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Hazard Model Reliability Analysis Based on a Wind Generator Condition Monitoring System

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Abstract: This paper presents an application of the hazard model reliability analysis on wind generators, based on a condition monitoring system. The hazard model techniques are most widely used in the statistical analysis of the electric machine's lifetime data. The model can be utilized to perform appropriate maintenance decision-making based on the evaluation of the mean time to failures that occur on the wind generators due to high temperatures. The knowledge of the condition monitoring system is used to estimate the hazard failure, and survival rates, which allows the preventive maintenance approach to be performed accurately. A case study is presented to demonstrate the adequacy of the proposed method based on the condition monitoring data for two wind turbines. Such data are representative in the generator temperatures with respect to the expended operating hours of the selected wind turbines. In this context, the influence of the generator temperatures on the lifetime of the generators can be determined. The results of the study can be used to develop the predetermined maintenance program, which significantly reduces the maintenance and operation costs.

Key words: Hazard model, failure rate, survival rate, mean time to failure, weibull distribution, generator age, generator temperature.

1. Introduction

The CMS (condition monitoring system) for wind turbine components is critical to developing an effective maintenance program. An inclusive monitoring system provides diagnostic information on the health of the turbine components, and issues warnings to the maintenance crew that potential failures or critical malfunctions might be imminent.CMS; therefore, can be used to schedule maintenance tasks or repairs before a technical problem causes downtime in the whole wind turbine [1, 2]. The CMS technique can be divided into two categories: off-line monitoring and on-line monitoring. The wind turbine must be taken out of service in order to allow the maintenance crew to inspect the conditions through the off-line monitoring. Usually this monitoring technique is applied as routine or scheduled maintenance at regular intervals. The maintenance includes verification of the oil condition, and an inspection of the functioning of the system components, and the control systems. The on-line monitoring, on the other hand, provides enough details about the performance of the turbine subsystems performance while they rotate under different loading conditions. The SCADA (supervisory control and data acquisition systems) in turn, present the performance of the turbine subsystems. In the recent years, many advanced on-line monitoring systems have been introduced to wind turbines. The most common ones are vibrationmonitors, temperatures monitors, electrical current monitors and fluid contamination monitors [1-5].

In wind generators—the temperature is extensively monitored—i.e., the temperature sensors are designed to monitor specific areas of the stator core and the cooling fluids of large electrical machines—such as wind turbine generators. The generator temperature has a direct relationship with the electrical loads, cooling systems, and ambient conditions—consequently, when

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the temperature measurement is combined with the information of the system conditions—the effective condition monitoring can be achieved [6-8]. Such monitoring systems increase the reliability of the generator component and reduce the operation and maintenance expenses.

The nature of the maintenance needs to determine which methods must be applied. There are two methods available: the calendar-based method (the component needs to be replaced after a specified time), and the condition-based method (the component needs to be replaced based on its physical condition). To improve the reliability of wind energy systems, the CBM (condition-based maintenance) approach is one of the most effective methods that can be applied. Based on CBM, the collected data can be summarized and analyzed, such as oil analysis, vibration analysis, acoustic emission analysis, and temperatures trend analysis. Furthermore, CBM can be applied to determine the appropriate time to replace a component, such as the wind generator [1-5, 9-11].

Many Researchers have improved several condition-monitoring techniques that can increase the reliability of the wind energy industry. Karki and Hu [12] present a simplified approach for reliability evaluation of wind power systems. The main idea of their work is to define the minimum multistate representation for a wind farm generation sample with respect to the estimated reliability of the power systems. Haitao and Simon [13] propose three-parameter Weibull failure rate function to perform life tests on wind turbine components, by utilizing two techniques: maximum likelihood and least-squares. A proposed CBM optimization using the ANN (artificial neural network-based) health condition prediction is presented in [10]. The CBM program is specified by a failure likelihood threshold value. Based on the ANN lifetime forecasting residuals on the test set through the ANN training and testing processes, the remaining life prediction uncertainty is estimated. In Ref. [5], a life cycle cost approach is considered in order to estimate the financial interest by using CMS as a tool to implement the CBM strategy. Ref. [9] presents an approach to evaluate the wind turbine degradation process based on an optimal maintenance program, which develops the reliability analysis of the system. Hall and Strutt [14] present an application of physics-of-failure models of component lifetimes in the existence of parameter and model uncertainties. The selected random variables and the characteristic life-time of the systems are described by using the knowledge of Weibull distribution. Then, the Monte Carlo technique is utilized to estimate the probability of failure of the selected component. E. Martınez et al. propose a life cycle assessment model to assess the wind energy and analyze the related emissions. This assessment helps decrease the negative environmental impacts of the various manufacturing processes, which are used to make the turbine and its components. Moreover, the proposed assessment helps todefine the energy payback time [15]. In this paper, a hazard reliability technique for wind generators based on CMS is employed to develop a proper maintenance strategy, which aims to extend the system life-time and reduce potential failure during operation due to high generator temperatures.

Monitoring the trend of the generator temperatures with respect to the expended working hours is beneficial. Reliability analysis of the wind generators can be performed based on generator temperature data in order to make appropriate decisions concerning generator maintenance. In order to estimate the failure and survival rates of the wind generators, the hazard rate function statistical method can be utilized. The main objective of this work is to estimate the MTTF (mean time to failure) of wind generators, and estimate the failure and survival rates of the wind generators. Consequently, the proper time to replace the generators can be determined, and the appropriate maintenance approach can be implemented. This leads to reduce the maintenance cost and improve the reliability of the wind energy system remarkably. Based on the collected generator temperature data of two wind turbines, a case study is presented to demonstrate the proposed approach.

The paper is arranged as follows: the theoretical background about the proposed hazard failure rate model is introduced in Section 2. To model the failure time of the wind generators, the hazard technique based on the Weibull distribution function is presented in this section. Then, the estimation of the mean time to failure for wind generators is described in Section 3. For the sake of testing the validity of the proposed method, a case study is provided in Section 4. The obtained results of the work and discussions are presented in Section 5. Concluding remarks are given in Section 6.

2. Theoretical Background on the Proposed Hazard Failure Rate Model

Years of experience with wind energy systems and machines in general, have provided the failure rate characteristic curve of wind turbines as shown in Fig. 1 [13-19]. This curve is called the life curve or bathtub curve, and it can be applied widely in reliability engineering applications for any component, such as a wind generator. It characterizes the hazard function, thus illustrating the component failure stages. The initial failures might occur during operation in the early life period of wind generators (first stage) due to many reasons, such as improper design, defective raw material, poor quality of work, and poor quality control. The failure rates in this stage are called the infant mortality or rapidly declining failure rates since the generator will be replaced once the fault is detected. During the operating period (second stage), the failure rates are relatively constant. In the third stage of the aging period, the wear out occurs due to operation conditions and/or electrical/thermal stress. The expended working hours also determine to a great extent the increase in the failure rates of wind generator.

The failure rate through this phase is dramatically increased; consequently, the reliability analysis on

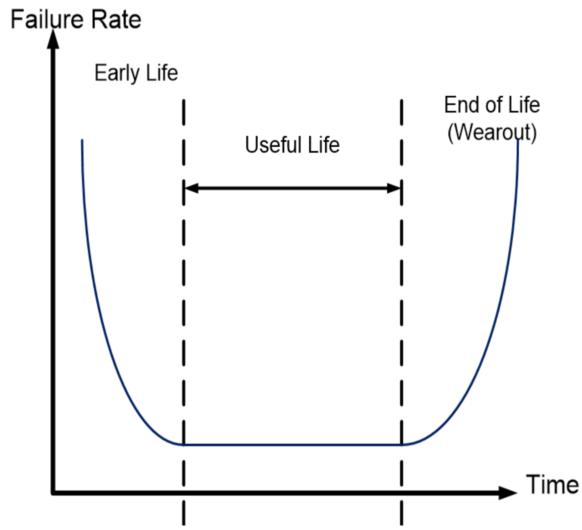

Fig. 1 The life curve of wind generator [13-19].

wind generators should be applied through this critical period. Furthermore, the models for such failure rate functions are required, when the life cycle of the system is studied.

In order to estimate the failure rates, survival rates, and the MTTF, several methods based on the reliability analysis can be utilized. The hazard analysis technique is one of the most effective approaches that can be used for this purpose. The failure rate is called the hazard rate, and can be represented by the hazard function $h(t)$,which measures the risk or the probability that the generator can still survive after time $t + \delta t$ as follows [17-23]:

$$h(t) = \lim_{\delta t \to 0} \frac{P(t \leq T < t + \delta t) \left| T \geq t \right.}{\delta t} \qquad (1)$$

where, T is the failure time of the wind generator.

The knowledge of CMS can be employed to estimate the hazard failure rate function, which is the most widely used statistical analysis tool of the lifetime data. The failure rates data of wind generators can be acquired in several forms, such as the historical failure rate data about the generator under monitoring, handbooks of failure rate data, which are available from commercial sources. In addition, the failure data can be obtained by exposing the generator to abnormal operation conditions in the lab.

To model the failure time, Weibull distribution function can be utilized, which is one of the most efficient functions that can represent the distribution of the lifetime data accurately. Furthermore, Weibull distribution has the advantage of flexibility in modeling the failure time data; consequently, accurate risk prediction for the component can be obtained. Therefore, Weibull distribution can is a guaranteed method to model the wind generators' time to failure. The Weibull hazard function $h(t)$ at time t is defined as follows [17-24]:

$$h(t) = \frac{f(t,\alpha,\beta)}{R(t,\alpha,\beta)} = \frac{\beta\, t^{\beta-1}}{\alpha^{\beta}} \quad (2)$$

where,

β is the shape parameter; α is the scale parameter or characteristic life; $f(t,\alpha,\beta)$ is the Weibull probability density function; and $R(t,\alpha,\beta)$ is the Weibull survival function [17-23]. The shape and scale parameters of the Weibull distribution function are defined as follows:

$$\beta = [\frac{\sigma_x}{\mu_x}]^{-1.086} \quad (3)$$

$$\alpha = \mu_x[0.568 + 0.433/\beta]^{-1/\beta} \quad (4)$$

where,

σ_x is the stander deviation of the group of data (x);

μ_x is the avarge value of the group of data (x)

Notice that:

$$h(t) \text{ is:} \begin{pmatrix} \text{a decreasing function of t when } \beta < 1 \\ \text{a constant when } \beta = 1 \\ \text{an increasing function of t when } \beta > 1 \end{pmatrix}$$

Therefore, the failure rate can be determined based on the Weibull probability density function, and reliability function. For distributions, such as Weibull distribution, the hazard function is not stable with respect to time. When the shape parameter increases, the mean of the distribution approaches the scale parameter value, and the variance approaches zero. The survival function $S(t)$ is the probability of survival until time *t* but not beyond time *t*. It is the reliability function that operates at time *t,* and can be estimated as follows [17-23]:

$$S(t) = P(T \geq t), t \geq 0 \quad (5)$$

The Weibull survival function is constructed as follows:

$$S(t) = R(t,\alpha,\beta) = 1 - F(t,\alpha,\beta) = e^{-(t/\alpha)^{\beta}} \quad (6)$$

The survival analysis is also an essential part for studying the period between the entry to the study of the fault, and the subsequent event. It is limited to the following ranges [18, 20-23]:

$$S(t) = 1 \text{ when } t = 0$$
$$S(t) = 0 \text{ when } t \to \infty$$

The Weibull probability density function of failure time for the wind generator can be defined as follows:

$$f(t,\alpha,\beta) = \frac{d}{dt}F(t,\alpha,\beta) = \frac{\beta\, .\, e^{[-(t/\alpha)^{\beta}]} . (t/\alpha)^{\beta-1}}{\alpha} \quad (7)$$

The mean and standard deviation of the Weibull probability density function are defined respectively as follows [18, 20-23]:

$$E(T) = (1/\alpha)^{1/\beta}\, \Gamma(1 + 1/\beta) \quad (8)$$

$$S.D = \left(\frac{1}{\alpha}\right)^{\frac{1}{\beta}} [\,\Gamma\left(1 + \frac{2}{\beta}\right) - \Gamma^2(1 + \frac{1}{\beta})]^2 \quad (9)$$

The cumulative distribution function $F(t)$ describes the continuous probability distribution of a random variable, such as the time in survival analysis. It can be defined as follows [18, 20-23]:

$$F(t) = P(T < t) = 1 - S(t) \quad (10)$$

The Weibull cumulative distribution function that characterizes the likelihood of failure prior to time *t* is estimated as follows [18, 20-23]:

$$F(t,\alpha,\beta) = 1 - e^{[-(t/\alpha)^{\beta}]} \quad (11)$$

In general, the cumulative distribution function is constructed to interpret the probability of the variable T, which will be lower than or equal to the probability of any value of t.

To estimate the MTTF of wind generators, the types of maintenance that can be applied for any wind turbine should be understood firstly. For wind energy systems, two main types of maintenance are usually performed, the PM (preventive maintenance), and the CM (corrective maintenance) as shown in Fig. 2, which illustrate the classification of the maintenance types. In this context, PM is further divided into the time-based maintenance, the usage or age-based maintenance, and condition based maintenance. In the time-based maintenance approach, the maintenance schedule is predetermined depending on the calendar time strategy. The age-time maintenance method is implemented based on the expended operation hours of the entire system, which represent the component age. The application of the condition based maintenance technique is based on data, which can be analyzed to acquire knowledge about the physical operation conditions. The CM, on the other hand, is applied when failure occurs according to unexpected operation or surrounding conditions. The classical replacement policy, however, is performed for both PM and CM due to failure or a certain age [2, 3, 5, 9, 10, 17].

The most important considerations that should take in the account when determining the proper maintenance program are the age of the component, and the performance history of this component until the moment of decision making. The use of reliability analysis, such as failure rates and MTTF can minimize the costs for inspections and repairs as well as the costs due to component downtime. The estimation of MTTF is presented in the following section.

3. The Estimation of the Mean Time to Failure of Wind Generators

The MTTF of a component in wind energy systems, such as the generator is a reliability term based on methods for lifecycle predictions. It is a numerical statistical value based on analyzing a group of data to identify the failure rate and determine the expected operation time. It can be defined as the expected mean time until the first failure occurs. Suppose the likelihood for a random variable T (lifetime) to take on a given value (density function) is $f(t)$, and the reliability ofthe maintained system with no maintenance is $R(t)$. In many instances, the PM approach is the most applicable maintenance type in the wind energy systems. After such a maintenance action is taken, the system is repaired to reach a condition “as good as new.” Fig. 3 indicates the effect of the PM on a wind generator [17]. As shown in this figure, no maintenance action is taken until $t = t_o$, and the reliability of the maintained system $R_m(t)$ through the interval $0 \leq t \leq t_0$ can be stated as follows [2, 3, 13, 17]:

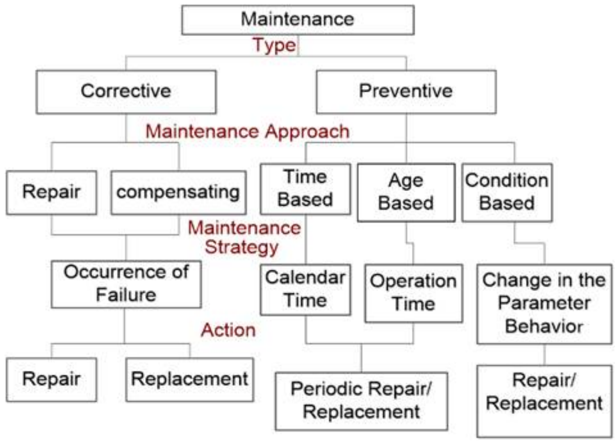

Fig. 2 The maintenance strategy application [2, 3, 10, 17].

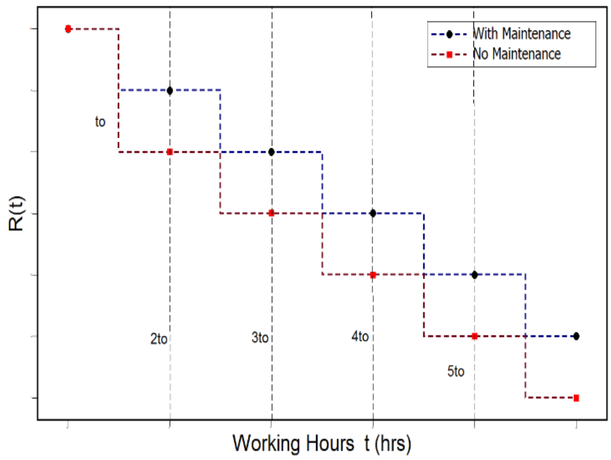

Fig. 3 The reliability of a wind generator with and without preventive maintenance [17].

$$R_m(t) = R(t);\ 0 \leq t \leq t_0 \quad (12)$$

At any time during the next interval of time$t_0 \leq t \leq 2t_0$, the reliability of the maintained system is defined as follows [3, 10, 17, 20, 25]:

$$R_m(t) = R(t_0)\ R\ (t - t_0);\ t_0 \leq t \leq 2t_0 \quad (13)$$

Consequently, the reliability of the maintained system during the interval$it_0 \leq t \leq (i+1)t_0$ can be expressed as follows [2, 3, 13, 17, 18, 20]:

$$R_m(t) = R^i(t_0)R(t - it_0);\ it_0 \le t \le (i+1)t_0\ ; \quad (i = 0, 1, 2, \ldots..) \tag{14}$$

The MTTF of a maintained system is determined as follows [3, 13, 17, 18, 20, 26]:

$$MTTF = \int_0^{\infty} R_m(t)dt = \int_0^{t_0} R_m(t)dt + \int_0^{2t_0} R_m(t)d + \cdots \int_{it_0}^{(i+1)t_0} R_m(t)dt \tag{15}$$

$$MTTF = \sum_{i=0}^{\infty} \int_{it_0}^{(i+1)t_0} R_m(t)dt \tag{16}$$

By substituting (14) into (16), we have:

$$MTTF = \sum_{i=1}^{\infty} R^i(t_0) \int_{t=it_0}^{(i+1)t_0} R_m(t - it_0)dt \tag{17}$$

Assuming $\tau = t - it_0$; Then, (17) can be rewritten as follows:

$$MTTF = \sum_{i=1}^{\infty} R^i(t_0) \int_{\tau=0}^{t_0} R_m(\tau)d\tau \tag{18}$$

In general, the MTTF is defined as follows:

$$MTTF = \frac{1}{1 - R(t_0)} \int_0^{t_0} R_m(\tau)d\tau \tag{19}$$

In the Weibull distribution, the MTTF can be estimated by using the next formula [2, 3, 13, 17, 18, 20,]:

$$MTTF = \frac{1}{\beta}\Gamma\left(\frac{1}{\beta}\right).\alpha \tag{20}$$

The variance of MTTF is defined as follows:

$$MTTF_{var} = \alpha^2[\Gamma\left(1 + \frac{2}{\beta}\right) - \left(\Gamma(1 + \frac{1}{\beta})\right)^2] \tag{21}$$

In addition, the Median Life (ML) of the MTTF is quite significant as it shows the sufficient information about the failure trend of the wind generator, which can be estimated as follows [3, 12, 13, 17, 18, 20]:

$$MTTF_{ML} = \alpha\,.(\ln 2)^{1/\beta} \tag{22}$$

The proposed methodology of Maintenance Decision—Making approach is described in the flowchart shown in Fig. 4.

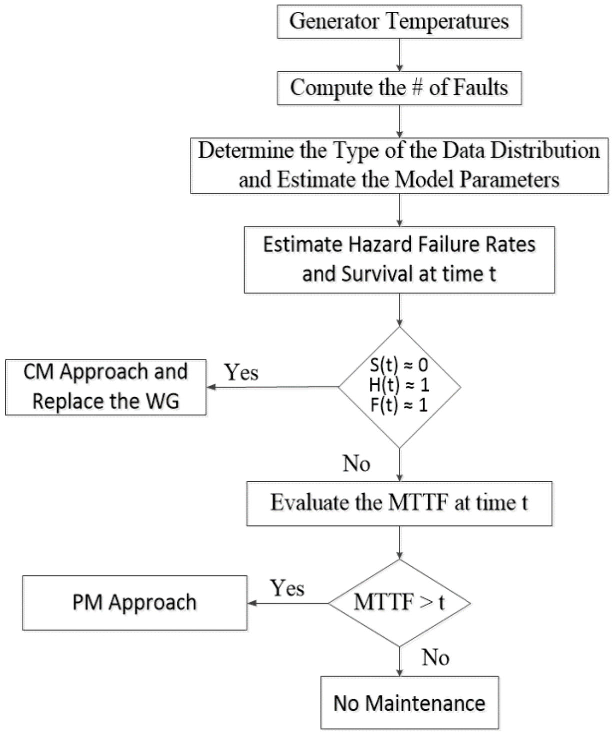

Fig. 4 The proposed methodology of Maintenance decision—making approach.

First, the recorded generator temperature data must be inserted to the model in order to compute the number of faults due to high temperature. Based on specifying the expended operating hours at each recorded fault, the previous step can be achieved. Then, defining the distribution of the failure data is significant to identify the model parameters and apply the reliability analysis. The survival and hazard failure rates with respect to the expended operating hours are required to analyze the system condition. When hazard rate nears to one and the survival rate approaches zero, the corrective maintenance process must be implemented immediately, and the wind generator has to be replaced. On the other hand, the MTTF at a particular expended operating hour t must be determined when $S(t) \gg 0$, and $H(t) \ll 1$, which means that the system does not suffer from any severity at the moment in which the data are collected. Finally, determining the need of preventive maintenance for the system is based on the estimation of MTTF. When MTTF exceeds the expended operating hours (*t*), the preventive maintenance must be applied immediately;

otherwise, the maintenance approach should apply according to the maintenance calendar method. A case study will be presented in the following section, to demonstrate the mechanism of using the hazard failure rate model. The case study will explain how to use the condition monitoring data to estimate the MTTF based on the expended working hours of wind turbines.

4. Case Study

In this section, a case study is provided in order to explain how to employ the proposed hazard approach to estimate the MTTF, failure rates, and survival rates of two wind generator sat any specific running time. Actual data are collected from the two variable speed wind turbines, which are installed in different wind farms in order to test the validity of the proposed model. The brand of each wind turbine is different, and each has a synchronous permanent magnet generator with the rated speed of 1500 rpm. The ratings of the two wind turbines are 750 kW, 60 Hz, and they have three blades upwind with 46 m rotor diameter. The SCADA system provides enough details about the generator stator temperature, which is considered in this work as the generator temperature for both wind turbines. Moreover, the generator temperatures are recorded since the first operation hour for both wind turbines.

According to the manufacturer's handbooks /manuals, the wind turbines will shut down when the generator temperature reaches 140 ºC over a continuous period of 60 seconds, and restart when the generator temperature drops to 120 ºC. The operation conditions of the wind turbines are classified as shown in Table 1. In this work, the fault condition will be considered when the generator temperature exceeds 100 ºC, because the operation condition below 100 ºC is normal [27, 28].The main goal of this work is to determine the effect of the high generator temperatures on the generator age, which can identify the failure rate and reliability of the wind generators and suggest the proper time to replace or repair the wind generator based on estimating the MTTF.

The recorded historical generator temperatures for both wind turbines are measured every 60 seconds, i.e., there are sixty recorded generator temperature values for each wind turbine in an hour. In order to simplify the proposed work, the average of the recorded generator temperatures for every 60 minutes (each working hour) is calculated [27, 28]. Consequently, through 50,000 working hours; for instance, there are 50,000 generator temperature values available to apply the proposed analysis. The recorded faults due to high generator temperatures (more than 100 ºC) through the specific working hour intervals for both wind turbines are classified as shown in Tables 2 and 3 respectively. The available recorded generator temperatures for Turbine A represent 54,000 expended working hours, while for Turbine B represent 60,000 expended working hours. The distribution of the number of faults due to high generator temperatures with respect to the expended working hours (the failure time distribution) of both wind turbines is shown in Figs. 5 and 6 respectively.

Based on the area fault graphs for both wind turbines, the numbers of times that the generator temperature

Table 1 The operation conditions of the study [27, 28].

State	Generator temperatures
Normal condition (no fault)	$T < 100\,°C$
Warning condition (fault)	$100\,°C < T < 135\,°C$
Critical condition	$T > 135\,°C$

Table 2 The recorded faults vs. the expended working hours for Turbine A [27, 28].

Working hours * 10^3 (hrs.)	Up to 25	25-30	30-36	36-46	46-54
Number of faults	426	522	1,212	4,789	7,211

Table 3 The recorded faults vs. the expended working hours for Turbine B [27, 28].

Working hours * 10^3 (hrs.)	Up to 25	25-30	30-36	36-46	46-60
Number of faults	343	487	967	2,103	7,124

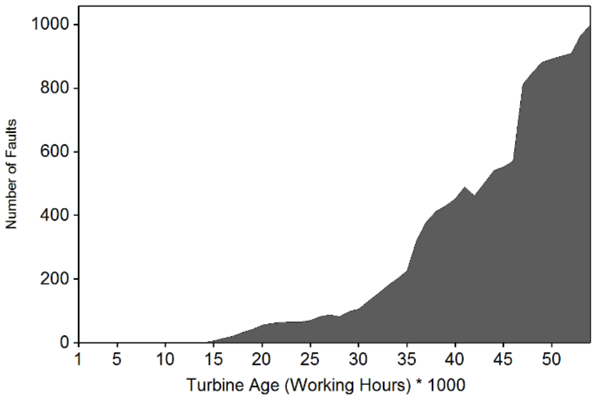

Fig. 5 The area fault graph for Turbine A.

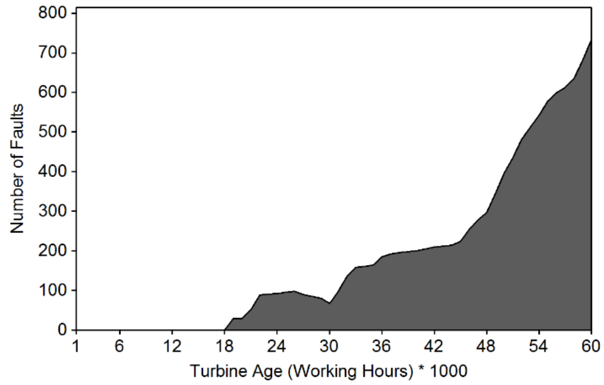

Fig. 6 The area fault graph for Turbine B.

exceeds 100 ºC at Turbine A are greater than that at Turbine B; although, the interval of the expended operating hours of Turbine B is bigger. This is due to the fact of the operation conditions and thermal stress were different, which causes variations in generator temperatures. Fig. 7 shows the comparison of both wind turbines regarding the number of faults with respect to the expended operation hours. It is found that the number of faults increases dramatically in the last period of study for both wind turbines with respect to the expended working hours. The inequality in the generator temperature values for both wind turbines is apparent. This indicates that the estimated working life of both wind generators will be unequal. The increase of the number of faults is occurred due to high temperatures, which reduces the average age of both wind generators.

The Weibull distribution can be utilized to obtain more accuracy on the reliability analysis of wind

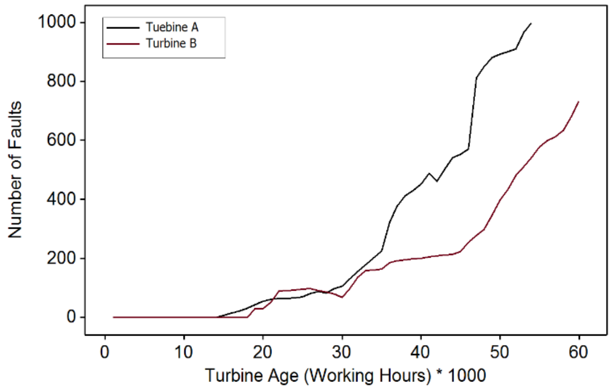

Fig. 7 The number of faults trend of the Turbine A, and B.

turbines than other distributions. This fact is confirmed by inserting the recorded generator temperatures of both wind generators into the Easy fit software, which deals with a wide range of distributions and selects the best mode that fits the collected data in seconds.

Table 4 shows the best five distributions, which are categorized according to Chi-Squared, Anderson Darling, and Kolmogorov Smirnov statistical tests of the collected data.

Based on the Chi-Squared test, the Weibull distribution has the smallest Chi-Squared statistical value for both wind turbines, which means that the Weibull distribution model fits the generator temperature data perfectly [29]. The Weibull probability plots of the generator temperatures for both wind turbines are required in order to confirm the fact of the Weibull distribution is appropriate to represent the data. Figs 8 and 9 respectively illiterate that there are acceptable Weibull probability plots in which the majority of the temperature points lie approximately along a straight line.

In order to estimate the generator failure rate and survival rate, the Weibull PDF (probability density function) is required for both wind turbines according to the recorded generator temperatures, and the expended working hours as shown in Fig. 10.The density function of the Weibull distribution is to present the frequency of the failure time when the generator temperature is above 100 ºC. Furthermore, the PDF chart describes the relative likelihood of the

Table 4 The best five distributions of the collected data for Turbines A, and B.

#	Turbine	Distribution type	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
			Statistic	Rank	Statistic	Rank	Statistic	Rank
1	A	Pert	0.09812	3	2.2164	1	29.684	3
	B	Pert	0.09652	3	2.176	1	34.611	4
2	A	Weibull	0.10488	4	2.3891	2	25.753	1
	B	Weibull	0.0872	2	2.221	2	24.672	1
3	A	Inv. Gaussian	0.0778	1	2.6511	3	29.709	4
	B	Triangular	0.0674	1	2.485	3	38.812	5
4	A	Cauchy	0.07952	2	2.9	4	26.153	2
	B	Log-Gamma	0.1875	4	3.0761	5	29.276	3
5	A	Normal	0.10564	5	3.0349	5	29.724	5
	B	Lognormal	0.19732	5	2.752	4	25.986	2

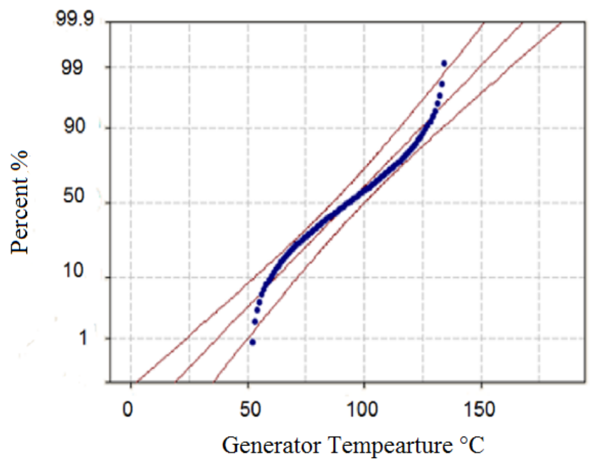

Fig. 8 The Weibull probability plot of the generator temperatures for the wind Turbine A.

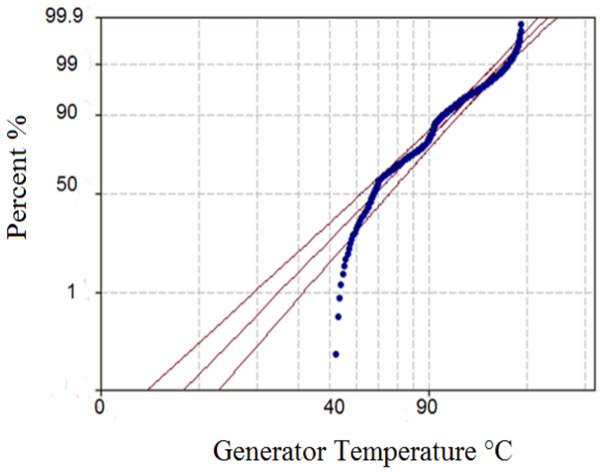

Fig. 9 The Weibull probability plot of the generator temperatures for the wind Turbine B.

generator temperatures as random variable varies with the change in the operation conditions [21-23, 29, 30]. Note each wind turbine has a different shape and scale

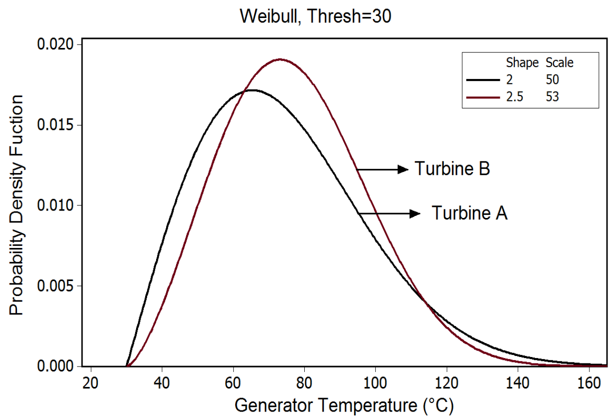

Fig. 10 The Weibull PDF According to the generator temperatures.

parameter due to the variation in the generator temperatures of both wind turbines. The shape and scale parameters affect the obtained results, which are presented in the following section.

5. Results and Discussions

In order to search the of effect the generator temperature on the wind turbine reliability with respect to the generator expended working hours, the data of Turbine B are taken as an example. This is because Turbine B has longer expended working hours than Turbine A, which helps to extend the analysis size of the current study. Fig. 11 shows several survival rate curves for Turbine B, based on the expended operating hours and the generator temperatures. It is found that the survival rate decreases when the expended operating hours increase at any generator temperature. Furthermore, when the generator temperatures increase, the survival rate or the generator decreases at any range of the expended operating hours. The cumulative distribution function $F(t)$ can utilize to determine the likelihood of failure that occurs at any generator temperature, with respect to the expended operating hours as shown in Fig. 12.

The influence of the generator temperature on the probability of failure prior to any specific time based on the generator ages is confirmed by this figure. Fig. 13 illustrates different failure rate curves for Turbine B based on the expended operating hours, and the generator temperatures.

As shown in Fig. 13, the Hazard failure rates show higher values with higher expended operating hours; however, the increases of the hazard failure rates become dramatic till the generator temperature reaches 115.8 ºC. After that, the Hazard failure rates fluctuate

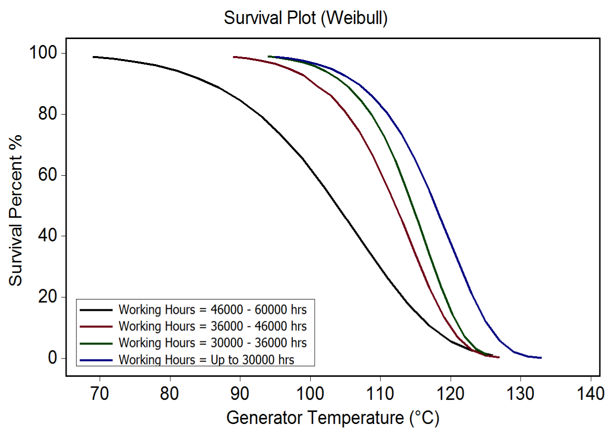

Fig. 11 The Weibull survival plot with respect to the generator temperatures and generator ages.

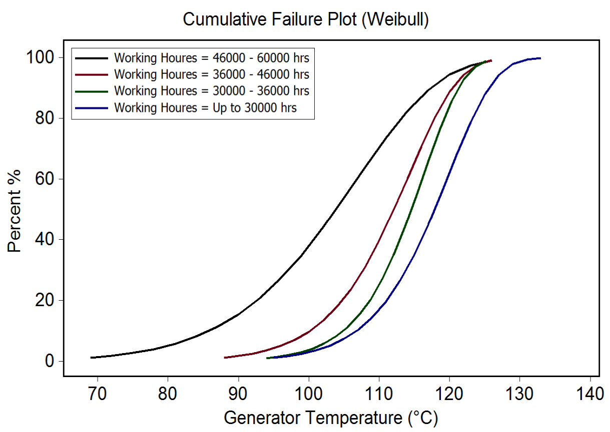

Fig. 12 The Weibull cumulative failure plot with respect to the generator temperatures and generator ages.

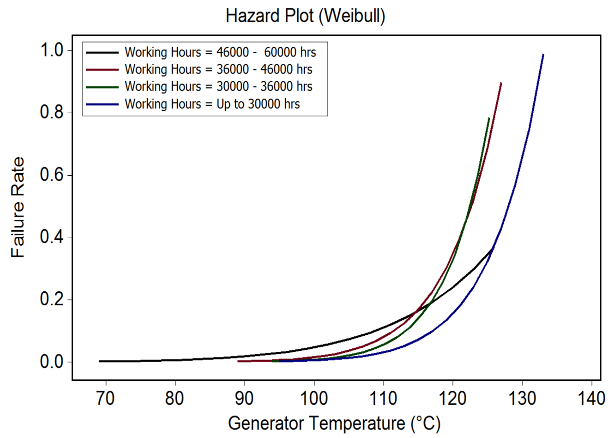

Fig. 13 The Weibull failure rate plot with respect to the generator temperatures and generator ages.

with increasing the generator temperatures and generator ages. This gives, indication about the presence of additional causes affecting the Hazard failure rates in addition to the generator temperature. Figs. 14-16 show the general reliability analysis for Turbines A and B according to the expended generators working hours, and the number of faults that considered due to high generator temperatures. Based on the simulation analysis of the collected operation data, it can conclude that the reliability of the generator of Turbine B is better than the generator of Turbine A, which further indicates that the surrounding operation conditions of Turbine A were different from Turbine B. There are several reasons that heighten the generator stator winding temperature, such as the increase of the electrical loads or inappropriate cooling systems in the generator. This leads to increases the thermal and electrical stresses and decrease the wind generator age, and thus have a negative effect on the overall system performance [6-8]. Figs. 17 and 18 respectively show the probability plot graphs of the failures that are occurred due to the high generator temperatures, with respect to the operating hours of each wind turbine. These figures present acceptable Weibull probability plots, in which the majority of the failure points lie approximately along a straight line [20-23, 29]. Tables 5 and 6 summarize the general reliability analysis results of both wind turbines, which indicate that the estimated life of the generator for Turbine A is approximately 64,000 h,while the generator for Turbine B is 75,500 h. The obtained reliability information helps to reduce the shutdown events, and to implement a suitable maintenance program.

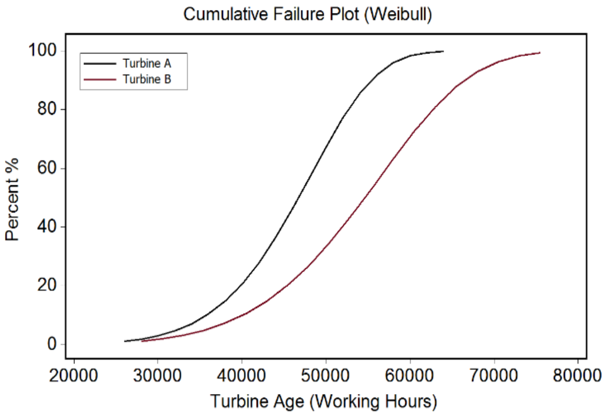

Fig. 14 The Weibull cumulative failure plots with respect to the generator operation hours and the number of faults for Turbines A, B.

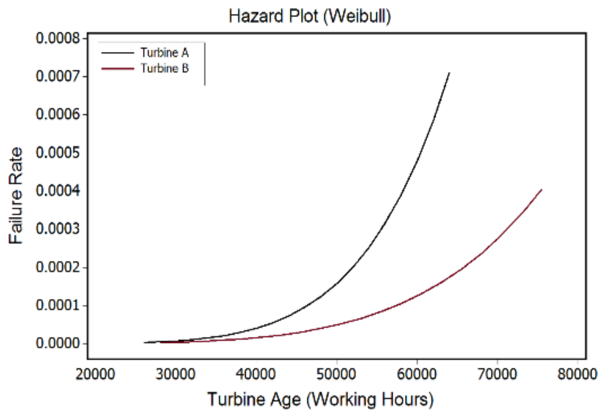

Fig. 15 The Hazard plots with respect to the generator operation hours and the number of faults for turbines A, B.

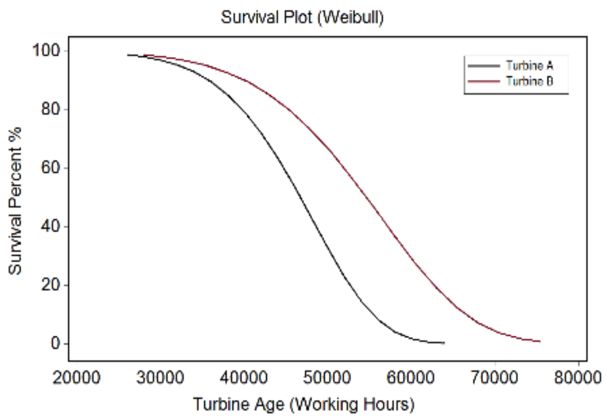

Fig. 16 The SR plots with respect to the generator operation hours and the number of faults for Turbines A, B.

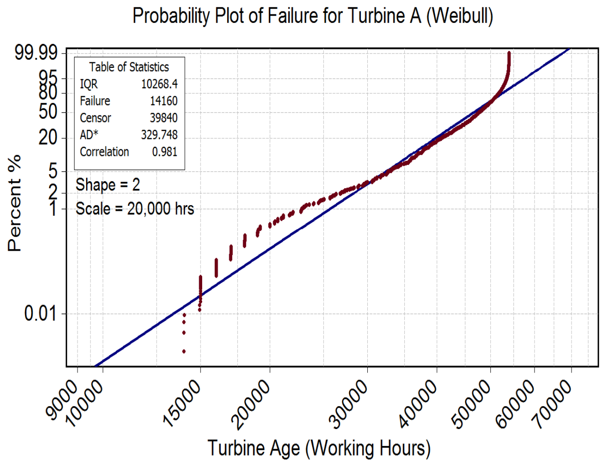

Fig. 17 The Weibull probability plot of the failure points for Turbine A.

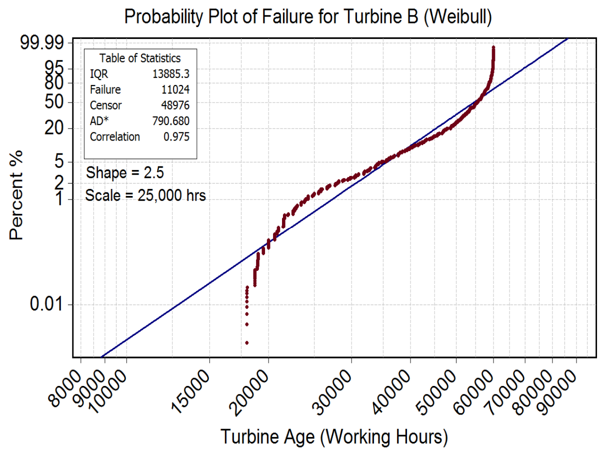

Fig. 18 The Weibull probability plot of the failure points for Turbine B.

With the increase of the number of faults (the number of times that the generator temperature exceeds 100 ºC), the survival rates of both turbines decrease. The results show that the survival rate of Turbine B is more than that of Turbine A, due to the high temperatures that the generator of Turbine A had experienced. In addition, there are other influencing factors lead to increased generator temperatures, such as the electrical loads, and efficiency of the generator cooling systems [6-8]. The further results an increase in the thermal and electrical stresses on the generators; consequently, the number of faults (the failure rate) grows as the wind generator ages, which eventually affects the reliability. The surface plots for Turbines A and B are shown in Figs 19, and 20 respectively. These

Table 5 The reliability analysis for Turbine A.

Working hours $\times 10^3$	26	34	44	54	64
Hazard failure rate $\times 10^{-4}$	0.03	0.15	0.73	2.6	7
Survival percent %	98.9	92.96	63.6	14.5	0.16
Cumulative failure percent %	1.1	7.04	36.4	85.5	99.8

Table 6 The reliability analysis for Turbine B.

Working hours $\times 10^3$	30.5	45.5	55.5	65.5	75.5
Hazard failure Rate $\times 10^{-4}$	0.04	0.31	0.84	1.96	4.05
Survival percent %	98.1	97.7	46.6	12.2	0.67
Cumulative failure percent %	1.95	20.3	53.4	87.8	99.3

Table 7 The statistical properties of the MTTF for Turbines A, and B.

	S.P. α(Hrs) $\times 10^3$	S.P. (β)	MTTF (Hrs) $\times 10^3$	$MTTF_{S.D.}$ (Hrs) $\times 10^3$	$MTTF_{ML}$ (Hrs) $\times 10^3$
A	≈ 20	≈ 2	17.725	9.265	16.651
B	≈ 25	≈ 2.5	27.727	9.492.	21.591

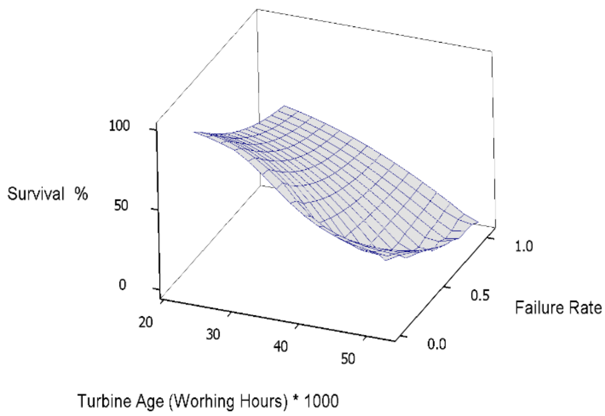

Fig. 19 The surface plot of Turbine A.

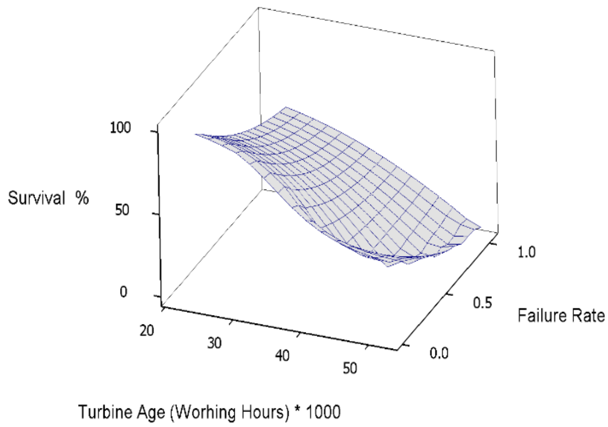

Fig. 20 The surface plot of Turbine B.

figures clearly present the relationship between the failure rate, and the survival rate, with respect to the turbine operating hours graphically in three dimensions.

According to Fig. 20, the Weibull mean time to failure MTTF for both generators can be estimated. Table 7 indicates that the average of the predicted operating hours of Turbines A and B before the first failure occurred is 17,725 h and 27,700 h respectively. In other words, the first fault that is occurred due to the high generator temperature (above 100 ºC) is recorded at the average time of 17,725 hrs for Turbine A and 27,700 hrs for Turbine B.Note that the estimation of the MTTF is based on the Weibull scale and shape parameters.

6. Conclusions

In this paper, an application of Hazard model reliability analysis based on a condition monitoring system of wind generators is proposed. The proposed technique can be utilized to address the technical problems that are related to wind generators, which leads to reduce maintenance and operation costs. The CMS knowledge can be employed to estimate the hazard failure and survival rate functions, which are the most widely used statistical analysis tools of the lifetime data. In order to perform a proper preventive maintenance on wind generators, the estimation of the MTTF (mean time to failure) is required, and the method of estimating this parameter is proposed in this paper. A case study is presented to demonstrate the proposed method based on condition monitoring data of two wind turbines. The purpose of the research is to investigate the influence of the high generator temperatures on the estimated generators age, which helps to plan a suitable maintenance program, and improves the system reliability. The reliability analysis is performed for each wind turbine, and the hazard lifetimes are estimated based on the Weibull distribution with respect to the generator temperatures, and expended working hours of both wind turbines. It is found that with the increase of the number of faults (the number of times that the generator temperature exceeds 100 ºC), the survival rate of both turbines decreases. The hazard life time, failure and survival rates, are deferent in each generator of the turbines. The two turbines show variations in the reliability analysis results, because the operation conditions of both wind turbines, such as electrical loads, and the generator cooling systems are dissimilar. By estimating the MTTF, the failure and survival rates of wind generators, an optimal maintenance decision can be made.

The future work will be focused on estimating the age of wind generators and the MTTF by inserting additional covariates to the model, such as the generator voltage or frequency to indicate their effects. Furthermore, constructing an optimized cost model by using the hazard model techniques or different degradation models will be beneficial.

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References

[1] Nilsson, J., and Bertling, L. 2007. "Maintenance Management of Wind Power Systems Using Condition Monitoring Systems—Life Cycle Cost Analysis for Two Case Studies." *Energy Conversion, IEEE Transactions* 22 (1): 223-9.

[2] Amayri, A., Tian, Z., and Jin, T. 2011. "A Condition Based Maintenance of Wind Turbine Systems Considering Different Turbine Types." Presented at Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE).

[3] Zhigang, T., Tongdan, J., Wu, B., and Ding, F. 2011. "Condition Based Maintenance Optimization for Wind Power Generation Systems under Continuous Monitoring." *Renewable Energy* 36 (5): 1502-09.

[4] Metwalley, S., and Abouel-seoud, S. 2013. "Condition Based Maintenance Optimization for Faulty Gearbox under Continuous Noise Monitoring." *British Journal of Applied Science & Technology* 3 (2): 320-35.

[5] Krokoszinski, H. 2003. "Effectiveness of Wind Farms—Keys to Cost Optimized Operation and Maintenance." *Renewable Energy* 28 (14): 2165-78.

[6] Abdusamad, K. B., David, G. W. and Muljadi, E. 2013. A Condition Monitoring System for Wind Turbine Generator Temperature by Applying Multiple Linear Regression Model." Presented at North American Power Symposium (NAPS).

[7] Khaled, B. A., and Gao, D. W. 2013. "The Application of Heat Transfer Analysis in Condition Monitoring System of Wind Generator." Presented at IEEE PES Asia-Pacific Power and Energy Engineering Conference.

[8] Guo, P., Infield, D., and Yang, X. 2012. "Wind Turbine Generator Condition-Monitoring Using Temperature Trend Analysis." *Sustainable Energy, IEEE Transactions* 3 (1): 124-33.

[9] Byon, E., and Ding, Y. 2010. "Season-Dependent Condition-Based Maintenance for a Wind Turbine Using a Partially Observed Markov Decision Process." *Power Systems, IEEE Transactions* 25 (4): 1823-34.

[10] Bairong, W., Tian, Z., and Chen, M. 2012. "Condition-Based Maintenance Optimization Using Neural Network-based Health Condition Prediction," Presented at Quality and Reliability Engineering International.

[11] Banjevic, D., Jardine, A. K. S., Makis, V., and Ennis, M. 2001. "A Control-Limit Policy and Software for Condition-Based Maintenance Optimization." *INFOR, OTTAWA* 39 (1): 32-50.

[12] Karki, R., Hu, P., and Billinton, R. 2006. "A Simplified Wind Power Generation Model for Reliability Evaluation." *IEEE Transactions on Energy Conversion* 21 (2): 533-40.

[13] Guo, H., Watson, S., Tavner, P., and Xiang, J. 2009. "Reliability Analysis for Wind Turbines with Incomplete Failure Data Collected from after the Date of Initial Installation." *Reliability Engineering & System Safety* 94 (6): 1057-63.

[14] Hall, P. L., and Strutt, J. E. 2003. “Probabilistic Physics-of-failure Models for Component Reliabilities Using Monte Carlo Simulation and Weibull Analysis: a Parametric Study.” *Reliability Engineering & System Safety* 80 (3): 233-42.

[15] Martinez, E., Sang, F., Pellegrinni, S., Jimenez, E., and Blanco, J. 2009. “Life Cycle Assessment of a Multi-megawatt Wind Turbine.” *Renewable Energy* 34 (3): 667-73.

[16] Zekai, Ş. 1997. “Statistical Investigation of Wind Energy Reliability and Its Application.” *Renewable Energy* 10 (1): 71-9.

[17] Rao, S. S. 1992. *Reliability-Based Design*. United States: McGraw-HillM.

[18] Christopher, W. 2006. *Wind Turbine Reliability: Understanding and Minimizing Wind Turbine Operation and Maintenance Costs*. United States: Department of Energy.

[19] Xie, M., Tang, Y., and Goh. T.N. 2002. “A Modified Weibull Extension with Bathtub-shaped Failure Rate Function.” *Reliability Engineering & System Safety* 76 (3): 279-85.

[20] Xie, M., and Lai, C.D. 1996. “Reliability Analysis Using an Additive Weibull Model with Bathtub-shaped Failure Rate Function.” *Reliability Engineering & System Safety* 52 (1): 87-93.

[21] Prabhakar Murthy, D. N., Bulmer, M., and Eccleston, J. 2004. “Weibull Model Selection for Reliability Modelling, Reliability.” *Engineering & System Safety* 86 (3): 257-67.

[22] Bagdonavicius, V., and Mikhail, N. 2001. *Accelerated Life Models: Modeling and Statistical Analysis*. USA: CRC Press.

[23] Manwell, J. F., Mcgowan, J. G., and Rogers, A. L. 2009. “Wind Energy Explained Theory.” In *Design, and Application*. Second edition. WILLY.

[24] Smith, T., Smith, B., and AK Ryan, M. 2003. “Survival Analysis Using Cox Proportional Hazards Modeling for Single and Multiple Event Time Data.” In *Proceedings of the Twenty-Eighth Annual SAS Users Group International Conference* SAS Institute, Inc, Cary.

[25] Coit, D. W., and Dey, K. A. 1999. “Analysis of Grouped Data from Field-failure Reporting Systems.” *Liability Engineering & System Safety* 65 (2): 95-101.

[26] Seebregts, A. J., Rademakers, L. W. M. M., and Van Den Horn, B. A. 1995. “Reliability Analysis in Wind Turbine Engineering.” *Microelectronics Reliability* 35 (9): 1285-307.

[27] Data of a Variable Speed Wind Turbine (A), 750 KW rated power, three phase permanent magnetic type 440/660 V 60 Hz. Provided by Dr. Kathryn Johnson, Colorado School of Mines, 2013.

[28] Data of a Variable Speed Wind Turbine (B), 750 KW rated power, three phase permanent magnetic type 440/660 V 60 Hz. Provided by Dr. Kathryn Johnson, Colorado School of Mines, 2013.

[29] Haldar, A., and Mahadevan, S. 2000. *Probability, Reliability, and Statistical Method in Engineering Design.* WILLY.

[30] Tavner, P. J., Spinato, F., van Bussel, G. J. W., and Koutoulakos, E. 2008. “Reliability of Different Wind Turbine Concepts with Relevance to Offshore Application.” Presented at Eropean Wind Energy Conference & Exhibition.