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Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation

Haitao Guo [a,*], Simon Watson [a], Peter Tavner [b], Jiangping Xiang [a]

[a] Centre for Renewable Energy Systems Technology, Loughborough University, Loughborough, Leicestershire LE11 3TU, UK
[b] School of Engineering, New & Renewable Energy, Durham University, Durham DH1 3LE, UK

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ABSTRACT

Reliability has an impact on wind energy project costs and benefits. Both life test data and field failure data can be used for reliability analysis. In wind energy industry, wind farm operators have greater interest in recording wind turbine operating data. However, field failure data may be tainted or incomplete, and therefore it needs a more general mathematical model and algorithms to solve the model. The aim of this paper is to provide a solution to this problem. A three-parameter Weibull failure rate function is discussed for wind turbines and the parameters are estimated by maximum likelihood and least squares. Two populations of German and Danish wind turbines are analyzed. The traditional Weibull failure rate function is also employed for comparison. Analysis shows that the three-parameter Weibull function can obtain more accuracy on reliability growth of wind turbines. This work will be helpful in the understanding of the reliability growth of wind energy systems as wind energy technologies evolving. The proposed three-parameter Weibull function is also applicable to the life test of the components that have been used for a period of time, not only in wind energy but also in other industries.

1. Introduction

Wind turbines are a renewable source of energy and will play an increasingly important role in providing electricity, because wind turbines capacities and the number of grid-connected wind turbines are increasing. Wind turbine reliability is a significant factor in ensuring the success of a wind power project. Walford outlined the issues relevant to wind turbine reliability for wind turbine power generation projects and the relationship between wind turbine reliability and operation and maintenance costs [1]. Reliability and condition monitoring apparently benefit the maintenance management of wind power systems [2] by reducing the O&M costs by giving advance warning of failures. Some authors have combined wind power generation and wind speed models to analyze power production reliability [3,4]. Others have applied probabilistic safety assessment (PSA) to wind turbines to assess system reliability qualitatively and quantitatively, based upon component failures [5,6]. Another authors used the monthly variation of energy production to weight the shutdown time, which included both maintenance and fault hours. This showed a large difference exists between the original downtime and weighted downtime [7]. After a wide review, Herbert et al. [8] concluded that fewer authors have worked on reliability evaluation of wind turbine systems. Valuable information for wind turbine reliability analysis can be derived from failure data by statistical analysis [9,10]. Climate change can also be taken into account using statistical data [11].

It is very common that reliability studies are based on field data, but the field failure data are usually tainted, incomplete, or lack sufficient detail, or does not satisfy the assumptions of a model selected for analysis. Some research has been done with regard to those situations. Xie et al. [17,18] proposed some modified Weibull models that are able to fit the whole bathtub-shaped failure rate. Ling and Pan [19] presented a simple and general method for parameter estimations using the Kolmogorov–Smirnov distance as objective, independent with specimen probability distribution. Red-horse and Benjamin [20] used polynomial chaos expansions to find the connection between limited probabilistic information and the output of reliability analysis. Coit and Dey [21] developed a hypothesis test to examine the suitability of the exponential distribution for grouped data with Type II censoring and an iid assumption. Sun et al. [22] introduced an extended Weibull model, in which parameters are no longer constants but functions of load. Hall and Strutt [23] analyzed how uncertain input parameters affect resulted Weibull model by using Monte Carlo method. Calabria et al. [24] introduced an unbiased maximum likelihood estimator for the shape parameter of Weibull model. Zhang et al. [25] showed a

* Corresponding author. Tel.: +44 1509635304; fax: +44 1509635301.
E-mail address: h.guo@lboro.ac.uk (H. Guo).

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simple method to reduce the bias of least-square estimator for the shape parameter of Weibull model. Murthy et al. [26] suggested a systematic and graphical method to choose a suitable model from several Weibull models when modelling a given data set.

In most cases of wind energy industry, data are grouped data and not collected from the time of the installation of wind turbines and the population of the investigated wind turbines changes. Because of lack of reliability research dealing with the available field data in wind energy and to study the reliability growth using the data, a new model considering the above problems is presented in this paper. From a practical point of view, it is advantageous to use a continuous and parametric function as the failure rate function for approximately evaluating the reliability growth for wind turbines as wind turbine technologies evolve. The new model is using a three-parameter Weibull failure rate function that introduces a third parameter into two-parameter Weibull function to look into the past running time. The three parameters are estimated by two techniques, maximum likelihood and least squares. Two wind turbine populations are analyzed using the presented methods and traditional Weibull function. The data are extracted from Windstats Newsletters [27].

The proposed three-parameter Weibull function is a generic model of reliability analysis, although this paper is particularly regarding to the reliability analysis of wind turbines. It can be used for the reliability analysis of other products, either under the situations where that record of failures is not available from the time of usage in field operation or where used products are considered for the life test to shorten testing time.

2. Windstats data

Windstats Newsletter is a quarterly international publication that provides various information about the wind energy converted in wind turbines in various countries in the world. The data analyzed in this paper have been extracted from Windstats Newsletters from wind turbines in Demark and Germany. The data collects the numbers of wind turbine subassembly failures in a fixed interval, 1 month for Danish turbines and one quarter for German turbines. To simplify the problem and concentrate on the methods demonstrated in this paper, it is assumed that any subassembly failure will lead to a wind turbine failure. By that assumption, the wind turbine failures in an interval is equal to the sum of subassembly failures.

Danish data starts from October 1994 to December 2003 with population varying from highest 2345 turbines to lowest 851 turbines; German data starts from March 1996 to September 2004 with population varying from highest 4285 turbines to lowest 1578. Danish data show a decreasing number of installed turbines, while German wind turbines increase rapidly [9,10]. Data examples are shown in Tables 1 and 2. Because there are 111 and 35 intervals for Danish data and German data, respectively, Table 1 gives only the first 3 months of Danish data, while Table 2 gives only the first four quarters of German data. Since the population changes, it is necessary to eliminate the population difference by normalizing the wind turbine reliabilities. Furthermore, individual wind turbines have similar subassemblies and architecture. Therefore, the number of failures in an interval is divided by corresponding number of turbines to get the average failure number of that interval, which means the number of failures per interval per turbine and is suitable for modelling the reliability of the wind turbines.

The interval of Danish data is not converted into a quarter (the interval of the German data) by synthesizing data for 3 months, because this paper is aimed at providing reliability analysis methods for wind turbines using incomplete failure data recorded in different intervals.

Windstats Newsletter also provides additional information, besides failure numbers, about wind turbines such as production, capacity factor, which can be used to analyze other aspects of wind turbines [11].

Table 1
Example of Danish data extracted from Windstats.

Turbine data	1994		
	October	November	December
No of DK turbines reporting	2036	2083	2164
Length of reporting period, h	744	720	744
Subassembly failures			
Blades	15	6	6
Hub	0	0	0
Main shaft	2	0	0
Airbrakes	9	4	2
Gearbox	5	2	4
Coupling	1	1	6
Mechanical brake	9	4	6
Generator	6	11	11
Yaw System	7	11	19
Tower	0	0	0
Foundation	0	0	0
Grid	5	10	9
Electrical control	23	23	48
Mechanical control	3	3	2
Hydraulic system	7	8	19
Entire nacelle	1	1	1
Entire turbine	13	11	15
Other	47	35	27
Total subfailures	158	130	175

Table 2
Example of German data extracted from Windstats.

Turbine data	1996			
	March	June	September	December
No of DE turbines reporting	1803	1830	1866	1902
Length of reporting period, h	2160	2134	2203	2208
Subassembly failures				
Rotor	168	99	150	140
Air brake	30	31	18	23
Mechanical brake	25	29	18	21
Pitch control	24	42	36	46
Main shaft	9	7	1	18
Gearbox	29	46	56	42
Generator	37	47	48	100
Yaw system	52	43	50	63
Measurement system	419	29	28	90
Electrical controls	141	127	96	125
Electrical system	166	130	163	163
Hydraulics	82	62	58	45
Sensors	43	69	39	60
Other	84	55	91	58
Total subfailures	1314	816	857	999

3. Weibull failure rate function

The Weibull failure rate function is widely used to model the non-homogeneous Poisson process. It has the form as below

$$\lambda(t) = \phi\, t^{\mu} \tag{1}$$

With $\mu<0$, $\mu=0$, $\mu>0$, the Weibull model can depict infant mortality stage, normal stage and wear-out stage of the so-called bathtub curve, respectively. Eq. (1) can also be written as the popular Eq. (2), which simplifies calculating the integral of intensity function,

$$\lambda(t) = \rho\beta t^{\beta-1} \tag{2}$$

where $\beta = \mu+1$ and $\rho = \phi/\beta$. In some literatures, ρ is called the scale parameter and β the shape parameter.

For a Poisson process, the probability of N events occurring over period $(a,b]$ is [12]

$$P\{n(a,b] = N\} = \frac{[\int_a^b \lambda(x)dx]^N e^{-\int_a^b \lambda(x)dx}}{N!} \tag{3}$$

The failure data of wind turbines collected by Windstats is grouped data, monthly for Danish wind turbines and quarterly for German. It is assumed that the distribution of wind turbine failures is of Weibull and individual groups are independent to each other. Thus, a joint probability distribution function PDF of k grouped data are

$$P\{n(t_0,t_1] = N_1, n(t_1,t_2] = N_2, \ldots, n(t_{k-1},t_k] = N_k\} = \prod_{i=1}^{k} P(n(t_{i-1},t_i] = N_i) \tag{4}$$

Combined with Eqs. (2) and (3), the following is derived:

$$P\{n(t_0,t_1] = N_1, n(t_1,t_2] = N_2, \ldots, n(t_{k-1},t_k] = N_k\} = \prod_{i=1}^{k} \frac{[\rho(t_i^\beta - t_{i-1}^\beta)]^{N_i} e^{-\rho(t_i^\beta - t_{i-1}^\beta)}}{N_i!} \tag{5}$$

Next, calculate the maximum likelihood estimates of β and ρ.

$$\begin{aligned}\operatorname{Ln} P\{n(t_0,t_1] = N_1, n(t_1,t_2] = N_2, \ldots, n(t_{k-1},t_k] = N_k\} &= \sum_{i=1}^{k} N_i \operatorname{Ln}\rho + \sum_{i=1}^{k} N_i \operatorname{Ln}(t_i^\beta - t_{i-1}^\beta) \\ &\quad - \sum_{i=1}^{k} \rho(t_i^\beta - t_{i-1}^\beta) - \sum_{i=1}^{k} N_i!\end{aligned} \tag{6}$$

Then

$$\frac{\partial \operatorname{Ln} P}{\partial \rho} = \sum_{i=1}^{k} \frac{N_i}{\rho} - \sum_{i=1}^{k} (t_i^\beta - t_{i-1}^\beta) \tag{7}$$

By Letting $\partial \operatorname{Ln} P/\partial\rho$ and if $t_0 = 0$, the estimate of ρ is

$$\hat{\rho} = \frac{\sum_{i=1}^{k} N_i}{t_k^\beta} \tag{8}$$

Substitute ρ in Eq. (6) by $\hat{\rho}$ of Eq. (8)

$$\begin{aligned}\operatorname{Ln} P\{n(t_0,t_1] = N_1, n(t_1,t_2] = N_2, \ldots, n(t_{k-1},t_k] = N_k\} &= \sum_{i=1}^{k} N_i \operatorname{Ln}\left(\sum_{i=1}^{k} N_i\right) - \sum_{i=1}^{k} N_i \beta \operatorname{Ln}(t_k) \\ &\quad + \sum_{i=1}^{k} N_i \operatorname{Ln}(t_i^\beta - t_{i-1}^\beta) - \sum_{i=1}^{k} N_i - \sum_{i=1}^{k} N_i!\end{aligned}$$

Then

$$\begin{aligned}\frac{\partial \operatorname{Ln} P}{\partial \beta} &= -\sum_{i=1}^{k} N_i \operatorname{Ln}(t_k) + \sum_{i=1}^{k} N_i \frac{t_i^\beta \operatorname{Ln} t_i - t_{i-1}^\beta \operatorname{Ln} t_{i-1}}{t_i^\beta - t_{i-1}^\beta} \\ &= \sum_{i=1}^{k} N_i \left[\frac{t_i^\beta \operatorname{Ln} t_i - t_{i-1}^\beta \operatorname{Ln} t_{i-1}}{t_i^\beta - t_{i-1}^\beta} - \operatorname{Ln} t_k\right]\end{aligned} \tag{9}$$

Again, by Letting $\partial \operatorname{Ln} P/\partial\rho$ and $t_0 \operatorname{Ln} t_0 = 0$, we can get $\hat{\beta}$ by solving the following formula:

$$\sum_{i=1}^{k} N_i \left[\frac{t_i^\beta \operatorname{Ln} t_i - t_{i-1}^\beta \operatorname{Ln} t_{i-1}}{t_i^\beta - t_{i-1}^\beta} - \operatorname{Ln} t_k\right] = 0 \tag{10}$$

The above result is the same as that in [13]. If the time interval T is fixed, which means $t_i = iT$, then the above formula is changed to

$$\sum_{i=1}^{k} N_i \left[\frac{i^\beta \operatorname{Ln}(iT) - (i-1)^\beta \operatorname{Ln}[(i-1)T]}{i^\beta - (i-1)^\beta} - \operatorname{Ln}(kT)\right] = 0 \tag{11}$$

Then, the estimates of ϕ and μ can be derived from ρ and β.

4. A three-parameter Weibull function

Failure rate function described in Section 3 is suitable for the situations where the data are recorded from the wind turbine installation. However, the data collected in Windstats is not necessarily from the date of wind turbine's installation as it may start from some years after later. Another parameter α called time factor in this paper is reasonably introduced into the Weibull function in order to describe the past running time. The α shifts the intervals along the time axis from $0, T, \ldots, kT$ to $\alpha T, \alpha T+T, \ldots, \alpha T+kT$. T for Danish turbines is the number of hours of a month and a quarter for German turbines. Therefore, the task has changed to estimate the parameters α, β, ρ.

4.1. Maximum likelihood estimates

After α is introduced, Eq. (1) becomes

$$\lambda(t) = \phi(t+\alpha T)^\mu \tag{12}$$

Correspondingly, Eq. (2) changes into

$$\lambda(t) = \rho\beta(t+\alpha T)^{\beta-1} \tag{13}$$

Following the same procedures in the last section, the estimate of ρ can be derived as

$$\hat{\rho} = \frac{\sum_{i=1}^{k} N_i}{[(k+\alpha)T]^\beta - (\alpha T)^\beta} \tag{14}$$

and the estimates of α and β are the solutions of the equations below which are solved by trust-region dogleg method [14].

$$\begin{aligned}\sum_{i=1}^{k} N_i \Bigg[&\frac{(i+\alpha)^\beta \operatorname{Ln}[(i+\alpha)T] - (i-1+\alpha)^\beta \operatorname{Ln}[(i-1+\alpha)T]}{(i+\alpha)^\beta - (i-1+\alpha)^\beta} \\ &- \frac{(k+\alpha)^\beta \operatorname{Ln}[(k+\alpha)T] - \alpha^\beta \operatorname{Ln}(\alpha T)}{(k+\alpha)^\beta - \alpha^\beta}\Bigg] = 0\end{aligned} \tag{15}$$

$$\frac{\beta}{T}\sum_{i=1}^{k} N_i \left[\frac{(i+\alpha)^{\beta-1} - (i-1+\alpha)^{\beta-1}}{(i+\alpha)^\beta - (i-1+\alpha)^\beta} - \frac{(k+\alpha)^{\beta-1} - \alpha^{\beta-1}}{(k+\alpha)^\beta - \alpha^\beta}\right] = 0 \tag{16}$$

Observed N_i is calculated through dividing the total subassembly failures by the number of turbines reporting of the corresponding interval (see data example in Tables 1 and 2). Then, the estimates of ϕ and μ can be derived from ρ and β.

4.2. Least-squares estimates

By calculating the integral of failure rate, the number of failures, N, over period (t_a,t_b) can be determined as below:

$$N(t) = \int_{t_a}^{t_b} \lambda(x)dx = \rho t_b^\beta - \rho t_a^\beta \tag{17}$$

From Eq. (17), the average number of failures in each interval is given by

$$N_1 = \rho t^{\beta}|_{\alpha T}^{(1+\alpha)T} = \rho((1+\alpha)T)^{\beta} - \rho(\alpha T)^{\beta}$$
$$N_2 = \rho t^{\beta}|_{(1+\alpha)T}^{(2+\alpha)T} = \rho((2+\alpha)T)^{\beta} - \rho((1+\alpha)T)^{\beta}$$
$$\vdots$$
$$N_k = \rho t^{\beta}|_{(k-1+\alpha)T}^{(k+\alpha)T} = \rho((k+\alpha)T)^{\beta} - \rho((k-1+\alpha)T)^{\beta}$$

Thus, for the interval i, the average number of failures is

$$N_i = \rho((i+\alpha)T)^{\beta} - \rho((i-1+\alpha)T)^{\beta} \quad i = 1,\ldots,k \tag{18}$$

Define

$$\xi = \rho T^{\beta} \tag{19}$$

then Eq. (18) becomes

$$N_i = \{(i+\alpha)^{\beta} - (i-1+\alpha)^{\beta}\}\xi, \quad i = 1,\ldots,k \tag{20}$$

Eq. (20) can then be written in matrix form as

$$\mathbf{N} = \mathbf{C}\xi \tag{21}$$

where

$$\mathbf{C} = \begin{bmatrix} (1+\alpha)^{\beta} - (0+\alpha)^{\beta} \\ (2+\alpha)^{\beta} - (1+\alpha)^{\beta} \\ \vdots \\ (k+\alpha)^{\beta} - (k-1+\alpha)^{\beta} \end{bmatrix} \tag{22}$$

and

$$\mathbf{N} = \begin{bmatrix} N_1 \\ N_2 \\ \vdots \\ N_k \end{bmatrix} \tag{23}$$

Next, the least-squares estimate of ξ can be derived as following:

$$\hat{\xi} = (\mathbf{C}^T\mathbf{C})^{-1}\mathbf{C}^T\mathbf{N} \tag{24}$$

which is a function of α and β. Inserting Eq. (24) into Eq. (20) gives the estimate of N_i

$$\hat{N}_i = [(i+\alpha)^{\beta} - (i-1+\alpha)^{\beta}]\hat{\xi}(\beta,\alpha) \tag{25}$$

Now the problem becomes

$$\min_{\beta,\alpha} Q(\beta,\alpha) \tag{26}$$

where

$$Q(\beta,\alpha) = \sum_{i=1}^{k}(N_i - \hat{N}_i)^2 \tag{27}$$

Since Q is highly non-linear, the above minimum is solved by a large-scale algorithm, which is a subspace trust-region method and is based on the interior-reflective Newton method [15,16]. Observed Ni is calculated through dividing the total subassembly failures by the number of turbines reporting of the corresponding interval (see data examples in Tables 1 and 2).

With the values α and β, by Eqs. (19) and (24) an estimate for the parameter ρ can be obtained. Then, the estimates of ϕ and μ can be derived from ρ and β.

5. Modelling results analysis examples

The two algorithms presented above are applied to Danish and German populations of Windstats data, analyzing the reliability growth. Before applying both algorithms, N_i in those equations should be calculated first. Table 3 gives an example of N_1–N_4 for German data. Note that there are 111 and 35 intervals for Danish data and German data, respectively. In order to simplify the discussion, T is set to 730(h) for Danish data and 2190(h) for German data. Table 4 gives estimated parameters for three-parameter and traditional Weibull functions. Regarding the results of three-parameter model in Table 4, ML means those of maximum likelihood estimates and LS means those of least-square estimates.

Danish population has a larger time factor(α) than German, which implies that Danish wind turbines are put into use earlier than German wind turbines. Windstats data in 2003 confirms Danish first turbine installations were in 1987 and German first turbine installations were in 1990. Therefore, combined with the starting points of data of two populations (Danish is October 1994 and German is March 1996), those α estimated by ML approximately show their consistence. Those α achieved by LS have a little bit larger deviation. The ML estimates coincide with the LS estimates when the noise is zero-mean Gaussian distributed. The noise in Windstats data are not of that characteristic [11].

Failure rate functions can be derived from the estimated parameters of Table 4. See Table 5. The unit of failure rates is h^{-1}. Failure rate curves of Danish wind turbines are shown in Fig. 1, while failure rate curves of German wind turbines are shown in

Table 3
Example of average failure numbers calculated (German).

	1996			
	March	June	September	December
No of DE turbines reporting	1803	1830	1866	1902
Total subassembly failures	1314	816	857	999
Average number of failures, N_i	0.73	0.45	0.46	0.53

Table 5
Failure rate functions estimated.

Population	Three-parameter Weibull model		Weibull model
	ML	LS	
Denmark	$7.33(t+68401)^{-0.9851}$	$9.89(t+81731)^{-0.9999}$	$0.0004t^{-0.1532}$
Germany	$15.36(t+50282)^{-0.9990}$	$17.22(t+61758)^{-0.9999}$	$0.0014t^{-0.2016}$

Table 4
Parameters estimated.

Population	Three-parameter Weibull model						Weibull model	
	α		β		ρ		β	ρ
	ML	LS	ML	LS	ML	LS		
Denmark	93.70 (7.8 y)	111.96 (9.33 y)	0.0149	1.025×10^4	491.90	9.648×10^4	0.8468	0.0005
Germany	22.96 (5.74)	28.20 (7.05)	0.0010	1.005×10^4	15,364	1.713×10^5	0.7984	0.0017

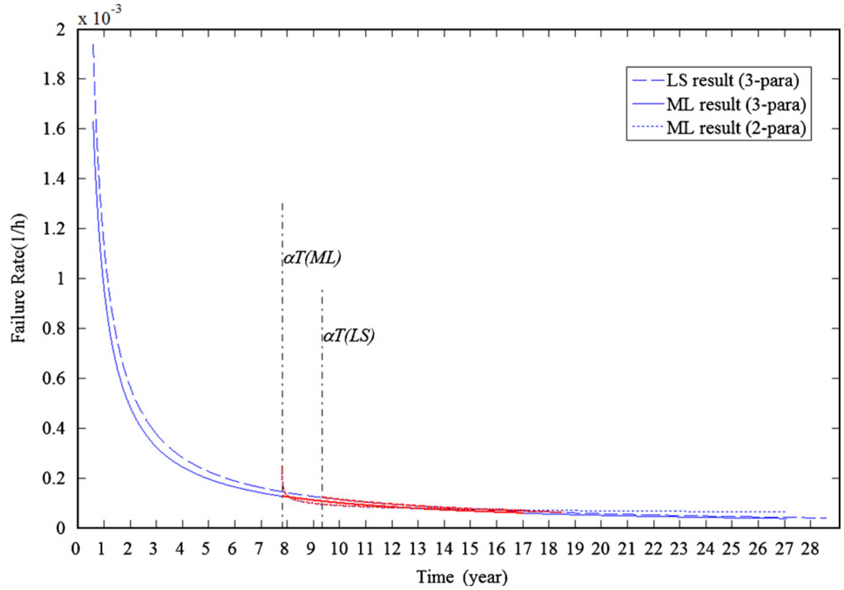

Fig. 1.

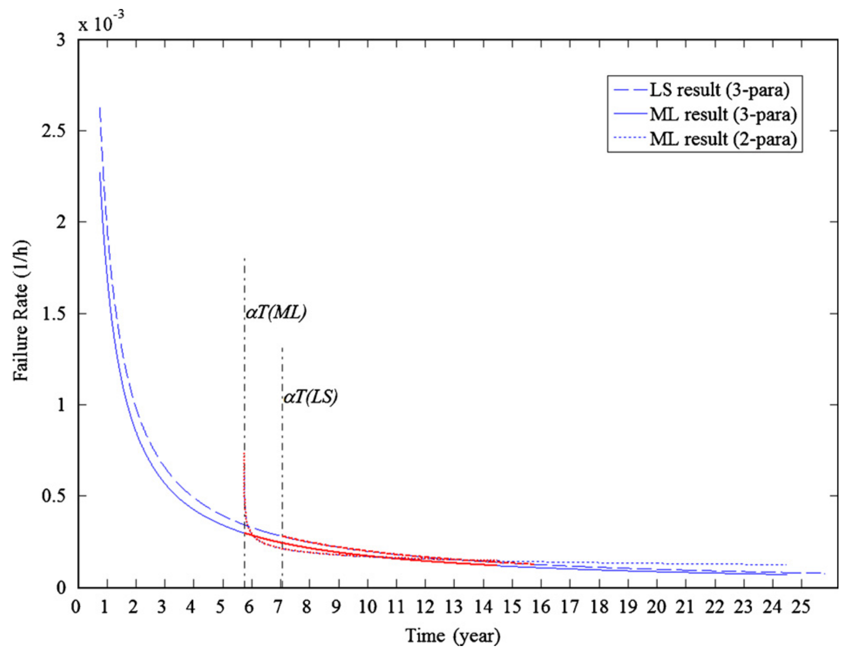

Fig. 2.

Fig. 2. Results of traditional Weibull function and three-parameter Weibull function are illustrated in the figures. The starting time points(αT) are marked out. Because ML and LS give close β parameters, ML and LS curves have similar shapes. In order to have an intuitive prediction of future reliability growth, all curves in Figs. 1 and 2 are extended by 10 years after the end of data reporting. There is a bold part in each curve, which represents the period when turbine failures are reported. Failure rates at the end of data reporting and 10 years after that are calculated using failure rate functions of Table 5. They are shown in Table 6 and 7 for Danish and German turbines, respectively.

It can be seen that:

- The Danish and German curves have similar shapes in accordance with the estimated values of β, which are close between the two populations.
- Failure rates of three-parameter functions are rather high (infinite) when the time is close to the first installation of wind turbines, whereas those of two-parameter functions are rather high (infinite) when the time is close to αT (the beginning of turbines reporting). That is a shortcoming of Weibull modelling. Because observed failure rate at time αT cannot be as high

Table 6
Failure rates of Danish turbines.

Time	Three-parameter Weibull model		Weibull model
	ML failure rate	LS failure rate	
End of data reporting	5.86×10^{-5}	6.08×10^{-5}	7.11×10^{-5}
10 years after the end of data reporting	3.71×10^{-5}	3.96×10^{-5}	6.35×10^{-5}

Table 7
Failure rates of German turbines.

Time	Three-parameter Weibull model		Weibull model
	ML failure rate	LS failure rate	
End of data reporting	1.1×10^{-4}	1.25×10^{-4}	1.44×10^{-4}
10 years after the end of data reporting	6.97×10^{-5}	7.63×10^{-5}	1.24×10^{-4}

as that predicted by two-parameter Weibull function, three-parameter Weibull functions have more accurate predictions after the point when the failure data of wind turbines were collected.

- The three-parameter model provides more information about the period before failure data were collected, but two-parameter model can only be used to predict reliability performance for the subsequent period.
- The wind turbines are all shown to be in the stage of infant mortality, because all the values of β are less than one.
- Similar curves are obtained by applying ML and LS techniques to three-parameter Weibull functions.
- LS gives a larger α than ML, but the time factor differences between two populations using two techniques are close to each other. From Table 4, it can be calculated that the time factor difference is 2.28 years for LS and 2.06 years for ML.
- It is predicted that reliability of Danish turbines would be improved by around 35% in extended 10 years (ML: 36.69%; LS: 34.87%) and reliability of German turbines would be improved by around 40% (ML: 40.93%; LS: 38.96%). For example, according to ML prediction, failure rate of Danish wind turbines will be improved from 5.86×10^{-5} to $3.71\times10^{-5}\,h^{-1}$, which means the mean time between failures will be increased from 1.95 to 3.08 years.

It should be noted that the populations of wind turbines were changing. New technologies were put into new wind turbines, which became more reliable than the elders. Clearly, older turbines and new turbines had different failure rates, so the trends were going down, which is in accordance with the results in this paper. It is not the case that there was a fixed population with its failure rate going down. Thus, examples in this section illustrate a method to evaluate wind turbine reliability growth as a function of wind turbine technologies. However, the *X*-axis is time not the wind turbine technologies. That is because no enough information is available to quantify the evolvement of technologies, but it is sure that technologies are improving along time axis.

If the population concerned is a fixed one and consists of the same components, the method presented in this paper can be used to estimate the intensity function of a non-homogeneous Poisson process for that specific component.

6. Conclusions

Windstats Newsletters provide failure data of wind turbines, but it is incomplete. In order to take such incompletion into account and obtain a more accurate reliability growth of wind turbines, a three-parameter Weibull failure rate function is presented to depict the reliability growth and its parameters are estimated by two techniques, maximum likelihood and least squares. Similar results have been achieved by the two techniques.

Three-parameter Weibull model presented in this paper has advantages over traditional Weibull in dealing with incomplete data. Three-parameter Weibull model is more accurate to predict the reliability trend. However, three-parameter Weibull model shrinks to the traditional Weibull model on the condition that α is set to 0. That is in accordance with the fact that three-parameter Weibull model is promoted from traditional Weibull model by introducing α into it. Therefore, the proposed three-parameter Weibull model is a general model that is applicable to both complete data, like life test data, and incomplete data, like field failure data in Windstats. Because three-parameter Weibull model provides an extra earlier part of reliability curve, it is helpful in planning a better maintenance schedule for wind energy systems. In other words, the remaining life time of a wind turbine can be estimated as a reference of the maintenance schedule, if a period of data is available for reliability analysis.

Examples show that three-parameter Weibull model can be used to evaluate reliability growth as a function of technologies for a mixed and changing population of device concerned. However, if the population concerned is a fixed one and consists of the same components, the method presented in this paper can be used to estimate the intensity function of a non-homogeneous Poisson process for that specific component.

The data used in examples of this paper are about wind turbines, but the presented method can be applied to not only Windstats grouped data but also other grouped data in any other industry. Therefore, it is a general technique.

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