

**Research
Article**

Reliability Analysis for Wind Turbines

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Modern wind turbines are complex aerodynamic, mechanical and electrical machines incorporating sophisticated control systems. Wind turbines have been erected in increasing numbers in Europe, the USA and elsewhere. In Europe, Germany and Denmark have played a particularly prominent part in developing the technology, and both countries have installed large numbers of turbines. This article is concerned with understanding the historic reliability of modern wind turbines. The prime objective of the work is to extract information from existing data so that the reliability of large wind turbines can be predicted, particularly when installed offshore in the future. The article uses data collected from the Windstats survey to analyse the reliability of wind turbine components from historic German and Danish data. Windstats data have characteristics common to practical reliability surveys; for example, the number of failures is collected for each interval but the number of turbines varies in each interval. In this article, the authors use reliability analysis methods which are not only applicable to wind turbines but relate to any repairable system. Particular care is taken to compare results from the two populations to consider the validity of the data. The main purpose of the article is to discuss the practical methods of predicting large-wind-turbine reliability using grouped survey data from Windstats and to show how turbine design, turbine configuration, time, weather and possibly maintenance can affect the extracted results. Copyright © 2006 John Wiley & Sons, Ltd.

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Introduction

An increasing number of wind turbines are being incorporated into European electrical networks. In some countries such as Denmark, Germany and Spain they are becoming a key part of networks and as such affect the overall system performance and reliability.¹

The configuration, technology and size of wind turbines have been changing rapidly over the last few years, and larger turbines (≥ 2 MW) incorporating new technology are being installed onshore throughout Europe. There is potential for more wind turbines to be erected in remote and offshore locations, to achieve a greater wind energy harvest, where the access to turbines for maintenance will be restricted. This is heightening the need for accurate reliability predictions so that wind turbine availability and life can be predicted and reasonable predictions of wind energy harvest over the life of the turbines can be made.

This article concerns the reliability of wind turbines in Denmark and Germany, using data extracted from Windstats (www.windstats.com) over the past 10 years. Both populations include modern turbines, but the

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German data include many larger wind turbines. One of the authors has previously shown, for electric motors,² that such data can be used to predict the reliability of future equipment. Reliability predictions for wind turbines will have an important bearing on the future development of wind power resources.

Windstats is a reliability survey which collects, organizes and groups failure data into periods of months or quarters. Therefore time to failure (TTF) information is not available. The data are collected from wind turbines, which, being both maintained and repaired, are typical repairable systems, for which failure times cannot in general be considered to be independent. Therefore the correct statistical model must be chosen.

This article analyses the failure rates derived from Windstats, considers problems that have arisen and provides evidence of how turbine failure rates are improving with time.

The article is organized to describe first the background to the reliability issue for wind turbines, then to describe the modelling methods available to analyse the data available, then to apply those methods to the collected data; finally, a discussion considers the various results, and conclusions are drawn.

Background

Windstats Data

Windstats is a commercial newsletter for the wind industry and records details of operation of wind turbines in many countries.

The overall period P investigated in this article was 10 years from October 1994 to September 2004. This period was restricted to ensure that the data being considered concerned modern designs of wind turbines. Data from two countries in particular have been analysed, Germany and Denmark, because the wind turbine populations reporting to Windstats from these two countries are large. The data give information about the items shown in Table I, including failures for the subassemblies which make up the turbines.

The German survey population includes up to 4500 turbines and the Danish survey population includes up to 2500 turbines, as will be shown below. The Windstats survey covers a fraction of the turbines installed in Germany and Denmark, which currently number approximately 20,000 and 6000 turbines respectively.

Windstats data are published quarterly, but the survey collects the number of failures occurring in the two turbine populations of successive Intervals of 1 month for Danish data and quarterly for German data.

The size of the population and the size of the interval are statistically important, since the larger the population and the larger the interval, the larger is the number of failures that are likely to occur in an interval. Over time the population is altering, as turbines are added or taken out of service, so the character of the population is changing. It would seem statistically that the German data are likely to give greater accuracy, since then represent a larger population and a longer interval and so are recording much larger numbers of failures per interval.

Table I. Data recorded in Windstats for the two populations

Information	Unit
Length of reporting interval i	Month or quarter
Number of intervals for which data were collected	I
Turbines reporting in a population	Number N_i per interval i
Turbines added and removed from the population	Number per interval
Total rating of all turbines in a population	kW
Energy produced by all turbines in a population in an interval	kWh
Failures in major subassemblies	Number $n_{i,k}$ per interval i per subassembly k (see Table II)
Time lost due to subassembly failures for all turbines N_i	Hours, T_s
Time lost due to non-subassembly failures for all turbines N_i	Hours, T_n
Time lost due to failures for which only hours recorded for all turbines N_i	Hours, T_h
Total time lost per interval for all turbines N_i	Hours, $T_i = T_s + T_n + T_h$

In fact, the Danish data show very low numbers of failures for some subassemblies in the most recent months of the survey. This may legitimately be the result of improving turbine failure rates, but it causes concern to the authors, because in some recording intervals the Danish data show zero failures for some turbine subassemblies, and this reduces the accuracy of those data.

Architecture of Wind Turbines

Within the survey populations there are many detailed variants, including:

- variations in turbine size from 100 kW up to 2.5 MW;
- variations in turbine blade aerodynamic and structural design;
- variations in mechanical architecture, including direct drive from the turbine to a low-speed generator or indirect drive with a gearbox and high-speed generator;
- variations in mechanical control for yaw;
- variations in mechanical control for speed, ranging from simple stall control, fixed speed turbines with induction generators to sophisticated pitch control, variable speed turbines with doubly fed induction or direct drive synchronous generators.

However, the vast majority of turbines covered by the survey will be of the Danish concept, i.e. a three-bladed, upwind turbine, mounted on a nacelle, on top of a cylindrical tower, such as shown in Figure 1.

One of the tasks of this article is to deduce some common facts from the failure data reported from this disparate range of turbines.



Figure 1. Typical Danish concept wind turbines as considered in this article (courtesy of GE Wind Power)

Wind Turbine Subassemblies

A wind turbine is made up of a number of key subassemblies, and Windstats provides failure information for each subassembly, as set out in Table II, for each interval. German and Danish data have slight variations in the name used for each subassembly, and there is no agreed descriptor for these subassemblies. In order to analyse the data in a common way, it has been necessary to group subassemblies as shown in Table II, which gives the subassembly name used in this article and that used by Windstats in each of the two national populations. The subdivision of faults by subassemblies cannot be taken to mean that the failure mode necessarily lies in the subassembly itself.

Modelling Wind Turbine Reliability

Machinery Life and Reliability, the HPP and PLP Models

The train of equipment at the heart of a modern wind turbine includes the key subassemblies shown in Table II. This article will use turbine and subassembly reliability results, plus a mathematical model, to interpret the data.

The subassemblies, and therefore the turbine, are repairable and the power law process (PLP) is commonly used in the reliability analysis of complex repairable equipment.^{3,4} Its intensity function $\lambda(t)$ describes the failure rate of a piece of machinery, such as a wind turbine, and has the form

$$\lambda(t) = \frac{\beta}{\theta} \left(\frac{t}{\theta} \right)^{\beta-1} \quad (1)$$

β is a parameter which describes the shape of the intensity function; θ , the scale parameter, has dimensions of time, and $\theta > 0$ for $t \geq 0$.

Figure 2 shows a complete failure intensity curve, usually referred to as the bathtub curve, whose three regions are described by equation (1) using different values for the shape parameter β :

- early failures, $\beta < 1$;
- constant failure rate, $\beta = 1$;
- deterioration, $\beta > 1$.

When $\beta = 1$, equation (1) reduces to a constant and the process becomes a homogeneous Poisson process (HPP), a particular case of a Poisson process for which the times between failures (TBFs) are independent and

Table II. Wind turbine subassemblies in the two populations

Subassembly name used in this article	Subassembly name used in Germany	Subassembly name used in Denmark
Rotor blades	Rotor	Blades, hub
Air brake	Air brake	Air brakes
Mechanical brake	Mechanical brake	Mechanical brake
Main shaft	Main shaft	Main shaft, coupling
Gearbox	Gearbox	Gearbox
Generator	Generator	Generator
Yaw system	Yaw system	Yaw system
Electrical controls	Electrical controls	Electrical control
Hydraulics	Hydraulics	Hydraulic system
Grid or electrical system	Electrical system	Electrical control
Mechanical or pitch control system	Mechanical control	Pitch control
Other	Other, instrumentation, sensor, windvane	Other

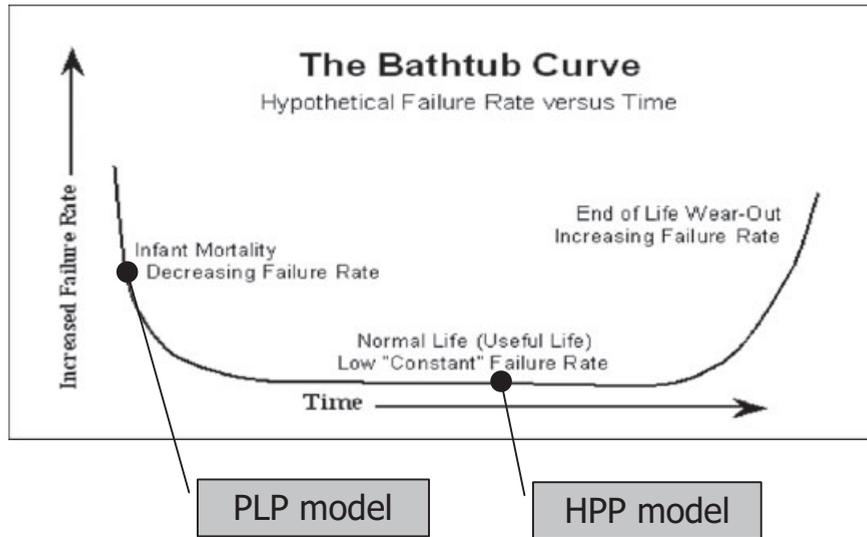


Figure 2. The intensity function of machinery

identically distributed (IID) exponential random variables. Thus θ becomes the mean time between failures (MTBF) of the turbine, and the maximum likelihood estimate (MLE) of θ is

$$\hat{\theta} = \frac{1}{\lambda} = \frac{\sum_{i=1}^I T_i}{\sum_{i=1}^I n_i} \quad (2)$$

The deterioration phase ($\beta > 1$) has not yet been encountered in wind turbines, probably owing to their relatively young age.⁵ Furthermore, if the reliability of a wind turbine reduces dramatically, it will be taken out of service before the deterioration phase can be detected.

If we collect data from a large number of turbines, we can deduce an average failure rate at a given interval by assuming that every turbine in the population lies on the constant failure rate part of the bathtub curve, which can be modelled by the HPP. The failure rate λ_i , expressed as the number of failures per turbine per year, can then be obtained at the i th interval by dividing the total number of turbine failures in this interval, $n_i = \sum_{k=1}^K n_{i,k}$, by the number of turbines, N_i , in the population for the interval and by the length in hours of the interval, T_i . The yearly based failure rate is then obtained by correcting the figure by the number of hours in a year as follows:

$$\lambda_i = \frac{\sum_{k=1}^K n_{i,k}}{N_i T_i / 8760} \quad (3)$$

Using the same method, a failure rate $\lambda_{i,k}$ for the k th subassembly in the i th interval can be obtained from each population at each interval i :

$$\lambda_{i,k} = \frac{n_{i,k}}{N_i T_i / 8760} \quad (4)$$

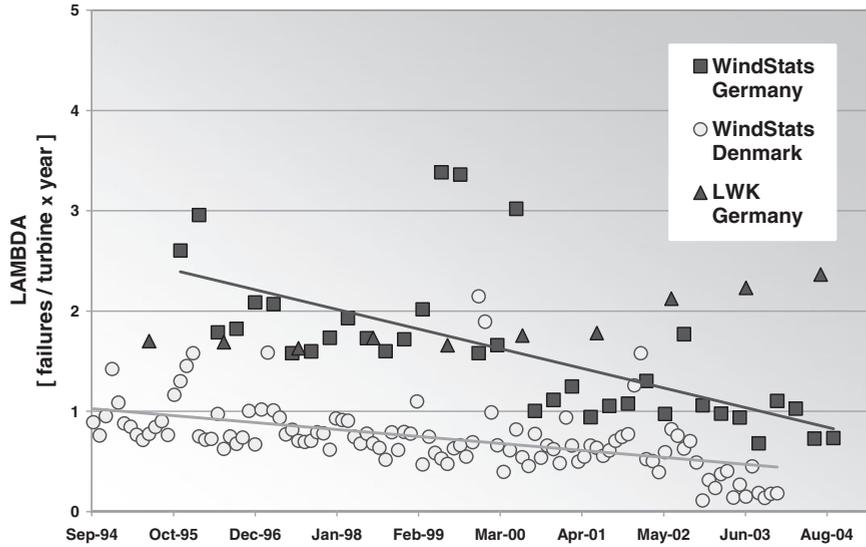


Figure 3. Turbine failure rates for two sets of data from turbines in Denmark and Germany using the HPP model

The average number of failures per turbine per year, λ , for the overall period $P = \sum_{i=1}^I T_i$ is given by

$$\lambda = \frac{\sum_{i=1}^I \sum_{k=1}^K n_{i,k} / N_i}{\sum_{i=1}^I T_i / 8760} \quad (5)$$

The failure rates for an average turbine in the two national populations in each interval from 1994 to 2004, using equation (3), are shown in Figure 3.

The Homogeneous Poisson Process Model

Probability

The data obtained from Windstats over the 10 years have a variable population at each interval, a month for Danish and a quarter for German data. The data have been reorganized so that populations and failure rates are available for 40 successive quarters for both Denmark and Germany, as statistical analysis shows that there is no loss of information after reorganization.

In order to use the HPP model for probability predictions, it is necessary to consider a group of turbines in a given interval of a month/quarter as an independent population which varies in each subsequent month/quarter. If it is assumed that the times between failures are IID exponential random variables, then the HPP model^{6,7} describes the probability $P(t)$ of having n failures through time t as

$$P(N(t) = n) = \frac{1}{n!} (\lambda t)^n e^{-\lambda t}, \quad n = 0, 1, 2, \dots \quad (6)$$

where the failure rate λ is the intensity function of the Poisson process, and the probability $P(t)$ that the n th failure will occur before time t is defined by

$$P(t_n < t) = \int_0^t \frac{\lambda^n t^{n-1}}{\Gamma(n)} e^{-\lambda t} dt \quad (7)$$

Considering the turbines in each quarter as an independent population, according to the HPP model, the failure rate is $\lambda = 1/\theta$ with MTBF θ constant for each quarter, and, if we take the average failure number of all the turbines reported in each quarter to be the failure number of a single average turbine, the varying population has no effect on the analysis. The assumptions are justified because the turbines have similar sub-assemblies, even though the populations vary from quarter to quarter.

To evaluate the reliability of a wind turbine and its subassemblies, the probability of observing n or more failures in the interval (t_1, t_2) can be calculated as

$$P_n = P(N \geq n) = \sum_n^{\infty} P(N = n) \quad (8a)$$

$$\therefore P_n = \sum_n^{\infty} \frac{1}{n!} \lambda (t_2 - t_1)^n e^{-\lambda(t_2 - t_1)} \quad (8b)$$

$$P_n = 1 - P(N \leq n-1) = 1 - \sum_0^{n-1} \frac{1}{n!} \lambda (t_2 - t_1)^n e^{-\lambda(t_2 - t_1)} \quad (8c)$$

Variation in MTBF between Subassemblies

Since the data from Windstats are processed by analysing I identical repairable populations for each interval, it is necessary next to test whether all I populations have the same MTBF θ . For each of k subassemblies to have the same MTBF, the following hypothesis needs to be satisfied:

$$H_0: \theta_{1,k} = \theta_{2,k} = \dots = \theta_{I,k} \text{ versus } H_1: \theta_{1,k} \neq \theta_{2,k} \neq \dots \neq \theta_{I,k}$$

The hypothesis-testing procedure is based on the likelihood ratio (LR) principle and the use of the chi-square approximation of the test statistic. The likelihood ratio LR_k is

$$\begin{aligned} LR_k &= \frac{\max_{H_0} L(\theta_{1,k}, \theta_{2,k}, \dots, \theta_{I,k})}{\max L(\theta_{1,k}, \theta_{2,k}, \dots, \theta_{I,k})} \\ &= \frac{\max_{\theta} \theta^{-\sum_{i=1}^I n_{i,k}} e^{-\sum_{i=1}^I T_i/\theta}}{\max_{\theta_{1,k}, \theta_{2,k}, \dots, \theta_{I,k}} \prod_{i=1}^I \theta_{i,k}^{-n_{i,k}} e^{T_i/\theta_{i,k}}} \\ &= \frac{\hat{\theta}_k^{-\sum_{i=1}^I n_{i,k}} e^{\sum_{i=1}^I T_i/\hat{\theta}_k}}{\prod_{i=1}^I \tilde{\theta}_{i,k}^{-n_{i,k}} e^{T_i/\tilde{\theta}_{i,k}}} \\ &= \frac{\prod_{i=1}^I \tilde{\theta}_{i,k}^{n_{i,k}}}{\hat{\theta}_k^{\sum_{i=1}^I n_{i,k}}} \end{aligned} \quad (9)$$

Where $\hat{\theta}_{i,k}$ is the value of $\theta_{i,k}$ which maximizes the denominator of the likelihood ratio, and $\hat{\theta}_k$ is the MLE of the expression in the numerator, i.e.

$$\tilde{\theta}_{i,k} = \frac{T_i}{n_{i,k}} \quad (10a)$$

$$\hat{\theta}_k = \frac{\sum_{i=1}^I T_i}{\sum_{i=1}^I n_{i,k}} \quad (10b)$$

Table III. Example of results from the likelihood ratio test (Danish data)

Subassembly	$\chi^2_{0,\kappa}$	H ₀	Conclusion
Main shaft	0.0017	Accepted	Identical
Gearbox	0.0025	Accepted	Identical
Mechanical brake	0.0036	Accepted	Identical
Generator	0.0064	Accepted	Identical
Hydraulic system	0.0016	Accepted	Identical
Yaw system	0.0041	Accepted	Identical
Electrical control	0.0012	Accepted	Identical
Air brakes	0.0024	Accepted	Identical
Coupling	0.0021	Accepted	Identical

The likelihood ratio statistic

$$-2 \ln LR_k = 2 \sum_{i=1}^I n_{i,k} \ln \hat{\theta}_k - 2 \sum_{i=1}^I n_i \ln \tilde{\theta}_{i,k} \quad (11)$$

is distributed approximately as a chi-square with $I - 1$ degrees of freedom.

Let $\chi^2_{0,\kappa} = -2 \ln(LR_k)$. Giving a specified value for the significance level α , we have $\chi^2_{\alpha, I-1}$ as the critical value. The test procedure calls for rejecting the null hypothesis H₀ when the value of this ratio $\chi^2_{0,\kappa}$ is large, say, whenever $\chi^2_{0,\kappa} > \chi^2_{\alpha, I-1}$. In other words a large value of $\chi^2_{0,\kappa}$ leads to a rejection of the null hypothesis. If the null hypothesis is not rejected, the θ s are equal and the populations are identical in the sense that their MTBFs are the same. For a test with $\alpha = 0.05$ we would reject the null hypothesis when $\chi^2_{0,\kappa} > \chi^2_{\alpha, I-1} = 18.3$. For a test with $\alpha = 0.10$, we would reject the null hypothesis when $\chi^2_{0,\kappa} > \chi^2_{\alpha, I-1} = 16.0$.

Table III gives the calculated results for the Danish subassembly data of the likelihood ratio statistic with $\alpha = 0.05$. It shows that it is reasonable to assume that the subassemblies in each quarter have the same MTBF.

Similar results were obtained for the German data.

The Power Law Process Model

The PLP model can be used to track the reliability improvement of a system and to predict the effectiveness of further design developments. The standard⁴ provides a procedure for the determination of the parameters of the intensity function for data collected in grouped form, like the data from Windstats. A goodness of fit test is also provided. Data are referred to as 'grouped' when only the number of failures in each period is known and the information about the actual TTFs is missing. The method has been applied considering one wind turbine subjected to the average number of failures of the population in each period. If the intensity function is rewritten as

$$\lambda(t) = \rho \beta t^{\beta-1} \quad (12)$$

then the MLE for the shape parameter $\hat{\beta}$ is obtained by solving numerically the non-linear equation⁸

$$\sum_{i=1}^I n_i \left(\frac{t_i^{\hat{\beta}} \ln t_i - t_{i-1}^{\hat{\beta}} \ln t_{i-1}}{t_i^{\hat{\beta}} - t_{i-1}^{\hat{\beta}}} - \ln t_i \right) = 0 \quad (13)$$

in which, by definition,

$$t_0^{\hat{\beta}} = \ln t_0 = 0 \quad (14)$$

and the set $[t_{i-1}, t_i]$ defines the i th interval. The MLE for the scale parameter $\hat{\rho}$ is then

$$\hat{\rho} = \frac{\sum_{i=1}^I n_i}{t_i^{\hat{\rho}}} \quad (15)$$

The assumption of considering the reliability of the population of wind turbines improving according to a PLP can be tested with a goodness of fit test. The test is built starting from the expected number of failures in the i th interval, which is approximated by

$$e_i = \hat{\rho}(t_i^{\hat{\rho}} - t_{i-1}^{\hat{\rho}}) \quad (16)$$

Thus the statistic

$$x^2 = \sum_{i=1}^I \frac{(n_i - e_i)^2}{e_i} \quad (17)$$

is approximately distributed as a chi-square random variable with $I - 2$ degrees of freedom, for which the critical values can be found in the usual tables. The hypothesis is accepted if the statistic assumes values smaller than the critical value, which is calculated for the level of confidence, α , chosen.

Discussion

Interpretation from Data

Turbine Reliability, Failure Rate

The average failure rates for each interval plotted using equation (3) are shown in Figure 3 and are striking.

- Failure rates in both populations are falling with time.
- German failure rates are higher than Danish failure rates.
- Danish monthly failure rates exhibit some periodicity, which the authors ascribe to the effect of the weather.
- There are some significantly high failure rates in both populations, and some of these high failure rates in the two populations coincide in time.

The first two results have also been reached independently in a report from the Netherlands by DOWEC.⁹ This work has previously been reported by the authors.^{10,11}

Subassembly Reliability, HPP

Figure 4 shows the failure rate for each subassembly in the two national populations of turbines during the period 1994–2004 using equation (4), the HPP Model, sorting the failure rates in their order of significance for German turbines.

Comparing the failure rates of subassemblies between Denmark and Germany, it can be seen that, as expected from Figure 3, Danish failure rates are lower, but for some subassemblies the two populations have similar failure rates, e.g. on the main shaft and mechanical brake. This implies that Danish and German turbines, using the HPP model, could have similar reliability features, not surprisingly, since brakes and shafts produced in varying sizes for the same industry are likely to have similar failure rates in different populations. On the assumption that the turbine subassemblies conform to the HPP model, the MTBFs for the subassemblies can be given as in Table IV.

The principal contributors to the higher German failure rate are the electrical control or system subassemblies (grid or electrical system, yaw system and mechanical or pitch control system) rather than mechanical subassemblies such as the gearbox. This is consistent with the introduction of variable speed drive technology but is contrary to the received wisdom that gearboxes are a major cause of turbine failure.

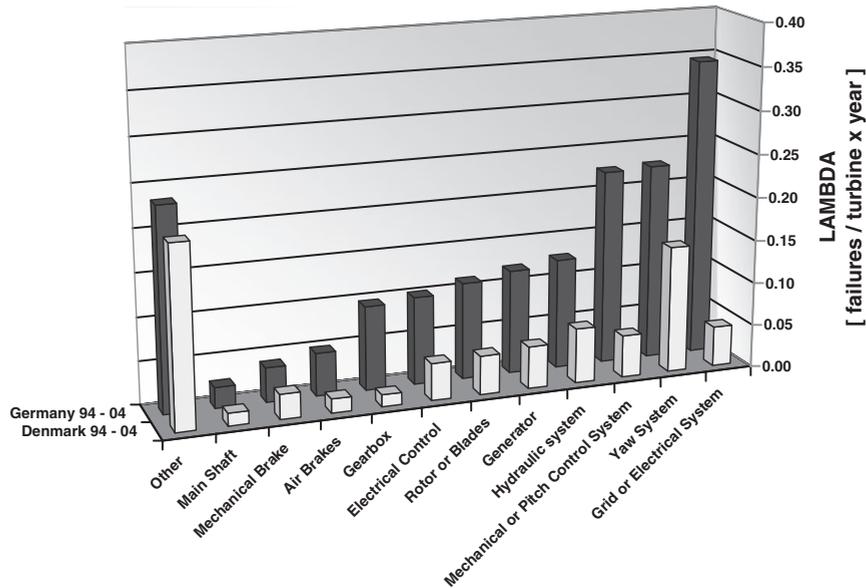


Figure 4. Variation in subassembly failure rates for the two populations in the overall period using the HPP model

Table IV. MTBFs of German and Danish turbine subassemblies calculated from Figure 4 assuming the HPP model

Subassembly	German turbine subassembly MTBF (h)	Danish turbine subassembly MTBF (h)
Rotor blades	39,297	252,033
Air brake	180,078	1,286,050
Mechanical brake	223,447	627,055
Main shaft	365,339	807,174
Gearbox	87,174	218,871
Generator	73,234	365,534
Yaw system	69,504	318,903
Electrical controls	39,205	175,561
Hydraulics	79,363	285,195
Grid or electrical system	25,708	450,643
Mechanical or pitch control system	90,472	1,236,712
Other	25,449	51,871

However, it must be understood that failure of a gearbox, or of a blade or generator for that matter, is likely to have a great impact on turbine availability owing to the extended mean time to repair (MTTR) necessary for its removal from a nacelle and replacement.

It should be noted that the distribution of subassembly failures shown in Figure 4 and their respective order will vary according to the span of years considered, but that the figure shown adequately summarizes the overall effect.

Comparison between German and Danish Turbine Populations

The failure rates in this article are an average over large populations of 900–4000 turbines, each of which population includes turbines of different technology and age, which may not necessarily lie on the flat part of the bathtub curve. Thus the HPP model implicit in Figures 3 and 4 needs to be used with caution. For example, newer turbines which are still in the early failure phase will have a rapidly falling failure rate, which will affect the averaging implicit in equation (3). However, this approach is recommended in Reference 3.

To select valid mathematical models, the data must be analysed further to determine the characteristics of the German and Danish populations. The Danish and German data have been investigated regarding the numbers and average sizes of turbines in each population, as presented in Figures 5 and 6. These figures show

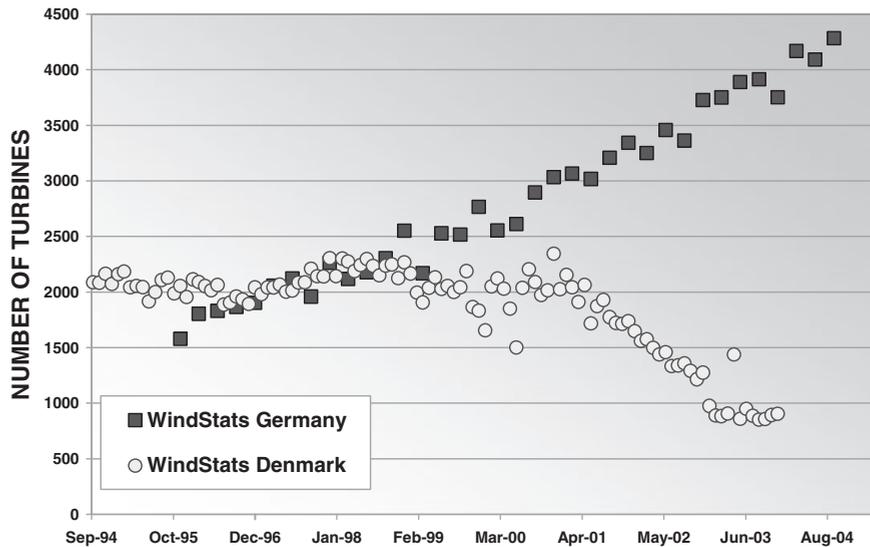


Figure 5. Numbers of turbines in the Danish and German populations

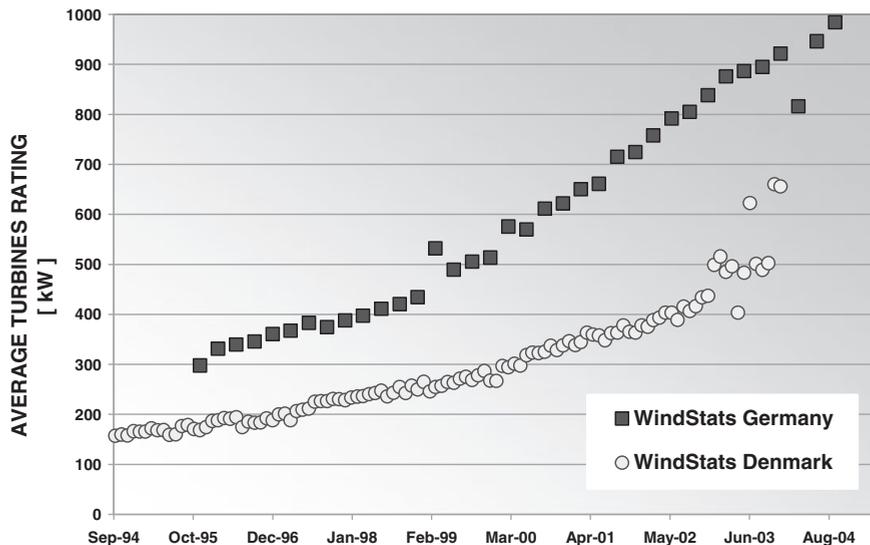


Figure 6. Sizes of turbines in the Danish and German populations

that the number of Danish turbines is decreasing but their rated size is half that of German turbines. This is consistent with the knowledge that Denmark started building large wind turbines before Germany but has had an installation moratorium, only replacing older, smaller turbines with newer, larger machines. The increase in German turbine numbers is a result of the growth in that market, which has been reported elsewhere.¹

The implication of Figures 5 and 6 is that the Danish turbines in the survey are smaller and older than the German turbines and are likely to be largely stall-regulated, constant speed machines.

Predictions from Data

Reliability Growth Curve, PLP

'Modelling Wind Turbine Reliability' showed how to fit the reliability growth curve to the failure data using the PLP model.

Using the procedure in 'The Power Law Process Model', the German and Danish estimated reliability growth curves are given in Figure 7, while in Figure 8 the two curves are directly compared.

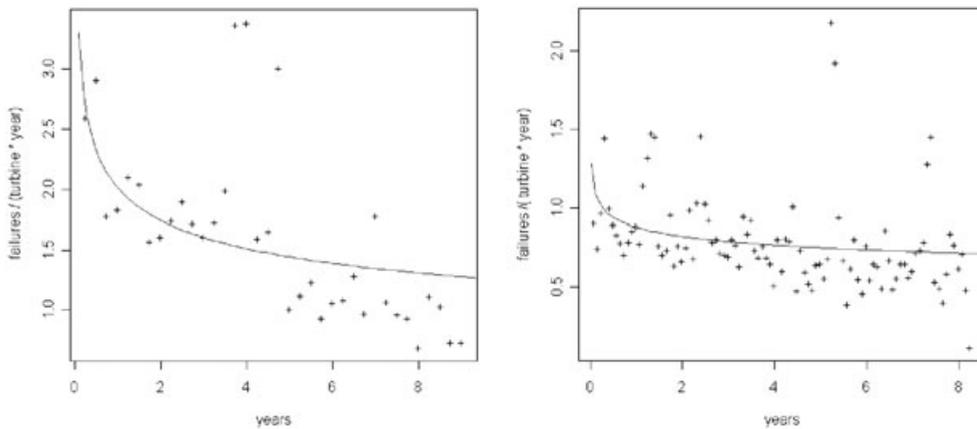


Figure 7. PLP model results, German on left and Danish on right

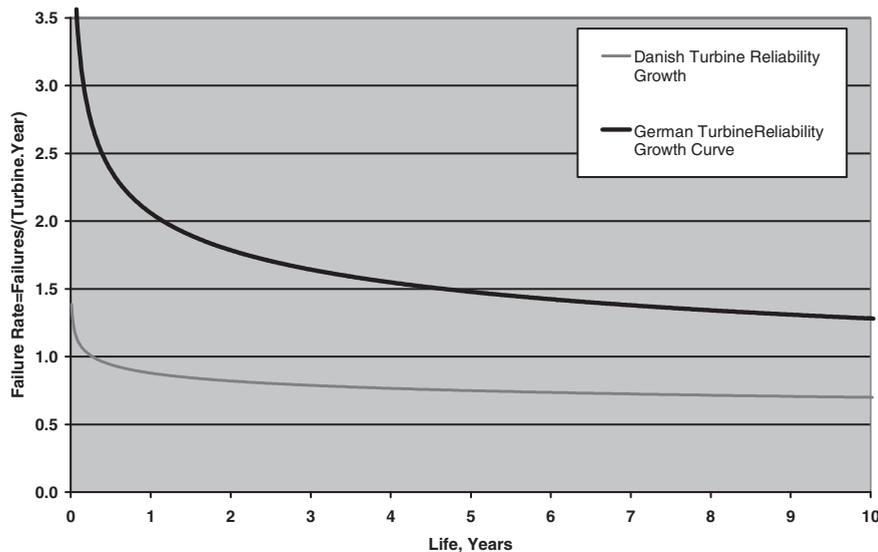


Figure 8. Calculated reliability growth curves using the method in 'The Power Law Process Model', confirming different history and trend for German and Danish populations

Table V. Parameters estimated with failure rate λ (failures per year); see equations (12)–(17)

	β	ρ	x^2	$\chi^2_{\alpha, I-2}$
German turbines	0.794	2.530	5.390	48.6
Danish turbines	0.901	0.975	0.906	121.0

The estimates for β and ρ from equations (12)–(17) for those are curves are given in Table V. This confirms that the shape parameters of the two curves are dissimilar, demonstrating a substantially different improvement history and current trend. Furthermore, the reciprocal value of the intensity function can be considered as the instantaneous MTBF, and the comparison of the two curves confirms the worse reliability for the German wind turbines. The value of the intensity function in the last interval may be interpreted as the constant failure rate that the system would have if the development phase was terminated.

The German turbines are newer than the Danish turbines, so a larger improvement in their reliability can be expected in the future. On the other hand, the reliability performance of the Danish wind turbines can hardly be improved owing to the maturity of their technology, attested by the shape of the intensity function.

These results are consistent with the data shown in Figures 5 and 6, concerning respectively the average number and the rating of the two populations of wind turbines, which might partially justify the results.

Failure Probability, HPP

'Modelling Wind Turbine Reliability' showed how the HPP model can be used to predict the probability of failure events. Here we will use that method to predict the probability of observing failures over the life of a turbine. Following equations (7) and (8), probabilities have been computed of observing, in periods of 1 and 25 years, the following numbers of failures, N :

- no failures, $P(N = 0)$;
- one or more failures $P(N \geq 1)$;
- two or more failures $P(N \geq 2)$.

Results are given in Figures 9(a) and 9(b) for the Danish turbines only, showing a negligible probability of subassembly failures in 1 year and a probability of very few failures after 25 years. This indicates that for these turbines a 1 year guarantee involves very little risk and a 25 year life looks reasonable.

Results for the German turbines are not displayed but do show that they deteriorate more rapidly than the Danish turbines on the basis of this model.

Maintenance and Lost Hours

It should be borne in mind that the predictions above were made using data from maintained turbines, maintenance operations were probably recorded in the survey as hours lost, and the data give no information on how much time was devoted to maintenance.

However, the survey does indicate, for the German population, the time lost on turbines in each interval (see Table I), and this has been plotted in Figure 10. The hours lost due to subassembly failures are reducing with time, but the total hours lost per turbine per quarter are steadily rising, although at *ca* 35 h per quarter they are not excessive. These data are informative, but the authors are unable at this time to separate the time lost due to failures from the time lost maintaining the turbine. This is of crucial importance to operators, since it is possible to achieve higher reliability by greater maintenance activity, but the ultimate goal of the industry would be to achieve higher reliability with decreased maintenance.

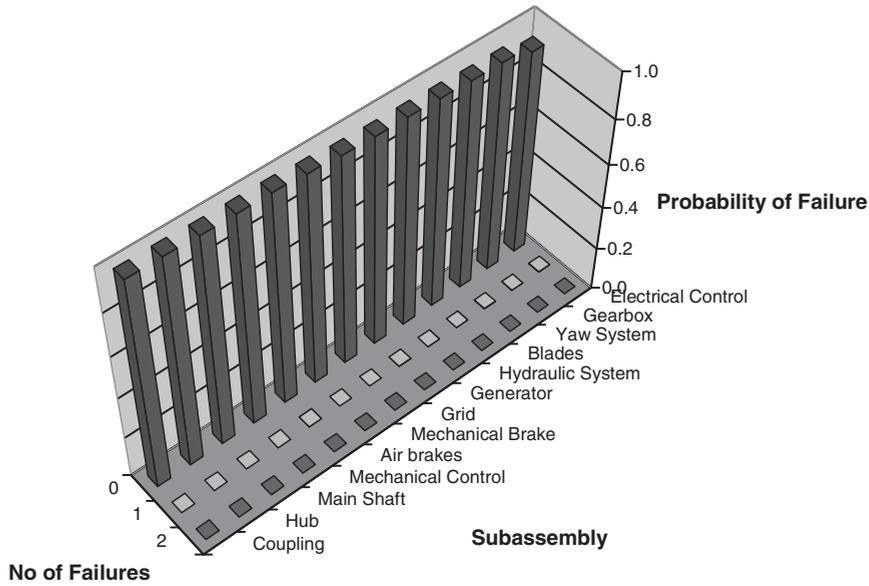


Figure 9(a). Prediction of failures in subassemblies of Danish turbines after 1 year

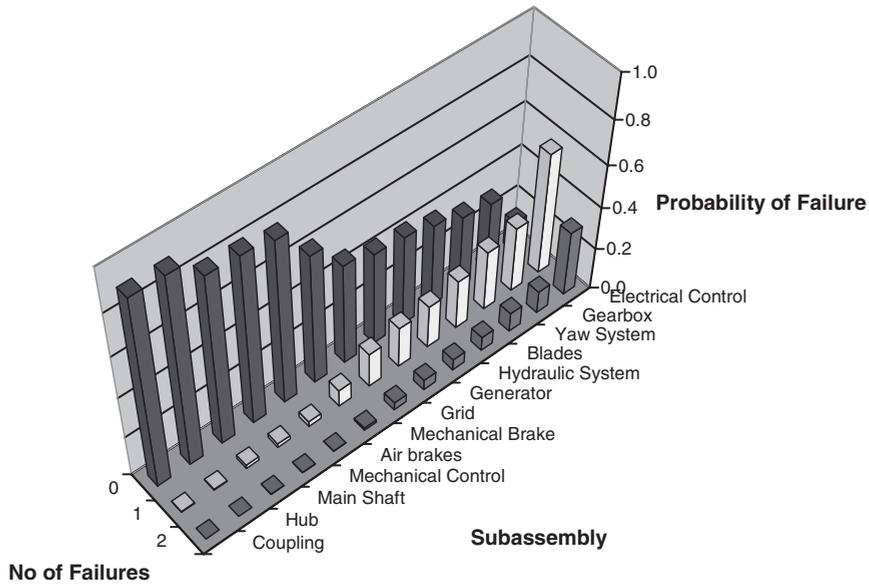


Figure 9(b). Prediction of failures in subassemblies of Danish turbines after 25 years

Historic Context of Turbine Reliability

The modern age for wind turbines has now extended over a number of decades, therefore the data collected by Windstats should be put into that historical context. Data are available from other sources, including from the USA (EPRI) and Germany (WMEP and LWK) in the DOWEC report.⁹ The Windstats data and these extra data have been plotted in Figure 11, using equation (3), with a logarithmic failure rate scale to accommodate the wide variation observed. The EPRI results go back to US experience in California, where turbine failure

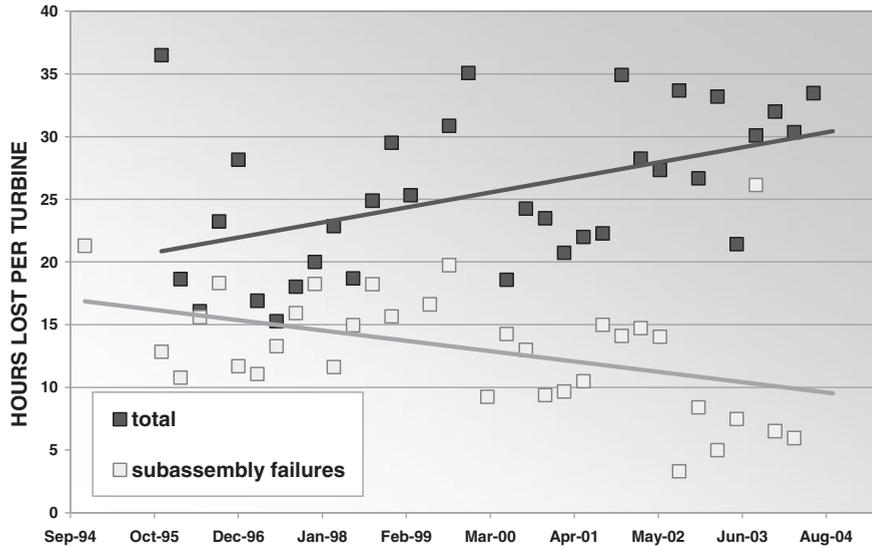


Figure 10. Hours lost per quarter due to failures and maintenance in German turbines

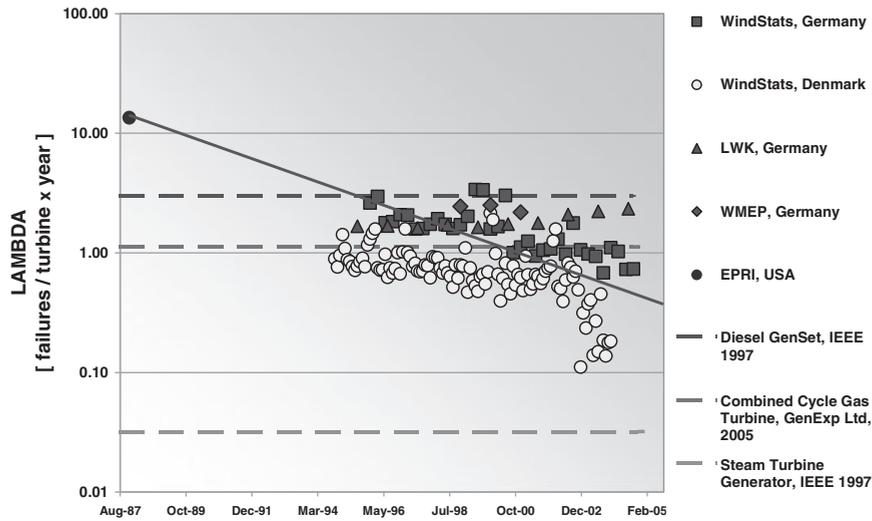


Figure 11. Average failure rates of German and Danish wind turbines in historical context and compared with failure rates of other power sources

rates were exceptionally high. The data from the other German surveys (WMEP and LWK) show similar figures to those given by Windstats, giving confidence in the validity of this information.

Figure 11 confirms the improving trend shown in this article and shows how much wind turbine reliability has improved over the past 16 years, particularly when placed alongside earlier US experience.

Figure 11 also compares wind turbine failure rates with those for diesel, combined cycle gas turbine (CCGT) and steam turbine generation, reported variously by the IEEE^{12,13} and GenExp (personal communication).

The striking observation here is that wind turbines are now achieving better reliability than diesel generation, have a similar level to CCGT in the UK and could achieve similar reliability to steam turbine generation within the next 10 years. It is important to note that all these reliability figures are achieved by maintenance.

Further Work

The article has shown that a considerable amount of information useful to turbine manufacturers and operators can be extracted from reliability data. However, it is also clear that more information could be extracted if the data were more extensive and were organized in a way more tractable to reliability theory. In particular, the following aspects need to be considered in any future work:

- to expand the reliability database by considering turbine reliability data from other sources where there are large numbers of turbines, possibly in Germany, the Netherlands and Spain;
- to collect reliability data from offshore wind turbines.

Conclusions

This article has extracted average failure rates and reliability growth curves for maintained, onshore German and Danish wind turbines from Windstats failure data, using respectively the homogeneous Poisson process and the power law process. The article has demonstrated the following.

- There is a downward trend in failure rate in both German and Danish wind turbine populations, however, there is no indication of the effect which maintenance is having on this downward trend.
- The data show a higher failure rate for German turbines than for Danish turbines.
- The HPP model for turbine life has been demonstrated to be applicable for Danish turbines because of the higher average age of their long-serving, reliable turbine designs, which lie in the constant failure rate region of the bathtub curve.
- The PLP needs to be used for German turbines, because they have lower average age and the majority are in the early failure region of the bathtub curve.
- The calculated reliability growth curves for the German and Danish turbines are substantially different, implying that the technologies involved have dissimilar maturities. Nevertheless, the margin for further improvement for German wind turbines is large.
- German turbines have a higher average failure rate because they are newer. Many of these new turbines are large and incorporate variable speed technology.
- The introduction in Germany of larger turbines with more technological complexity is raising their average failure rate in the first few years of life, but the downward trend in failure rate is faster than in the Danish population. This suggests that the newer turbines are not potentially less reliable than their smaller predecessors, despite their increased complexity.
- The Windstats data show that the principal contributors to the higher German failure rate are electrical control or system subassemblies rather than mechanical subassemblies such as the gearbox. This is consistent with the introduction of variable speed drive technology. However, it is understood that the failure of a gearbox is likely to have a much greater impact on turbine availability owing to the extended MTTR compared with an electrical control failure.
- The analysis shows that the configuration of wind turbines affects reliability, but it does not show that eliminating gearboxes or variable speed technology will necessarily improve modern wind turbine reliability, which is improving anyway.
- Maintained, onshore wind turbines in Germany and Denmark have been demonstrated to have a better reliability than indicated by a US survey of diesel generating sets and are approaching the reliability indicated for UK combined cycle gas turbine generating sources. The trend in reliability improvement suggests that within the next 10 years they will approach the reliability indicated by a US survey of steam turbine generating sources.
- There appears to be a periodicity in the failure rates of Danish wind turbines, which the authors ascribe to the effect of the weather.
- If this work is to be applied to offshore wind turbines, some estimate must be made of the impact on the data in this article of onshore maintenance and the likely effect of changing that to planned maintenance for offshore turbines.

- It would be beneficial to devise a European code to standardize the recording of wind turbine reliability data, bearing in mind US experience in reliability surveys with electrical plant,^{12,13} so that:
 - failure codes are harmonized between countries and concentrate on failure modes;
 - names and descriptions of subassemblies are harmonized between countries;
 - maintenance outages are recorded and differentiated from failures;
 - lost hours from turbines due to faults and maintenance are recorded in a standard way,
- It would be beneficial to consider the impact of weather on turbine reliability.

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Appendix: Nomenclature

α	statistical significance level
β	shape parameter from power law function
$\hat{\beta}$	MLE for shape parameter
Γ	gamma function
λ	average failure rate of a turbine
λ_i	average failure rate of a turbine, i.e. failures per turbine per year, in i th interval
$\lambda_{i,k}$	average failure rate for k th subassembly of a turbine, i.e. failures per subassembly per year, in i th interval
$\lambda(t)$	intensity function of Poisson process, equated to failure rate
θ	scale parameter of power law function
$\theta_{i,k}$	average MTBF in i th period for k th subassembly
$\hat{\theta}$	MLE for denominator of likelihood ratio
$\hat{\theta}$	MLE for numerator of likelihood ratio, MLE for θ in HPP
ρ	scale parameter of intensity function (alternative form)
$\hat{\rho}$	MLE for ρ
χ^2	chi-square distributed random variable
x^2	deviation statistic for chi-square test
e_i	expected number of failures in interval i for PLP goodness of fit
H_0	null hypothesis
i	integer counting intervals
I	total number of intervals in survey
k	integer counting subassemblies
K	total number of subassemblies in a turbine
n_i	number of failures during interval i
$n_{i,k}$	number of failures in subassembly k during interval i
N_i	number of turbines in population at interval i
P	overall period for which data were collected
$P(t_n < t)$	cumulative distribution function for n th failure
T_i	length of reporting interval, which varies according to month (h)
T_s	time lost due to subassembly failures (h)
T_n	time lost due to non-subassembly failures (h)
T_h	time lost due to failures for which only hours recorded (h)
T_t	total time lost, $T_t = T_s + T_n + T_h$ (h)

t_i	time to i th failure (h)
A	availability, $A = \text{MTBF}/(\text{MTBF} + \text{MTTR})$
HPP	homogeneous Poisson process
IID	independent and identically distributed
LR	likelihood ratio
MLE	maximum likelihood estimate
MTBF	mean time between failures
MTTR	mean time to repair
PLP	power law process
TBF	time between failures
TTF	time to failure

References

1. E.ON Netz. Wind report 2004. *Technical Report*, 2004.
2. Tavner PJ. Predicting the design life of high integrity rotating electrical machines. *IEE 9th International EMD Conference*, Canterbury, 1999, pp 286–290.
3. Billinton R, Allan RN. *The Reliability of Engineering Systems* (2nd edn). Plenum: New York, NY, 1992.
4. *Reliability Growth Management (Military Handbook 189)*. Department of Defense: Washington, DC, 1981.
5. ISET. Wind energy report, WMEP. *Technical Report*, 2004.
6. Pulcini G. A bounded intensity process for the reliability of repairable equipment. *Journal of Quality Technology* 2001; **33**: 480–492.
7. Rigdon SE, Basu AP. *Statistical Methods for the Reliability of Repairable Systems*. Wiley: New York, NY, 2000.
8. Buchanan JL, Turner PR. *Numerical Methods and Analysis*. McGraw-Hill: New York, NY, 1992.
9. DOWEC. Estimation of turbine reliability figures within the DOWEC project. *Report Nr 10048, Issue 4*, 2003.
10. Tavner PJ, Xiang J. Wind turbine reliability, how does it compare with other embedded generation sources. *IEE RTDN Conference*, London, 2005.
11. Tavner PJ, Xiang J, Spinato F. Improving the reliability of wind turbine generation and its impact on overall distribution network reliability. *IEE 18th International Conference on Electrical Distribution, CIRED*, Turin, 2005.
12. Report on reliability survey of industrial plants. Part I: Reliability of electrical equipment. In *IEEE Gold Book (IEEE Std 493–1997)*. IEEE: New York, NY, 1997; 201–223.
13. Reliability survey of 600–1800kW diesel and gas turbine generating units. In *IEEE Gold Book (IEEE Std 493–1997)*. IEEE: New York, NY, 1997; 403–417.