Summers are long and pleasantly hot, with cool nights; there is little rainfall or humidity
		Maximum temperature is 19.7°C, with the highest on record 42.2°C The mean minimum is 6.9°C, with the lowest on record, −10°C	Lake Davos: up to 20°C in summer	Decreasing relative humidity in summer months	Winters are cold with some rain and snow
Topography	A port city, situated on the Atlantic Ocean coast	Has three contrasting landforms	Altitude 1560 m above sea level (Davos Platz)	Altitude 50 m above sea level	Altitude 850 m above sea level
	Lies on a plain area mostly, with slopes rising 50–100 m	Lowland of undulating hills including the floodplains mostly below 600 m	Highest location: Flüela Schwarzhorn 3146 m above	9.5 km away from the Saron Bay on the Aegean Sea surrounded by mountains in the north and east	Lies in the centre of Anatolia on the eastern edge of the great, high Anatolian Plateau
	Some 50 km away from the Cambrian Mts in the North, Aran Fawddwy, the highest point, 905 m	Forested mountain slopes rising to 1200 m	Lowest location: Brombenz 1260 m above		
		Upland of steep ridges, mountain peaks			

Table 1 (*continued*)

	Cardiff	Canberra	Davos	Athens	Ankara
Lat.	51.30N	35.18S	46.48N	38.00N	39.55N
Lon.	3.13W	149.08E	9.50E	23.44E	32.50E
		rising above 1800 m			
Wind speed measurement	3-cup rotor anemometer	3-cup rotor anemometer	3-cup rotor anemometer	3-cup rotor anemometer	Recorded by R. Fuess type of anemograph in a synoptical station
	Values taken every 10 s were averaged over 5 min and stored in a data-logger. The 5-min averaged data were further averaged over 1 h	Values taken every 30 s were averaged over 10 min. The 10-min averaged data were further averaged over 1 h	Values taken every 5 s were averaged over 1 min and stored in a data-logger. The 1-min averaged data were further averaged over 1 h	Values taken every 10 s were averaged over 10 min and stored in a data-logger. The 10-min averaged data were further averaged over1 h	Continuously recorded wind speed data averaged over 1 h and stored

Ungrouped observation, however, is very difficult to read in any meaningful sense. Therefore, the wind data have to be grouped to bring out the important aspects of a distribution [14]. By grouping, the data in time-series format is converted into frequency distribution format. The wind speed is grouped into classes (bins), see Table 2 (the second column). The mean wind speeds are calculated for each speed class intervals (the third column). The fourth column gives the frequency of occurrence of each speed class (f_i). As presented in the fourth column, the probability of a given wind speed is then,

$$f(v_i) = \frac{f_i}{\sum_{i=1}^{n} f_i} = \frac{f_i}{N}. \tag{2}$$

The mean wind speed and its standard deviation are calculated using the following equations, respectively, as given in [15],

$$\bar{v} = \frac{\sum_{i=1}^{n} f_i v_i}{\sum_{i=1}^{n} f_i} = \frac{1}{N}\left[\sum_{i=1}^{n} f_i v_i\right], \tag{3}$$

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

Table 2
Data arranged in frequency distribution format based on the measured data in time-series format for January of Cardiff 1996, measured at TyB site near Cardiff, UK, and the probability density distribution calculated from the Weibull function, $f_w(v_i)$

i	v	v_i	f_i	$f(v_i)$	$F(v)$	$f_w(v_i)$
1	0–1	0.59	61	0.082	0.082	0.096
2	1–2	1.47	119	0.160	0.242	0.187
3	2–3	2.56	164	0.220	0.462	0.222
4	3–4	3.49	166	0.223	0.685	0.198
5	4–5	4.44	127	0.171	0.856	0.147
6	5–6	5.42	54	0.073	0.929	0.093
7	6–7	6.46	26	0.035	0.964	0.049
8	7–8	7.44	17	0.023	0.987	0.023
9	8–9	8.50	10	0.013	1.000	0.009
10	9–10	9.50	0	0.000	1.000	0.003
			$\sum_{i=1}^{n} f_i = N = 744$	$\sum_{i=1}^{n} f(v_i) = 1.0$		$\sum_{i=1}^{n} f_w(v_i) = 1.02$

However, if the probability function is already known, Eqs. (3) and (4) are determined using

$$\bar{v} = \int_0^\infty v f(v)\,\mathrm{d}v, \tag{5}$$

$$\sigma = \left[\int_0^\infty (v - \bar{v})^2 f(v)\,\mathrm{d}v\right]^{1/2}. \tag{6}$$

The mean wind speed and its standard deviation for this particular month are 3.29 and 1.73 m/s, respectively. The monthly mean wind speeds and their standard deviations are presented in Table 3 for the locations given. Most of the monthly mean wind speeds are between 2.0 and 3.0 m/s, some over 3.0 m/s and few over 4.0 m/s and under 2.0 m/s. While December of Cardiff 1994 has the highest mean wind speed value with 4.1 m/s, January of Davos exhibits the minimum monthly mean wind speed value, which is 1.69 m/s. The yearly mean wind speeds range from 2.17 to 2.89 m/s. As these wind speeds suggest, the locations studied represent poor wind sites. The monthly and yearly mean standard deviation values are mostly between 1.0 and 2.0 m/s, only a few over 2.0 m/s. The deviation values could only be assessed together with the wind speed. While a large monthly deviation with a high wind speed value indicates large day-to-day variation in the wind speed, a small monthly deviation with a high wind speed value indicates little day-to-day variation but longer windy time spans and a following windless time span. The cumulative probability given in the sixth column of Table 2 is calculated from

$$F(v_i) = \sum_{i=1}^{j} f(v_i), \tag{7}$$

Table 3
Monthly and yearly mean wind speeds and standard deviations in m/s for different locations

	Cardiff 1991		Cardiff 1994		Cardiff 1995		Cardiff 1996		Canberra		Davos		Athens		Ankara	
	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ	$\bar{v}$	σ
January	3.12	2.10	3.36	2.31	3.31	2.01	3.29	1.73	2.36	1.88	1.69	1.79	3.15	2.32	1.91	1.48
February	2.70	1.48	2.47	1.47	3.27	1.94	2.68	1.94	2.37	1.89	1.75	1.75	2.09	1.61	2.33	1.61
March	3.12	1.73	4.07	2.27	3.12	2.07	2.31	1.32	2.31	1.87	2.21	1.76	3.17	2.28	2.40	1.60
April	3.77	1.93	3.29	1.92	2.68	1.43	2.22	1.33	1.76	1.52	2.62	1.83	2.43	1.76	2.26	1.28
May	2.73	1.29	2.45	1.30	2.10	1.18	2.42	1.26	1.72	1.53	2.59	1.73	2.82	1.93	2.35	1.59
June	3.07	1.50	3.24	1.72	2.59	1.21	2.33	1.39	2.33	1.84	2.74	1.78	2.19	1.44	2.44	1.22
July	2.71	1.44	2.26	1.11	2.69	1.35	2.48	1.35	2.36	1.84	2.97	2.06	2.52	1.84	2.99	1.48
August	2.49	1.30	2.41	1.49	2.18	1.25	1.92	1.30	2.22	1.86	2.78	1.99	2.15	1.40	2.75	1.61
September	2.65	1.43	1.94	1.28	2.33	1.52	2.18	1.33	2.16	1.87	2.63	1.93	2.11	1.36	2.38	1.40
October	2.59	1.69	2.17	0.99	2.01	1.27	2.36	1.61	2.03	1.70	2.37	1.82	2.91	2.32	1.98	1.66
November	2.71	1.74	1.99	1.36	1.82	1.17	2.48	1.96	2.31	1.74	2.04	1.68	2.55	2.29	2.09	1.57
December	3.03	2.12	4.10	2.44	2.18	1.20	2.39	1.60	2.09	1.57	1.77	1.64	2.49	1.79	2.71	1.68
Average	2.89	1.65	2.81	1.64	2.52	1.47	2.42	1.51	2.17	1.76	2.35	1.81	2.55	1.86	2.38	1.52

where $j \leqslant i$ and for $i=1, 2, \ldots, n$

$$F(v_n) = \sum_{i=1}^{n} f(v_i) = 1. \tag{8}$$

Replacing $f(v_i)$ by the continuous Weibull function given by

$$f_{\mathrm{w}}(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right], \tag{9}$$

where c is the scale parameter in m/s, k is the unitless shape parameter, and by substitution of $\xi = (v/c)^k$ and solving Eq. (5) for v, Γ being the gamma function ($\Gamma(x) = \int_0^\infty \xi^{x-1} \exp(-\xi)\,\mathrm{d}\xi$), the following are obtained,

$$\bar{v} = c\Gamma\left[1 + (1/k)\right], \tag{10}$$

$$\sigma = c\left[\Gamma(1 + 2/k) - \Gamma^2(1 + 1/k)\right]^{1/2}. \tag{11}$$

Knowing $\Gamma(1 + x) = x\Gamma(x)$ for the gamma function, Eqs. (10) and (11) can be solved together to identify the c and k parameters, using the Stirling approximation for the gamma function given by

$$\Gamma(x) = \sqrt{2\pi x}\, x^{x-1} \mathrm{e}^{x}\left[1 + \frac{1}{12x} + \frac{1}{288x^2} + \cdots\right]. \tag{12}$$

There are different ways to calculate the Weibull distribution model parameters, c and k. Jamil [16] presents two ways to determine the Weibull parameters. As well as the method addressed above, using the gamma function, the cumulative probability method, which employs least-squares fit (LSQM) to the observed distribution, is explained by Jamil. Besides the commonly used graphical method (known as LSQM), Seguro and Lambert [17] present two more methods for calculating the parameters: the maximum likelihood method, and the proposed modified maximum likelihood method. The reference energy output was calculated using the sample time-series data set. This value was then compared to the total energy output corresponding to each of the three estimated Weibull distributions. It was concluded by Seguro and Lambert [17] that the maximum likelihood method is recommended for use with time-series wind data, and the modified maximum likelihood method is recommended for use with wind data in frequency distribution format. Lun and Lam [18] calculated the two parameters of the Weibull density distribution function for three different locations in Hong Kong, using a long-term data source, consisting of 30 years of hourly mean wind speed data. Garcia et al. [19] dealt with the estimation of the annual Weibull and Lognormal parameters from 20 locations in Navarre, Spain. The wind speed data used in [19] were in hourly time-series format, collected every 10 min and then averaged over 1 h. Both Lun and Lam [18] and Garcia et al. [19] used the traditional graphical method for the Weibull parameters. Protogeropoulos [20] studied the influence of wind speed frequency on wind resource calculation, using two time steps, hourly and 5 min data. He concluded that the hourly time resolution, compared to 5 min resolution, provides satisfactory accuracy in wind resource estimation. As the references indicate, the resolution of time-series wind data used in wind probability distribution analysis is hourly, which is the average of measurements at shorter time intervals, 5 s to 10 min. In the literature, it was also noted that the data used in wind probability distribution analyses are of the hourly time-series type, rather than any other type (such as gusty type).

The c and k parameters calculated for this particular month in the present study are 3.72 m/s and 1.89, respectively. The Weibull probability density distribution $f_w(v_i)$ calculated using these values are given in the last column of Table 2. When it is compared to the measured probability density distribution given in the fifth column, it is obvious that the Weibull model is a reasonable fit for this particular month. However, the main criterion in judging the suitability of a distribution function is its success in predicting the wind energy output, which will be dealt with in the next section. The monthly Weibull distribution parameters identified are given in Table 4 for the selected locations. The monthly scale parameter mostly changes between 2.0 and 4.0 m/s, it is over 4.0 m/s in only 3 months and under 2.0 m/s in 5 months. As expected, most of the monthly shape parameters are between 1.0 and 2.0, it is over 2.0 in 5 months and under 1.0 only in 1 month. For a k value close to 1, the relative frequency distribution as a function of velocity is relatively flat, indicating a highly variable wind regime, whereas for $k \geqslant 3$, the relative frequency distribution becomes more peaked, which indicates more regular, steadier winds.

4. Wind energy output

In the present article, the wind energy calculations were carried out for a wind turbine of 50 W nominal power with 0.65 m^2 swept area. The power output can be calculated either by using the analytical model for the performance of this type of wind turbine or, alternatively, by correlating the wind generator response to wind speed by a polynomial curve. The output power for this wind turbine was measured for a range of wind speeds at the outdoor hybrid experimental site of the Solar Energy Unit of Cardiff University, and fitted with a polynomial curve of 3rd degree [21]. The fitted curve is given by the following form:

$$P_{\text{out}} = 0.964 - 2.299v + 1.214v^2 - 0.0572v^3 \tag{13}$$

with the cut-in and cut-out wind speed values of 1.45 and 13.0 m/s, respectively. Energy output comparison is used as the main test to determine the accuracy of the Weibull-representative wind speed data. The energy output calculated using the time-series data serves as the 'reference energy output' E_{TS}, which is determined by

$$E_{\text{TS}} = \sum_{i=1}^{N} P_{\text{out},i} \Delta t_i, \tag{14}$$

where Δt_i is the hourly time interval. The energy output using the Weibull-representative data, which will be referred to as the 'Weibull-representative energy

Table 4
Monthly and yearly Wiebull wind speed distribution parameters, c in m/s and unitless k, for different locations

	Cardiff 1991		Cardiff 1994		Cardiff 1995		Cardiff 1996		Canberra		Davos		Athens		Ankara	
	c	k	c	k	c	k	c	k	c	k	c	k	c	k	c	k
January	3.46	1.50	3.71	1.46	3.72	1.66	3.72	1.89	2.55	1.27	1.65	0.95	3.45	1.37	2.07	1.31
February	3.05	1.84	2.76	1.76	3.67	1.69	2.95	1.39	2.55	1.26	1.76	1.01	2.27	1.31	2.57	1.47
March	3.53	1.81	4.59	1.80	3.46	1.51	2.61	1.76	2.48	1.25	2.38	1.27	3.48	1.40	2.66	1.52
April	4.28	1.95	3.71	1.73	3.04	1.88	2.49	1.70	1.86	1.17	2.90	1.45	2.66	1.39	2.55	1.79
May	3.10	2.09	2.78	1.90	2.37	1.80	2.74	1.93	1.80	1.14	2.88	1.51	3.13	1.48	2.61	1.50
June	3.49	2.03	3.66	1.88	2.94	2.12	2.62	1.69	2.51	1.27	3.06	1.55	2.44	1.54	2.77	2.00
July	3.07	1.88	2.57	2.04	3.05	1.98	2.81	1.86	2.56	1.30	3.28	1.45	2.77	1.39	3.40	2.01
August	2.81	1.92	2.69	1.63	2.45	1.77	2.12	1.50	2.36	1.20	3.04	1.40	2.39	1.55	3.08	1.71
September	2.99	1.86	2.17	1.54	2.59	1.55	2.45	1.66	2.27	1.16	2.88	1.37	2.35	1.58	2.67	1.71
October	2.89	1.55	2.47	2.17	2.25	1.60	2.62	1.48	2.16	1.21	2.58	1.31	3.13	1.26	2.12	1.21
November	3.02	1.57	2.20	1.48	2.03	1.58	2.68	1.28	2.53	1.35	2.17	1.22	2.66	1.12	2.28	1.35
December	3.36	1.44	4.62	1.69	2.47	1.84	2.66	1.51	2.29	1.35	1.83	1.09	2.75	1.41	3.05	1.64
Average	3.25	1.79	3.16	1.76	2.84	1.75	2.71	1.64	2.33	1.24	2.53	1.30	2.79	1.40	2.65	1.60

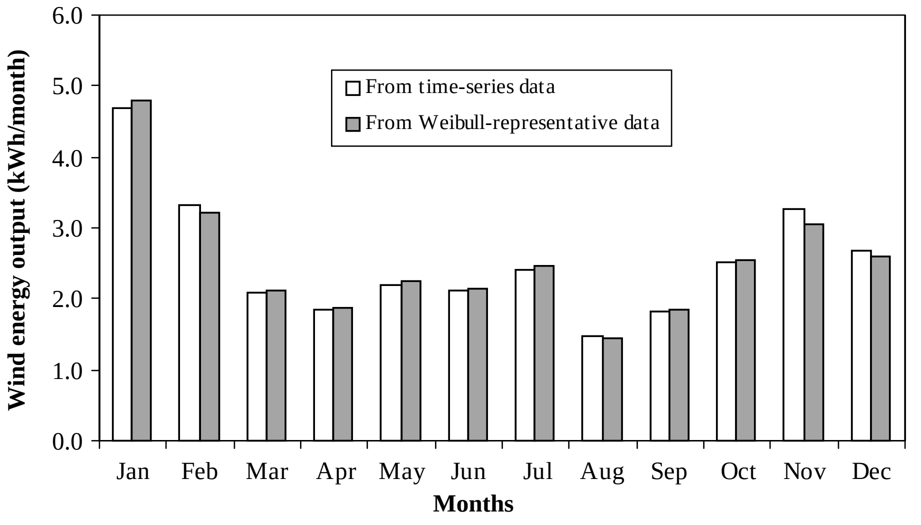

Fig. 1. Monthly wind energy output calculated using the measured data in time-series format and the Weibull-representative data, for a wind turbine of 50 W nominal power, for Cardiff 1996 data.

output', E_{WR}, is calculated from

$$E_{\mathrm{WR}} = \sum_{i=1}^{n} P_{\mathrm{out},i} f_{\mathrm{w}}(v_i) N \Delta t_i. \tag{15}$$

Fig. 1 presents the monthly reference energy outputs versus the Weibull-representative energy outputs for Cardiff 1996. For this particular site in Cardiff, it could be concluded that the wind energy generator works, for most of the time, under the rated power output. The yearly average monthly energy output value of 2.53 kWh for this specific wind turbine (of 50 W nominal power) proves that fact. The most energy contribution is made in January with 4.67 kWh, while the least energy contribution is observed to be 1.48 kWh in August. Fig. 2 shows the magnitude of the monthly errors in the Weibull-representative energy outputs relative to the reference energy outputs. It could be said that the Weibull-representative energy outputs agree well with the reference energy outputs. The Weibull-representative data overestimate the energy output in 8 months, and underestimate in 4 of the months. For this particular year, the maximum error is a 6.45% underestimation, occurring in November, while the minimum error is a 1.30% overestimation that occurs in October. The yearly average error is 2.25% for this particular year, determined from the following equation

$$\mathrm{Error}(\%) = \frac{1}{12} \sum_{i=1}^{12} \left| \frac{E_{\mathrm{WR},i} - E_{\mathrm{TS},i}}{E_{\mathrm{TS},i}} \right|. \tag{16}$$

The errors in the Weibull-representative energy outputs relative to the reference energy outputs are given in Fig. 3 for selected locations. It is noted that the reference

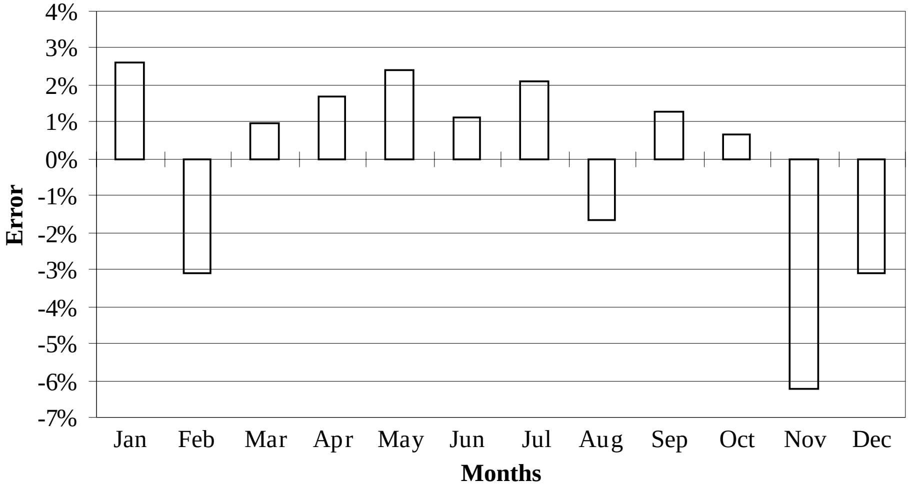

Fig. 2. Error in wind energy output estimation using the Weibull-representative data in reference to the energy output using the measured data in time-series format, for Cardiff 1996 data.

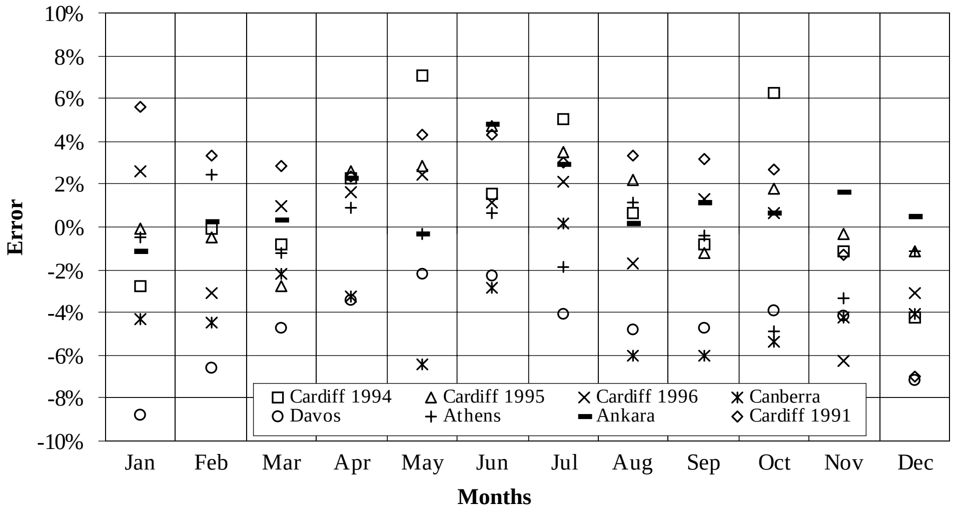

Fig. 3. Error in wind energy output estimation using the Weibull-representative data in reference to the energy output using the measured data in time-series format, for various locations.

energy outputs are underestimated by the Weibull-representative data in every month of Davos and in 11 months of Canberra. It is also interesting to note that these two locations have the lowest yearly mean wind speeds amongst the given 8 locations, as could be seen from Table 3. Out of 96 months analysed, the maximum error is an 8.8% underestimation, which occurs in January of Davos. No error occurs in January of Cardiff 1995. The yearly average errors calculated from Eq. (16)

Table 5
Yearly average errors in calculation of the wind energy output using the Weibull-representative data for various locations calculated from Eq. (16)

	Error (%)
Cardiff 1991	3.60
Cardiff 1994	2.72
Cardiff 1995	1.97
Cardiff 1996	2.25
Canberra	4.11
Davos	4.73
Athens	1.57
Ankara	1.35
Average	2.79

are presented in Table 5 for the locations given. The overall error in the wind energy output estimation using the Weibull-representative data relative to that using the measured data in time-series format is 2.79%, for the total of 96 months.

5. Conclusions

Estimation of wind energy output for small-scale systems has been the subject of this paper. The main aim has been to use the Weibull-representative wind data instead of the measured data in time-series format for estimating the wind energy output. The Weibull function parameters were calculated analytically on a monthly basis, using the gamma function, from the measured data in time-series format. The wind speed data in frequency distribution format have been generated based on the Weibull distribution function, using the parameters identified earlier.

The monthly energy outputs were calculated for a wind turbine of 50 W nominal power, using the Weibull-representative and measured data in time-series format. Energy output comparison was used as the main test to determine the accuracy of the Weibull-representative wind speed data. The energy outputs calculated using the measured data in time-series format were used as the 'reference energy output'. Finally, the monthly energy outputs calculated using the Weibull-representative data were compared to the reference energy outputs. A total of 96 months of data were used from 5 different locations in the world. As the overall error of 2.79% shows, the Weibull-representative data are very successful in representing the time-series data as far as the locations analysed are concerned.

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