Wind Turbine Maintenance Optimisation: principles of quantitative maintenance optimisation

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Abstract

Maintenance optimisation is a crucial issue for industries that utilise physical assets due to its impact on costs, risks and performance. Current quantitative maintenance optimisation techniques include Modelling System Failures MSF (using monte-carlo simulation) and Delay-Time Maintenance Model (DTMM). The MSF investigates equipment failure patterns by using failure distribution, resource availability and spare-holdings to determine optimum maintenance requirements. The DTMM approach examines equipment failure patterns by considering failure consequences, inspection costs and the period to determine optimum inspection intervals. This paper discusses the concept, relevance and applicability of the MSF and DTMM techniques to the wind energy industry. Institutional consideration as well as the benefits of practical implementation of the techniques are highlighted and discussed.

Key words: *Wind turbine, Maintenance optimisation, Modelling System Failures, Monte Carlo Simulation, Delay-time maintenance model.*

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1 Introduction

Wind is becoming an increasingly important source of energy in order to reduce the emission of greenhouse gases and mitigate the effects of global warming. Improvements in the design of wind turbines **[1]** and the ready availability of wind resources in most parts of the world are contributing to the rapid development of the industry. In recent years, the industry has experienced a significant shift in the development of wind farms from onshore to offshore locations **[2]** due to more favourable wind resources and the possibility of installing higher power turbines.

Wind turbines are usually purchased with a 2-5 years all-in-service contract, which includes warranties, and corrective and preventative maintenance strategies [3]. These maintenance strategies (corrective and preventative) are often adopted by wind farm operators at the expiration of the contract period to continue the maintenance of wind turbines [4]. However, Andrawus et al [5] explained the inadequacy of these strategies to meet the current maintenance demands of the wind industry. A hybrid of Reliability Centred Maintenance (RCM) and Asset life-cycle analysis (ALCA) technique [6] was used to determine suitable maintenance strategies for wind turbines. Arthur [7] explains that RCM is a qualitative approach to maintenance optimisation which can be clouded with subjective opinion and experience. Thus, Scarf [8] recommends the incorporation of simple mathematical models which are quantitative in nature into the maintenance optimisation processes of physical assets. Given these limitations of RCM, this paper discusses the concept and relevance of two quantitative maintenance optimisation techniques to the wind industry. It proposes practical applications of the approaches to assess the failure characteristics of wind turbines and to optimise the maintenance activities on wind farms. Finally, the benefits of maintenance optimisation are presented with the necessary conclusions and suggestions for future work.

2 Maintenance Optimisation

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"* [9]. Maintenance optimisation 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.)"*[10]. Basically, the main purpose of maintenance optimisation is to determine the most cost-effective maintenance strategy. This strategy should provide the best possible balance between direct maintenance costs (labour, materials, administration) and the consequences or penalty of not performing maintenance as required (i.e. labour, materials, administration, loss of production and anticipated profit etc) without prejudice to Health, Safety and Environmental (HSE) factors. The concept of maintenance optimisation is illustrated conceptually in Figure 1.

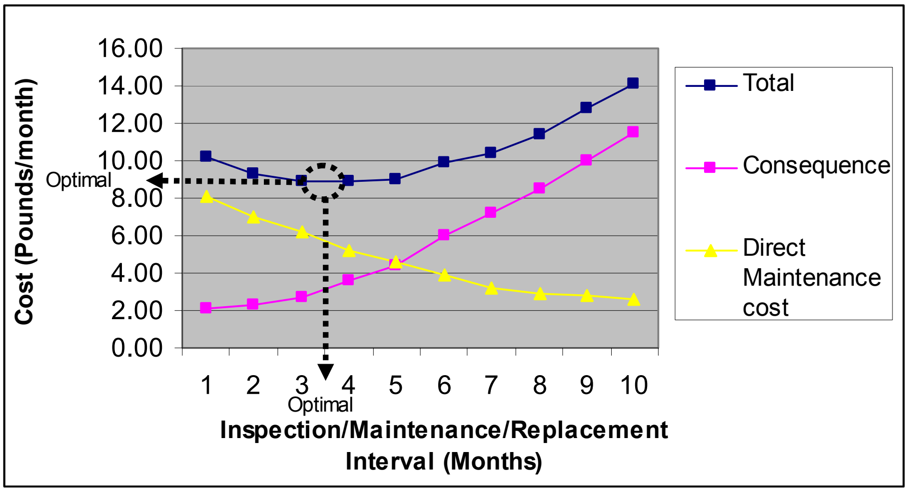

Figure 1 Maintenance Optimisation Concept

Evidently, carrying out maintenance activities such as inspection, preventative maintenance, and replacement of components more frequently, increases the direct cost of maintenance. Thus, the risk exposure or the consequences of not performing maintenance activities as required, reduces. However, the less frequent the maintenance activities, the lower the maintenance cost, and the higher the risk exposure. Optimisation 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, where maintenance activities are carried out at the lowest total impact (optimal cost and interval) as shown in Figure 1.

The optimisation of wind turbine maintenance is a promising way to maximise the return on investment in wind farms over a defined period, given that, "*the net revenue from a wind farm is the revenue generated from sale of electricity less operation and maintenance (O&M) expenditure*" [11]. Therefore, the wind industry has a clear opportunity to consider the strategic importance of maintenance optimisation and to proactively realise the benefits that are available through practical implementation of optimal maintenance strategies over the life-cycle of wind farms. Essentially, there are two approaches to maintenance optimisation; qualitative and quantitative. The latter is the focal point of this paper while bearing in mind that optimisation 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.

3 Quantitative Maintenance Optimisation

Quantitative maintenance optimisation (QMO) techniques employ a mathematical model in which both costs and benefits of maintenance are quantified and an optimum balance between both is obtained [12]. There are a number of QMO techniques in the field of Applied Mathematics and Operational Research, for example, Markov Chains and Analytical hierarchy processes [13]; Genetic Algorithms [14] etc. However, most of the approaches are criticised for being developed for mathematical purposes only and are seldom used in practical asset management to solve real-life maintenance problems [12]. Furthermore, Arthur [7] observed that, *"…quantitative maintenance optimisation can be clouded through the rigorous data demands of mathematical modelling and these same models require data that is often unavailable"*.

Modelling System Failures (MSF) has been recommended as the best approach to assess the reliability and optimise the maintenance of mechanical systems [15]. Delay-Time Maintenance Model (DTMM) [8] is well-known for its simplistic mathematical modelling and has been applied practically to optimise the inspection intervals of some physical assets with considerable success. Arthur [7] has employed it to optimise inspection intervals for and Oil and Gas water injection pumping system. The approaches of the two QMO are now discussed in more detail.

4 Modelling System Failures and Monte Carlo Simulation

This 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 [15]. 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 a Reliability Block Diagram (RBD) which permits the use of Monte Carlo simulations to determine the optimal levels of key maintenance variables such as costs, spare holdings, the level of reliability and availability required etc.

4.1 Statistical Distributions

Fundamentally, there are three failure patterns that describe failure characteristics of mechanical systems [15]. These include reducing, constant and increasing failures as illustrated in Figure 2. 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* symbolises failures that occur at the later life of equipment, that is, the likelihood of occurrence increases with the age of the equipment. It is worth noting, that the bath-tub curves differ for different pieces of equipment in the wind turbine. The reader is referred to [16] for a more detailed study on types of failure pattern.

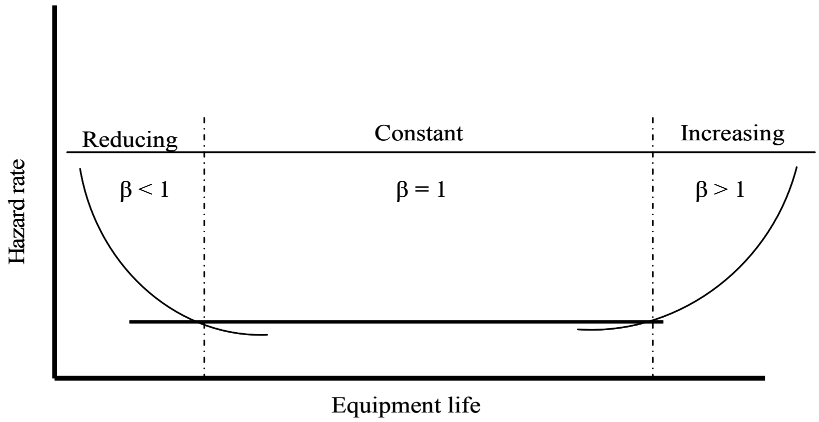

Figure 2 a 'Bath-Tub' curve showing failure patterns

A number of statistical distributions exist to fit the failure patterns afore described. Exponential distribution describes a constant hazard rate [15] while Normal and Lognormal describe the increasing hazard rate [15]. However, the most commonly used distribution is the *Weibull* named after a Swedish engineer Waloddi Weibull (1887-1979) who formulated and popularised the use of the distribution for reliability analysis. The distribution is very versatile as it fits all the three basic patterns of failure. Note that the Weibull distribution is also employed in the analysis of wind speed distribution but this is outside the scope of this paper.

4.2 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)* given in Equations 1 and 2 respectively is considered exclusively.

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

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

Where β and η represent the *shape* and *scale* parameter respectively. The value of β describes the failure pattern of the equipment. As a general rule, (β< 1) means a reducing failure pattern, (β=1) signifies a constant failure pattern and (β>1) indicates an increasing failure pattern, as depicted in Figure 2. Conversely, 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 [15]. Estimating the parameters requires a suitable method that will best fit the characteristics of the collated data.

4.2 Parameter Estimation Methods

Common parameter estimation methods include probability plot, 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 [17]. 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.

4.3 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 [17], 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*.

Note: Harris and Stocker [18] defined a likelihood function L (α) as "*the probability or probability density for the occurrence of a sample configuration x_1, ..., x_n given that the probability density f(x; α) with parameter α is unknown i.e. L (α) = f(x_1; α)... f(x_n; α)*"

Substituting equations 1 and 2 in 4

$$L = C \prod_{j=1}^{n} \frac{\beta}{\eta} \left(\frac{T_j}{\eta}\right)^{\beta-1} e^{-\left(\frac{T_j}{\eta}\right)^{\beta}} \prod_{i=1}^{k} \left[1 - \left(1 - e^{-\left(\frac{T_i}{\eta}\right)^{\beta}}\right)\right]^{r_i} \tag{5}$$

Then taking the natural logarithm

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

Taking the partial derivatives of Equation 6 with respect to β and η will result in Equations 7 and 8. These can be used to estimate the values of β and η respectively. Note that Equation 7 is obtained by equating the partial derivative of β to zero. This allows the maximum likelihood of β to be estimated by using an iterative procedure or trial and error approach. Alternatively, the equation can be programmed in Excel and the estimate obtained easily by using a Micro Soft solver.

$$\beta(0) = \frac{\sum_{j=1}^{n} (T_j)^{\beta} \ln T_j + \sum_{i=1}^{k} r_i (T)_i^{\beta} \ln T_i}{\sum_{j=1}^{n} (T_j)^{\beta} + \sum_{i=1}^{k} r_i (T)_i^{\beta}} + \frac{1}{\ln\left(\dfrac{\sum_{j=1}^{n} (T_j)^{\beta} + \sum_{i=1}^{k} r_i (T)_i^{\beta}}{n}\right)} - \frac{1}{n}\sum_{j=1}^{n} \ln T_j \tag{7}$$

$$\eta = \left(\frac{\left[\sum_{j=1}^{n} (T_j)^{\beta} + \sum_{i=1}^{k} r_i (T_i)^{\beta}\right]}{n}\right)^{\frac{1}{\beta}} \tag{8}$$

The estimated values of β and η of each component within a subsystem are used to design Reliability Block Diagrams (RBD) to model the failures of the subsystem. Similarly, the β and η values for each subsystem within a system are estimated to model the failures of the system. For example, consider a wind turbine as a system and the gearbox of the turbine as a subsystem with the following components; shafts, intermediary speed shaft (IMS) bearings, high speed shaft (HSS) bearings, key ways, gear-teeth etc. The β and η of each of the components are estimated to the model the failure behaviour of the gearbox. Similarly, the β and η of each subsystem of the turbine such as the generator, yaw, hub etc are estimated to model the failures of the wind turbine. In the modelling, Reliability Block Diagrams (RBD) are designed for the subsystems to incorporate the failure characteristics of the components. Then, the RBD of the subsystems are used to model the failures of the wind turbine as illustrated conceptually in figure 3. Thus, the failure behaviour of the wind turbine can be used in modelling the failure characteristics of a selected wind farm. It is worth noting however, that the modelling processes depend on the availability of failure data to estimate the β and η values for the components and subsystems of the wind turbine. The models are simulated using Monte Carlo simulation software to assess the reliability, availability and maintainability of the wind turbine as well as the wind farm. The effects of different maintenance strategies such as the Failure-Based, Time-Based and Condition-Based on the wind farm model can be assessed to determine the most cost effective strategy by taking into account the costs and availability of maintenance crew and spare holdings.

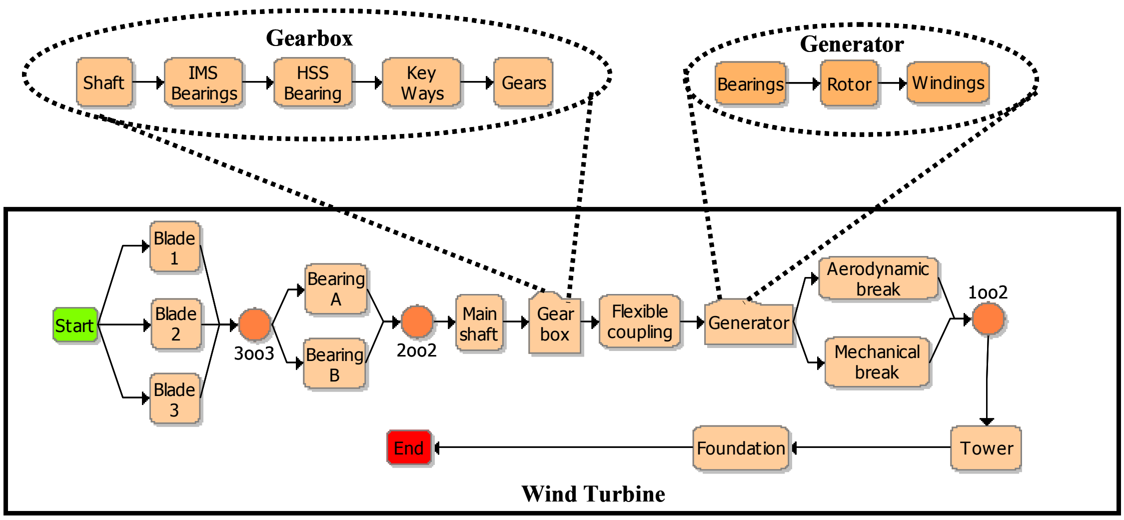

Figure 3 Modelling wind turbine failures

5 The Delay-time Maintenance Mathematical Model

This technique examines equipment failure patterns by taking into account failure consequences, inspection costs and intervals to determine an optimal inspection interval. In [6], suitable Condition Based Maintenance (CBM) actions were selected for wind turbines. The selection was based upon identifiable warning signs that can be measured to assess the actual condition of incipient failures. The availability of reasonable time that permits proactive action to avoid catastrophic events was also taken into account. Therefore, the time taken by an incipient failure to deteriorate from inception to catastrophic event is fundamental to determining maintenance intervals. This is illustrated in Figure 4.

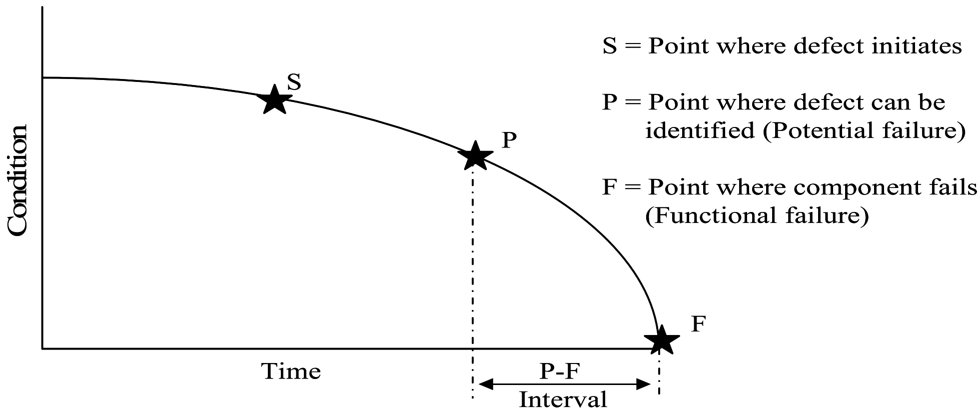

Figure 4 Potential-to-Functional failure intervals

In an RCM approach, P-F intervals are determined subjectively on the basis of engineering judgement and experience [19]. The P-F interval determines the frequency of CBM activities and is usually carried out at a time $\leq P\text{–}F\ Interval/2$. Moubray [16] suggested five ways to determine P-F intervals for equipment but concludes: "*it is either* *impossible, impracticable or too expensive to try to determine P-F intervals on an empirical basis*".

A simple quantitative mathematical model known as the delay-time maintenance model [8] allows the determination of the optimal inspection interval by taking into account costs, risks and performance. The delay-time is the time between a defect becoming apparent and functional failure actually occurring. This is synonymous to the P-F interval. The concept of the delay-time model is discussed in the next subsection.

5.1 Concept of the Delay-time Maintenance Mathematical Model

This maintenance mathematical model proposes a Poisson process of defects rate of arrival (α); exponentially distributed delay-times with mean ($1/\gamma$), and perfect inspection. Perfect inspection permits the detection of all expected failure modes. Note the defects rate of arrival connote complete failure of an item or defects found during inspection. Suppose all the gearboxes of wind turbines in a particular wind farm are subjected to regularly spaced inspections (such as vibration analysis) with inspections occurring every Δ in the interval [0, T]; where T is a multiple of Δ as shown conceptually in figure 5. Two defect arrival scenarios (F_1 and F_2) underpinning the principles of the delay-time mathematical model are shown in the figure. Incipient failure F_1 occurs between inspection intervals, is detected at the next inspection 2Δ which is then followed by a repair or F_2 occurs, fails catastrophically at t_i before the next inspection 3Δ.

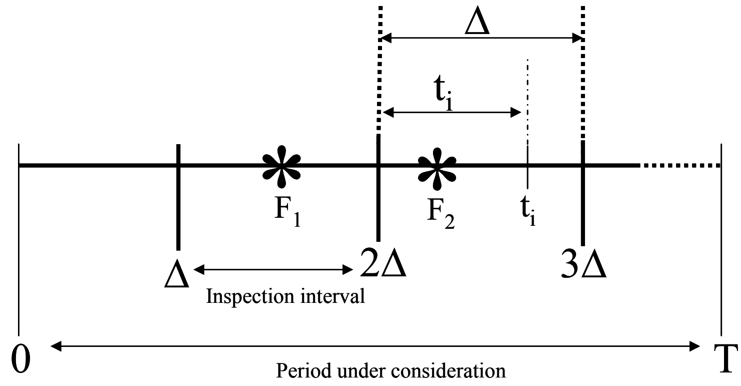

Figure 5 Delay-time concept

Thus, for a component observed over a period of T days with inspections equally spaced at intervals of Δ days, the maximum likelihood estimates satisfy the expressions;

$$\hat{\alpha} = \frac{n}{T} \tag{9}$$

Where; $\hat{\alpha}$ = defect rate, n = total number of defects observed (i.e. the sum of failed and repaired equipments), and T = period under consideration. Also

$$\sum_{i=1}^{k} \frac{\hat{\gamma} t_i}{e^{\hat{\gamma} t_i} - 1} + \frac{(n-k)\,\hat{\gamma}\Delta}{e^{\hat{\gamma}\Delta} - 1} = (n-k) \tag{10}$$

Where k failures are observed at times t_i $(i = 1, ..., k)$ from the last inspection, and $n-k$ defects are found at inspections. $\hat{\gamma}$ *and* $\hat{\alpha}$ are estimates of γ *and* α respectively. The optimal inspection interval, Δ^* satisfies the expression

$$(1+\gamma\Delta^*)e^{-\gamma\Delta^*} = 1 - \frac{\gamma c_1}{\alpha c_2}\text{, which has a solution provided } \gamma c_1 < \alpha c_2 \tag{11}$$

Where c_1 is the cost of inspection and repair, and c_2 the cost or consequences of failure. The reader is referred to [20-22] for detailed derivation of the delay-time equations.

6 Data Requirement and Collation

Historical failure data pertinent to the components and subsystems of wind turbines will be extracted from the Supervisory Control and Data Acquisition (SCADA) system. The SCADA system records failures and the date and time of occurrence; this will be used in conjunction with maintenance Work Orders (WOs) of the same period to ascertain the specific type of failure and the components involved. In the compilation, information will be sourced from wind farms (comprising of turbines of different designs and capacity ratings) located within the same geographical region. The collated data will first be organised in accordance with the type, design and capacity of the wind turbines. For example, failure data of all 600 kW horizontal axis turbines will be extracted and collated. This will further re-grouped according to the subsystems and components of the wind turbine and then re-arranged in order of failure modes and dates.

7 Benefits and Institutional consideration of Maintenance Optimisation

Effective implementation of maintenance optimisation will improve the reliability and availability of wind turbines as well as address the Health, Safety and Environmental issues. In addition, it will reduce the overall cost of operation and maintenance by revealing and focusing attention on problem areas. These will facilitate elimination of root causes of failures and also maximise the overall return on investment in wind farms.

Improving the reliability, availability and maintainability of wind turbines and the associated grid connection facilities require useful infield failure and maintenance data. The significance of collating and storing the correct type of data has been emphasised in [23]. It is imperative to have comprehensive inventories (including specific location) of all wind turbines of each type in an integrated asset register and data management system. The system should be robust to accommodate sequential recording of maintenance and failure data for each component in an RCM format. This will keep maintenance track record of each asset in a meaningful format that can be used for optimisation process and for an informed decision making process.

8 Conclusion and Future Work

This paper has discussed the concept of two quantitative maintenance optimisation techniques; modelling system failures using monte-carlo simulation and the delay-time maintenance mathematical model. It has also discussed the relevance and applicability of the techniques to optimise the maintenance of wind turbines. The benefits as well as the institutional barriers have been presented. Further research work is being undertaken to collate field failure and maintenance data from collaborating wind farm operators. The collated data will be analysed using the two quantitative maintenance optimisation techniques presented in this paper. The results of the analyses will be compared and the overall out come is to be used in developing an optimised maintenance strategy for wind turbines.

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