MAINTENANCE OPTIMIZATION OF WIND TURBINES: LESSONS FOR THE BUILT ENVIRONMENT

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Maintenance optimization is indispensable to the core business objectives of industries that utilizes physical assets. A quantitative maintenance optimization technique known as the Modelling System Failures (MSF) is critically reviewed to identify its relevance to industries that employs physical assets. Practical application of the approach to optimize the maintenance activities of wind turbines is explored and discussed in a case study. The analysis is based maximum likelihood parameter estimation in the Weibull distribution. Shape and scale parameters for a gearbox and its components are estimated. The estimated parameters are used to design Reliability Block Diagrams to model the failures of the gearbox of a selected wind turbine. The models are simulated using Monte Carlo simulation software to assess the reliability, availability and maintainability of the gearbox, and the resultant effects on the wind turbine operation. The methodology presented in the paper is sufficiently generic to any mechanical system in the Built Environment/Construction Industry.

Keywords: wind turbine, maintenance optimization, Monte Carlo simulation, reliability block diagrams. .

INTRODUCTION

Wind turbine is becoming a major source of electricity to green building developments in rural areas. This is to mitigate the effects of global warming and avoid costs associated with grid connection from conventional sources of electricity. Smaller wind turbines are currently installed on roof of buildings in the urban areas to generate energy independent of the national grids. These current developments have made the wind turbine one of the assets in the built environment. Wind turbine just like any other mechanical system in the built environment is subject to failure. The consequences of failure however, can be reduced through the application of an appropriate and optimized maintenance strategy.

Maintenance can be defined as "…the combination of all technical and associated administrative actions intended to retain an item or system in, or restore it to, a state in which it can perform its required function" (BS3811). Common maintenance strategies applied to wind turbines include 'Time-Based' which involves carrying out maintenance tasks at predetermined regular-intervals and 'Failure-Based' which entails using a wind turbine until it fails. However, Andrawus *et al.* (2006) explained the inadequacy of these strategies to support the current commercial drivers of the wind industry. Thus, an appropriate maintenance strategy for wind turbines was

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selected using a hybrid of Reliability Centred Maintenance (RCM) and Asset life-cycle analysis (ALCA) techniques (Andrawus *et al.* 2006). On the other hand, Arthur (2005) and Scarf (1997) explains that RCM is a qualitative technique to maintenance optimization which can be clouded with subjective opinion, and further recommend the use of quantitative techniques to underpin the processes of maintenance optimization of physical assets.

Maintenance optimization is "…a process that attempts to balance the maintenance requirements (legislative, economic, technical, etc.) and the resources used to carry out the maintenance program (people, spares, consumables, equipment, facilities, etc.)" (System Reliability Center). Quantitative maintenance optimization (QMO) techniques employ a mathematical model in which both the costs and benefits of maintenance are quantified and an optimum balance between both is obtained (Dekker 1996). Basically, the main purpose of quantitative optimization is to determine an optimal maintenance strategy that is technically feasible and economically viable over the life-cycle of physical assets. The strategy should provide the best possible balance between maintenance costs, risks involved, equipment reliability and availability without prejudice to Health, Safety and Environmental (HSE) factors.

This paper discusses the concept and relevance of a quantitative maintenance optimization technique to the wind industry. It proposes practical application of the approach to assess the failure characteristics of wind turbines and to optimize its maintenance activities. Finally, a number of lessons for the construction industry are presented with the necessary conclusions and suggestions for future work.

RATIONALE AND OBJECTIVES

Improving the reliability and HSE factors of a system reduces the operating costs, frequency and consequence of failures and hence the overall maintenance cost of the system. On the other hand, low reliability and HSE factors will result in high operating and maintenance costs, catastrophic failures with severe consequences. Maintenance optimization deals with the interaction between these factors and aims to determine the optimum level. This is usually obtained at the lowest point on the total combination of the key variables.

Optimization of wind turbine maintenance is a promising way to maximize the return on investment in wind farms, given that, "the net revenue from a wind farm is the revenue generated from sale of electricity less operation and maintenance (O&M) expenditure" (Learney *et al.* 1999). Therefore, the wind industry has a clear opportunity to consider the strategic importance of quantitative maintenance optimization and to proactively realize the benefits that are available through practical implementation of optimal maintenance strategies over the life-cycle of wind farms.

APPROACH AND METHODOLOGY

A number of QMO techniques exist in the field of Applied Mathematics and Operational Research, for example, Markov Chains and Analytical hierarchy processes (Chiang and Yuan 2001); Genetic Algorithms (Tsai *et al.* 2001) etc. However, most of the approaches are criticized for being developed for mathematical purposes only and are seldom used to solve practical maintenance problems (Dekker 1996). On the contrary, Modelling System Failures (MSF) a quantitative approach to maintenance optimization has been recommended as the best technique to assess and optimize the reliability, availability and maintainability of mechanical systems (Davidson and Hunsley 1994).

The MSF technique investigates the operations and failure patterns of equipment by taking into account failure distribution, repair delays, spare-holding, and resource availability to determine optimum maintenance requirements (Davidson and Hunsley 1994). The first step in the approach is to identify a suitable statistical distribution that will best fit the assessed failure characteristics of the physical asset. Secondly, a suitable parameter estimation method is selected to calculate the parameters of the identified statistical distribution. Then, the calculated parameters are used to build Reliability Block Diagrams (RBD) which permits the use of Monte Carlo simulation to determine the optimal levels of key maintenance variables such as costs, spare holdings as well as the level of reliability and availability required.

Statistical Distributions

Fundamentally, there are three failure patterns that describe failure characteristics of mechanical systems (Davidson and Hunsley 1994). These include reducing, constant and increasing failures as illustrated in Figure 1. The Figure displays a curve usually referred to as a hazard rate or most commonly a bath-tub curve. The reducing failure pattern usually known as the infant mortality denotes failures that occur at the early-life of equipment and the likelihood of occurrence reduces as the age of the equipment increases. The constant failure pattern represents failures that are independent of equipment age, that is, the likelihood of occurrence is invariable through out the life-cycle of the equipment. Lastly, the increasing failure pattern commonly referred to as wear-out symbolizes failures that occur at the later life of equipment, that is, the likelihood of occurrence increases with the age of the equipment. The reader is referred to Moubray (1991) for a more detailed study on types of failure pattern.

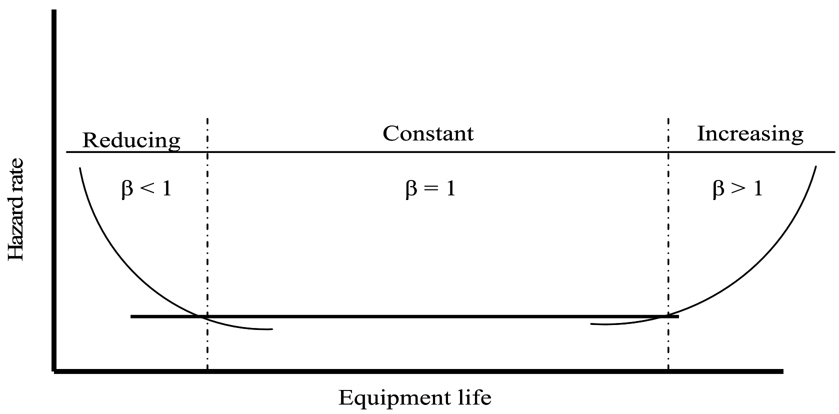

Figure 1: a 'Bath-Tub' curve showing failure patterns

A number of statistical distributions exist to fit the failure patterns afore described. Exponential distribution describes a constant hazard rate (Davidson and Hunsley 1994) while Normal and Lognormal describe the increasing hazard rate (Davidson and Hunsley 1994). However, the most commonly used distribution is the Weibull named after a Swedish engineer Waloddi Weibull (1887-1979) who formulated and popularized the use of the distribution for reliability analysis. The distribution is very versatile as it fits all the three basic patterns of failure.

The Weibull Distribution

This distribution can be represented in 3 different forms; 3-parameter, 2-parameter and 1-parameter. The 2-parameter Weibull distribution denoted by a probability density function (pdf) and cumulative distribution function (cdf) as given in Equations 1 and 2 respectively is considered exclusively.

$$f(T) = \frac{\beta}{\eta}\left(\frac{T}{\eta}\right)^{\beta-1} e^{-\left(\frac{T}{\eta}\right)^{\beta}} \; ; T \geq 0,\; \beta > 0,\; \eta > 0 \tag{1}$$

$$F(T) = 1 - e^{-\left(\frac{T}{\eta}\right)^{\beta}} \tag{2}$$

Where and represent the shape and scale parameter respectively. The value of describes the failure pattern of the equipment. As a general rule, (< 1) means a reducing failure pattern, (=1) signifies a constant failure pattern and (>1) indicates an increasing failure pattern, as depicted in Figure 1. The scale parameter denotes the characteristic life of the equipment; the time at which there is an approximately 0.632 probability that the equipment will have failed (Davidson and Hunsley 1994). Estimating the parameters requires a suitable method that will best fit the characteristics of the collated data.

Parameter Estimation Methods

Common parameter estimation methods include probability plots, regression analysis and Maximum Likelihood Estimation (MLE). The characteristics of data collated influence the estimation method to be used. Field or life-failure data are seldom complete as they are often subjected to suspensions or censorings. An item could have been temporarily removed from the test during the test-interval or the test-interval could elapse before an item fails. The probability plot and the regression analysis are limited in dealing with data sets containing a relatively large number of suspensions or censorings (Cohen 1965). The MLE takes into account the times-to-suspension or censoring in the estimation process which makes it a more robust and rigorous estimation method. The process of using the maximum likelihood to estimate the parameters of the weibull distribution when data are censored is discussed in the next subsection.

Maximum Likelihood Estimation in the Weibull Distribution

Consider a random failure sample consisting of multiple censoring or suspension. Suppose that censoring occurs progressively in k stages at times T_i where $T_i > T_{i-1}$, i=1,2......k and that at the ith stage of censoring r_i sample specimens selected randomly from the survivors at time T_i are removed from further observation. If N designates the total sample size and n the number of specimens which fail at times T_j and therefore provide completely determined life spans (Cohen 1965), it follows that

$$N = n + \sum_{i=1}^{k} r_i \tag{3}$$

The likelihood function is

$$L = C \prod_{j=1}^{n} f(T_j) \prod_{i=1}^{k} [1 - F(T_i)]^{r_i} \tag{4}$$

Where C is a constant, $f(T)$ is the pdf, and $F(T)$ is the cdf.

Substituting equations 1 and 2 in 4, then taking the natural logarithm and then the partial derivatives with respect to β and η will result in Equations 5 and 6. These can be used to estimate the values of β and η respectively.

$$\beta(0) = \frac{\sum_{j=1}^{n}(T_j)^{\beta}\ln T_j + \sum_{i=1}^{k} r_i (T)_i^{\beta} \ln T_i}{\sum_{j=1}^{n}(T_j)^{\beta} + \sum_{i=1}^{k} r_i (T)_i^{\beta}} - \frac{1}{n}\sum_{j=1}^{n}\ln T_j + \frac{1}{\ln\left(\dfrac{\sum_{j=1}^{n}(T_j)^{\beta} + \sum_{i=1}^{k} r_i (T)_i^{\beta}}{n}\right)} \tag{5}$$

$$\eta = \left(\frac{\left[\sum_{j=1}^{n}(T_j)^{\beta} + \sum_{i=1}^{k} r_i (T_i)^{\beta}\right]}{n}\right)^{\frac{1}{\beta}} \tag{6}$$

The estimated values of β and η are used to design Reliability Block Diagrams (RBD). These are employed in modelling failures of the gearbox and the wind turbine. The models will be simulated using Monte Carlo simulation software. It is worth noting that the approach and methodology presented in this paper is sufficiently generic to any mechanical system in the built environment/ construction industry.

A CASE STUDY

This section presents a case study to demonstrate practical application of the Modelling System Failures approach.

Data collation

Historical failure data pertinent to the gearbox of a 600 kW wind turbine shows critical components of a 600 kW wind turbine) were extracted from the Supervisory Control and Data Acquisition (SCADA) system. The SCADA system records failures and the date and time of occurrence; this was used in conjunction with maintenance Work Orders (WOs) of the same period to ascertain the specific type of failure and the components involved. Table 1 contains the failure data of the 600 kW wind turbines' gearbox over a period of 7 years.

In sorting out the data confidentially, the wind farms were labelled alphabetically. For instance, the 'WF-F' in Table 1, column 1 denotes Wind Farm F. Furthermore, the wind turbines are numbered in each of the wind farms; for example, the 'WF-F-WT-1' in Table 1, column 2 denotes 'Wind Farm F-Wind Turbine 1'. Also, the manufacturers of the failed components are numbered and recorded in column 3. The fail-date and fail-time from the base-date as well as the causes of failure are recorded in the table.

Result and Discussion

This subsection presents the results and discussion of the practical application of the modelling system failures technique.

- **Shape and Scale Parameters**

The shape (β) and scale (η) parameters for the gearbox and its components are estimated using the ReliaSoft Weibull ++7 software which is based on the fundamental mathematical principles presented in the approach and methodology section. The results are presented in Table 2. Fisher Matrix (FM) confidence bound method and median (MED) ranking were selected to underpin the statistical evaluation.

Table 1: Gearbox failure data

Wind Farm (*WF*)	Wind Turbine (WT)	Component Manufacturer	Fail date dd/mm/yyyy	HSS bearing	IMS bearing	Gear wheels	Gearbox catastrophic
WT-F	WF-F-WT-1	8	"24/11/1999"	F	S	S	F
WT-F	WF-F-WT-18	8	"13/01/2000"	F	S	F	F
WT-F	WF-F-WT-24	8	"26/03/2001"	F	S	S	F
WT-F	WF-F-WT-07	8	"23/07/2001"	F	S	S	S
WT-F	WF-F-WT-15	8	"19/11/2001"	F	S	F	S
WF-A	*WF-A-WT-8*	9	"05/05/2003"	F	F	S	S
WF-A	*WF-A-WT-14*	9	"06/06/2003"	F	F	S	S
WF-A	*WF-A-WT-23*	9	"04/08/2003"	F	S	S	S
WF-A	*WF-A-WT-9*	9	"27/08/2003"	F	F	S	S
WF-B	*WF-B-WT-6*	9	"11/09/2003"	F	F	S	S
WF-B	*WF-B-WT-10*	9	"04/11/2003"	S	S	S	S
WF-B	*WF-B-WT-6*	10	"04/11/2003"	S	S	S	S
WF-B	*WF-B-WT-14*	9	"22/11/2003"	S	S	S	S
WF-F	*WF-F-WT-19*	9	"18/06/2004"	S	S	F	S
WF-G	*WF-G-WT-9*	9	"30/06/2004"	F	F	S	F
WF-A	*WF-A-WT-33*	8	"09/10/2004"	S	S	F	F
WF-A	*WF-A-WT-1*	8	"18/10/2004"	S	S	S	S
WF-A	*WF-A-WT-19*	8	"30/10/2004"	S	S	S	S
WF-C	*WF-C-WT-7*	11	"01/11/2004"	F	S	F	S
WF-D	*WF-D-WT-20*	10	"04/02/2005"	S	S	F	S
WF-A	*WF-A-WT-19*	10	"02/04/2005"	S	S	F	S
WF-D	*WF-D-WT-2*	8	"11/05/2005"	S	S	S	S

Table 2: Shape and scale parameters of components of a 600 kW wind turbine gearbox

Components	Analysis	Shape (β)	Scale (η)	Likelihood	Failed	Suspended
Gearbox	MLE	1.05	29051	-56	5	72
Gears	MLE	2.50	5715	-75	7	70
HSS bearings	MLE	1.52	7244	-125	12	64
IMS bearings	MLE	3.63	4694	-53	5	72
Key way	MLE	0.84	101790	-35	3	74

The estimated values of β and η for the gearbox are 1.05 and 29051 respectively. The β value of 1.05 indicate a random failure pattern while the η value of 29051 implies that there is an approximately 0.632 probability that all the gearbox in the wind turbine of a selected wind farm would have failed within 29051 days or approximately 79 years, given the assessed failure behaviour of the gearbox and the current maintenance strategy employed.

The Weibull probability plot of this failure characteristic at 95% confidence bound and the failure rate plots are shown in Figures 2 and 3 respectively. The failure rate plot shows a horizontal line which explains the randomness of the failure pattern of the gearbox.

- **Modelling System Failures**

The estimated values of β and η are used to model the failures of the gearbox. In the modelling, Reliability Block Diagrams are designed to incorporate the failure characteristics of the components. Figure 4 shows the Reliability Block Diagram of a typical gearbox in the 600 kW horizontal axis wind turbine. The components are connected in series and the estimated β and η values of each component are incorporated into the RBD. Note that any component which failure data was not available has been set to 'block cannot fail' in the modelling. This is to avoid subjective and illogical assumptions about the component and to ensure the modelling is based solely on field failure data.

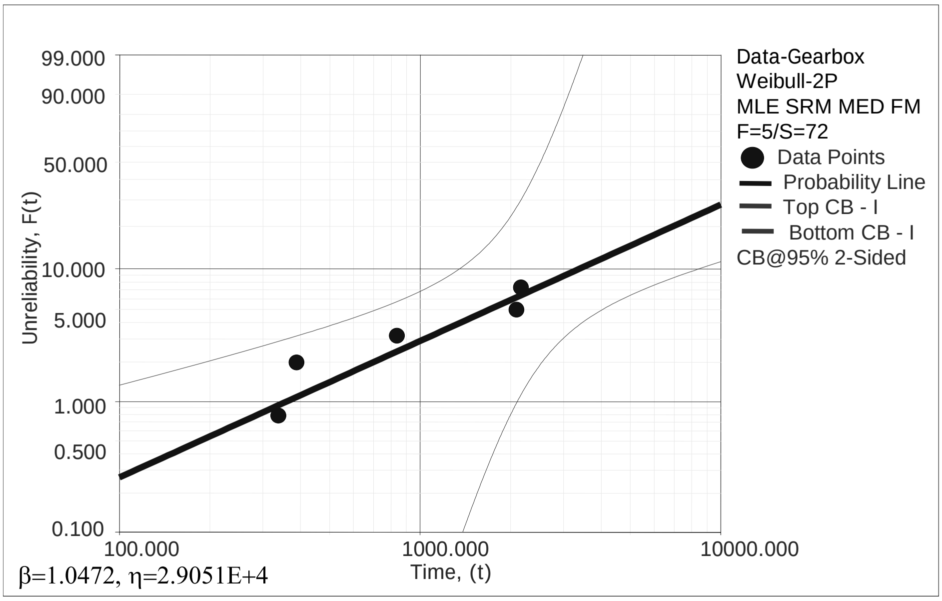

Figure 2: Weibull probability plot of gearbox

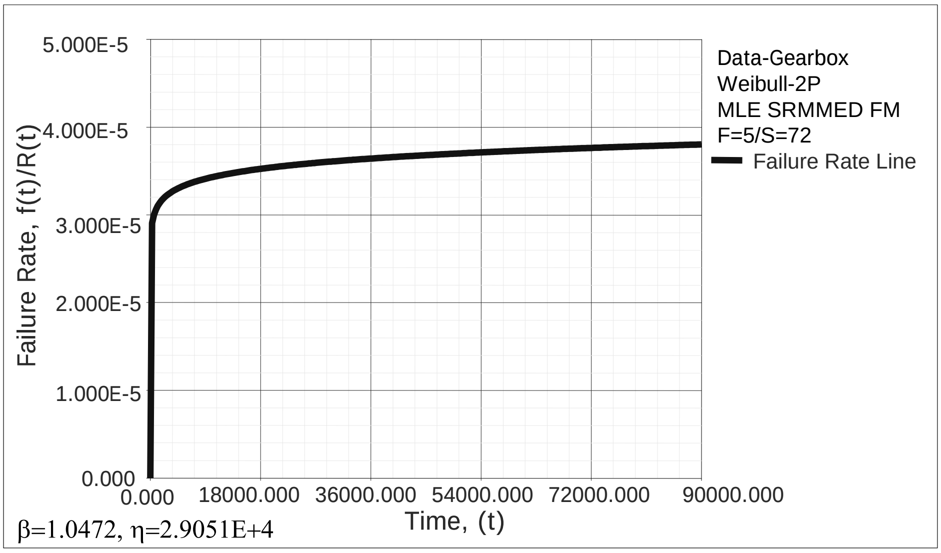

Figure 3: Weibull-failure rate plot for gearbox

The blades of the turbine are connected in parallel as they operate independently. However, all the blades must be in good operating condition before the wind turbine can function. This operating condition is depicted in the 3-out of-3 node (i.e. 3oo3) in Figure 4. Similar condition applies to the main bearings which require a 2-out of-2. The operating condition of the mechanical and aerodynamic brakes are however different, one of the breaks is enough to stop the turbine (i.e. 1-out of-2).

- **Model Simulation**

The wind turbine model is simulated over a period of 10 years (3650 days) using a ReliaSoft BlocSim software as shown in Figure 2 to assess the effects of the gearbox's failure behaviour on the wind turbine operation. After a 10,000 number of simulations, the overview of the turbines operational characteristic is presented in Table 3. The reliability of the turbine decreases from 0.98 in the first year to 0.32 in the 10th year. The probability of failure of the wind turbine increases from 0.02 in the first year to about 0.68 in the 10th year. These show the significant effect of subsystems failures behaviour on the systems operation. The availability however, decreases from 99.21 in the first year to 73.67 in the 10th year of operation.

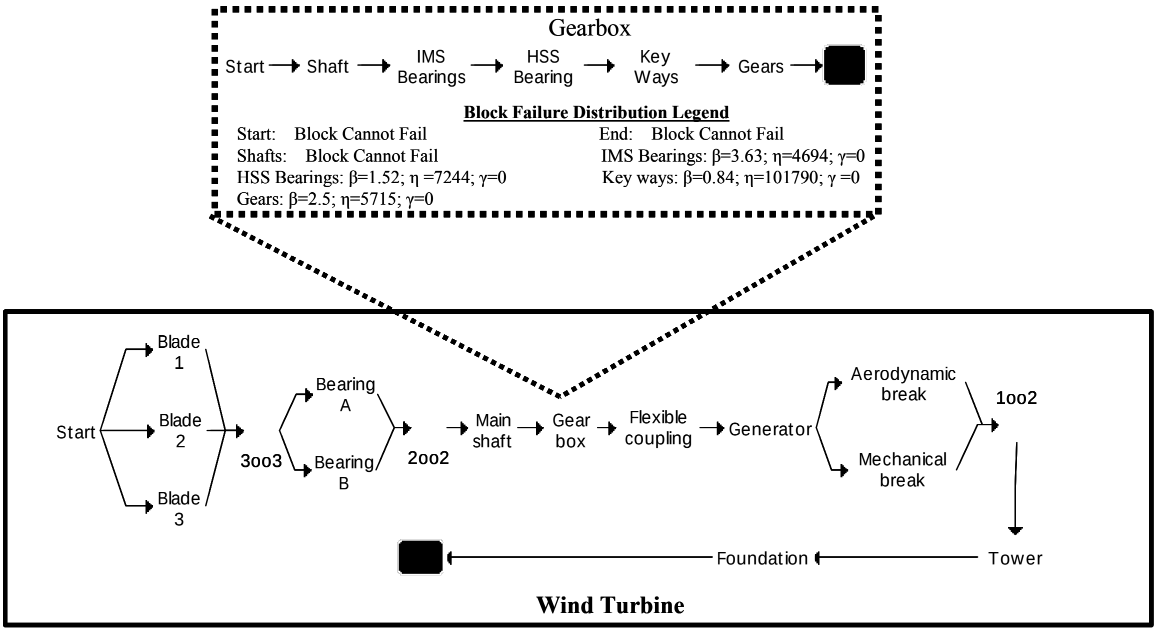

Figure 4: Reliability Block Diagram of 600 kW Wind Turbine

Table 3: Model simulation overview result

Time (days)	Reliability	Prob. of failure	Failure rate x 10^{-3}	Availability (%)
365	0.98	0.02	0	99.21
730	0.95	0.05	0	97.91
1095	0.90	0.10	0	96.24
1460	0.85	0.15	0.2	94.22
1825	0.78	0.22	0.2	91.78
2190	0.70	0.30	0.3	88.84
2555	0.61	0.39	0.3	85.49
2920	0.51	0.49	0.5	81.76
3285	0.42	0.59	0.5	77.79
3650	0.32	0.68	0.8	73.67

LESSONS TO THE BUILT ENVIRONMENT

There are a number of assets in the built environment/ construction industry that exhibit a similar pattern of performance to a wind turbine gearbox. These assets are mostly mechanical systems such as Lifts, Elevators and Escalators, Water pumps, Expellers or Extractors etc. The failure data of these assets can be collated, modelled to assess their reliability, availability and maintainability. Indeed, comparative studies can be undertaken on similar asset but different manufacturers to recommend future specification in prospective development. For example, field failure data of lifts from different manufacturers can be collected and modelled in the manner described in the case study. The lift with a better reliability and availability will have less maintenance cost and hence the total life-cycle cost of the building will be reduced.

Thus, for built environment/construction industry to appreciate the uniqueness of the Modelling System Failures approach to maintenance optimization and harvest the enormous potential benefits.

- It is imperative for the industry to realize the essence of collating and storing field failure and maintenance data of assets.
- Stakeholders of the industry should strive to evaluate data requirements for asset performance optimization from the beginning of ownership and set up data bases to incorporate appropriate recording format for all necessary information about the asset.
- To start utilizing field failure data to assess failure characteristics of components and subsystems of an asset in a bid to optimize its maintenance activities, reliability and availability.
- To bear in mind that optimization process is not a one-off procedure but a continuous process which requires periodic evaluation of performance and improving on the successes of the past.

CONCLUSIONS

This paper has discussed the concept and relevance of a quantitative maintenance optimization technique known as the Modelling System Failures, and has used the approach to assess the reliability, availability and maintainability of 600 kW wind turbine’s gearbox. Field failure data of the 600 kW wind turbine’s gearbox have been collated from collaborating wind farm operators.

The data has been analysed using MLE in the Weibull distribution. The β and η parameters of the gearbox and its components were estimated. The estimated β and η parameters were used to design RBD to model the failures of the gearbox and the wind turbine. The models have been simulated using Monte Carlo simulation software to assess the reliability, availability and maintainability of the gearbox and the resultant effect on the wind turbine.

The approach and methodology presented in this paper is sufficiently generic to any mechanical system in the built environment/ construction industry. It is, however, crucial for the industry to realize the essence of collating and storing field failure and maintenance data of assets.

Further research work is currently undertaken to assess other critical subsystems of the wind turbine using the MSF approach. The results will be incorporated into the turbines failure model presented in Figure 5 and the resultant effects on a selected wind farm will be assessed under three common maintenance regime.

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