Quantification of Condition Monitoring Benefit for Offshore Wind Turbines

by

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David McMillan and Graham W. Ault
Institute for Energy & Environment, University of Strathclyde, Royal College Building, 204 George Street, Glasgow, G1 1XW
Email <dmcmillan@eee.strath.ac.uk>, <g_ault@eee.strath.ac.uk>

ABSTRACT
Condition monitoring (CM) systems are increasingly installed in wind turbines with the goal of providing component-specific information to wind farm operators, theoretically increasing equipment availability via maintenance and operating actions based on this information. In the offshore case, economic benefits of CM systems are often assumed to be substantial, as compared with experience of onshore systems. Quantifying this economic benefit is non-trivial, especially considering the general lack of utility experience with large offshore wind farms. A quantitative measure of these benefits is therefore of value to utilities and operations and maintenance (O & M) groups involved in planning and operating future offshore wind farms. The probabilistic models presented in this paper employ a variety of methods including discrete-time Markov Chains, Monte Carlo methods and time series modelling. The flexibility and insight provided by this framework captures the necessary operational nuances of this complex problem, thus enabling evaluation of wind turbine CM offshore. The paper concludes with a study of baseline CM benefit, sensitivity to O & M costs and finally effectiveness of the CM system itself.

Keywords: Wind Farms, Condition Monitoring, Operations and Maintenance, Markov Chain, Monte Carlo, Probabilistic Model.

NOMENCLATURE

CM	Condition Monitoring
SCADA	Supervisory Control Alarm and Data Acquisition
CBM	Condition Based Maintenance
WT	Wind Turbine
O & M	Operation and Maintenance
F	Annual Maintenance Frequency
R	WT Revenue
MWh_T	Mega-Watt Hours Generated During Time Period T
MP_{ROC}	Market Price of Renewable Obligation Certificates
MP_{ELEC}	Market Price of Electricity
Pr(event)	Probability of Occurrence of an Event
Im(event)	Impact of Event
L	Confidence Limit
s	Standard Deviation of Sample
N	Number of Samples
WS_t	Wind Speed at Time t

WS_{t-1}	Wind Speed at Time t-1
μ	Mean Wind Speed
$\varnothing$	Autoregressive Model Parameter
ε_t	Gaussian Error Term
σ^2	Variance of Gaussian Error Term
Z	Z score for Gaussian Distribution

1. INTRODUCTION

Global concerns regarding energy security, alongside increasing public acceptance of human influence on global warming have motivated a recent surge in support for renewable energy technologies. Wind Farms have emerged as the technology regarded by most policy makers and utilities as the renewable energy source most suited to delivering desired targets on carbon emission reductions and diversity of supply. The long term focus in the UK and elsewhere is gradually switching from onshore to offshore, because of less problematic visual intrusion and significantly higher yields due to larger WT ratings and stronger wind profiles. Large projects such as the proposed 1 GW London Array [1], 0.5 GW Greater Gabbard [2] and 0.25 GW Lincs [3] have illustrated substantial interest and growth potential in this area.

Various forms of condition monitoring (CM) systems have become increasingly common as part of the turbine Supervisory Control Alarm and Data Acquisition system (SCADA system). The theoretical benefits of such systems are well known, and indeed these benefits have already been realised by operators of traditional generating sets (gas, coal etc.). The CM information is utilised to detect incipient faults, thus enabling more effective and efficient maintenance scheduling (as compared to the well known and oft-used periodic maintenance policy). However it must be noted from the operational viewpoint that any prospective maintenance policy based on condition information must have clear economic benefits; otherwise the initial outlay for the CM system and associated costs cannot be justified.

Large offshore wind farms have their own distinct characteristics which further challenge widely held assumptions with respect to CM applied to wind turbines. A commonly held assumption is that CM systems will become cost effective for offshore wind farms, due to a number of factors:

- Increased lost energy, and hence lost revenue, due to larger capacity ratings of offshore turbines and stronger wind profiles
- Longer downtimes (harsh weather, large distances involved, modes of transport required)
- Larger, heavier, more costly components for larger capacity rated turbines designed for the offshore environment, requiring higher outlay for O&M

The research presented in this paper aims to address these issues via a framework of highly flexible probabilistic models which are capable of capturing the subtleties of wind farm operational activities. These models are informed both by the literature and by direct dialogue with Scottish Power PLC: a utility involved in operation and maintenance of an extensive wind farm portfolio.

The paper proceeds as follows. Section 2 provides a summary of existing research upon which this work is built. Section 3 gives an extensive overview of the models used to quantify offshore WT CM system benefit, as well as the sources of information used to guide and populate those models. Section 4 presents a set of case studies designed to investigate the cost effectiveness of offshore WT CM. Section 5 draws some conclusions from the results and suggests possible implications for offshore wind farms.

2. WIND TURBINE CONDITION MONITORING AND MODELLING

Most modern wind turbines are now manufactured with some form of integrated CM system, interfaced to the operator via a Supervisory Control Alarm and Data Acquisition System (SCADA system). Such CM systems are commonly based on vibration monitoring of the WT drive-train as well as temperature measurement of bearings, machine windings etc. [4] and [5] provide particularly insightful reviews of the state of the art in WT CM systems. Additionally, several emerging systems [6] are commercially available based on technologies such as lubrication oil particulate content and optical strain measurements. Various other systems have been proposed in literature, such as the blade monitoring system presented in [7], and the holistic set of intelligent models developed in [8]: however, temperature and vibration are the main condition monitoring tools used in commercially available systems.

Published research has shown that via different approaches, the benefit of a condition-based maintenance scheme for onshore wind farms can be quantified. Andrawus et al. [9] compiled detailed costs and extracted sub-component failure rates from 6 years of wind turbine SCADA data, with the goal of deciding a suitable maintenance strategy. A combination of reliability-centred maintenance and asset life-cycle analysis was used, and Monte Carlo Simulation was employed to introduce uncertainty into key variables. This approach suggested that, for the conditions evaluated, a Condition Based Maintenance (CBM) strategy is the most cost-effective option. The total savings of £180,152 were discounted using net present value, and equate to an annual saving of £385 per turbine over the 18 year life cycle of a 26 turbine onshore wind farm. A contrasting approach by the authors of this paper [10] brought together a set of models representing physical component condition (based on a Markov Chain solved via Monte Carlo Simulation), turbine yield and asset management objectives. The problem was formulated and populated with data from various sources, including published data and anecdotal evidence from Scottish Power. Maintenance models were developed and the output validated using simple calculations. Probabilistic simulations were run in order to compare the performance of two maintenance policies (periodic and condition-based) and thus quantify the benefit of WT CM. The results indicated that while a mean yearly benefit of £2,000 was calculated in favour of CBM, the confidence limits were such that the case for onshore condition-based maintenance of WTs appeared to be uncertain.

The work contained in this paper builds on the previous work by the authors, modifying the models to reproduce offshore conditions. The strength of this approach is its flexibility: data from a variety of sources are taken advantage of, and since experience of large offshore wind farms is limited, the results enable insight for owners and operators of future large offshore wind farms.

Given that the CM system is monitoring the status of a set of components, capturing the deterioration process of those components is a vital part in any maintenance simulation. When this process is adequately represented, condition monitoring can be modelled as knowledge of the current state. Research related to this area of 'deterioration modelling' and maintenance modelling exists in literature, with many interesting applications, providing useful insight for this work. Marseguerra [11] and Baratta [12] approach the problem as a discrete event simulation: the Markov Chain deterioration model represents key components in the nuclear safety sector. Both sets of authors identify an optimal deterioration threshold limit (in terms of availability and profit) at which condition-based maintenance should be conducted: however while Baratta uses sensitivity studies, Marseguerra uses a genetic algorithm to achieve the optimisation. Endrenyi and associates have published a number of influential contributions on deterioration modelling and the effects of maintenance including [13] and [14]. Sayas and Allan [15], as well as Billinton [16], have both developed wind turbine models for use in reliability studies: although these understandably neglect intermediate states. Markov models have been applied successfully by a number of authors in asset management applications, with insightful contributions in the fields of oil-filled circuit breakers [17], water infrastructure [18], and road networks [19].

Continuous-time models with analytical solution are favoured by most authors: however this can be problematic when representing more complex systems and processes due to a lack of flexibility in the modelling framework. Discrete-time models solved via simulation provide a degree of insight and flexibility which is essential to capture the nuances of operational activities, since the problem does not have to be expressed in closed-form equations. Therefore, a discrete-time simulation-solved model is adopted in this work.

3. WIND TURBINE ASSET MANAGEMENT MODELLING

In order to represent the various facets of the complex problem of quantifying the effects of CM on WTs, a multi-level modelling approach is being adopted, as shown in Figure 1. The three levels enable a diverse range of processes to be effectively modelled such as physical deterioration and faults, wind farm yield modelling and weather effects, and high-level asset management decisions: these individual aspects are now discussed.

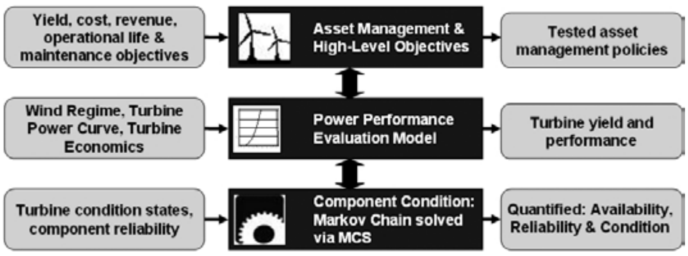

Figure 1. Multi-level WT Asset Management Modelling Framework

3.1 Wind Turbine Sub-Component Model

The sub-component representation of a physical system has been implemented in several different ways in literature, as shown in Figure 2. Moving from left to right, the two-state representation such as that used in older reliability studies is unsuitable for this application as it does not consider the 'derated' or deteriorated states which the CM system can infer over time (refer to Figure 6 for an example). The single component approach (centre) would require parallel simulation to solve: this should be avoided as far as possible due to the chance of introducing undetected simulation correlations causing bias in the result [20]. Thus the multi-component, intermediate state model (right) is adopted for this work.

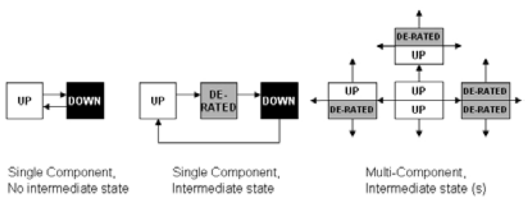

Figure 2. Sub-Component Models

The next stage is to decide which components should be considered in the analysis, and how the component states map to the measured condition variables provided by the CM system. Both of these issues are very important, having a significant impact on the model accuracy. Two main sources of information were used to determine which of the WT sub-components should be included in the modelling: published sub-component reliability data; and wind farm operational experience. Once these issues are addressed, the state-space of the Markov model is effectively defined.

3.2 Wind Turbine Sub-Component Reliability Data

Reliability data for wind turbine sub-components are collected by some turbine operators, but are not readily available in the public domain. When available to researchers, this information (although limited)represents a useful starting point for modelling the wind turbine sub-components, ultimately for use in the condition monitoring evaluation study. A summary plot of three studies containing WT sub-component reliability data are shown in Figure 3: these have been taken from various published sources (Left to right: [21], [22] and [23]).

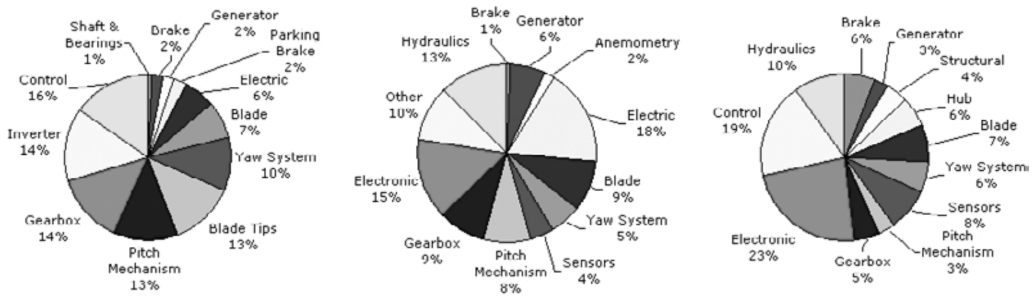

Figure 3. Causes of WT Failures in Published Studies

The data plotted in Figure 3 are predominantly characteristic of the experiences of Danish and German utilities. Many failures are electronic related, with small downtime although replacement or repair in the offshore environment is likely to be more time-consuming than on land. Indeed, it is important to note that these results reflect only relative failure frequency: not duration of downtime, or cost of components. Hence, other factors beyond the failure rate should be considered.

3.3 Wind Farm Operational Experience

Dialogue with a Scottish Power yields interesting contrast with published results as outlined in the previous section. It is clear through this dialogue that the most significant operational failures are associated with the gearbox and generator components. The reasons are:

- High capital cost and long lead-time for replacement
- Difficulty in repairing in-situ
- Large physical size and weight
- Position in nacelle at top of tower
- Lengthy resultant downtime, compounded by adverse weather conditions

The final point can be reinforced when it is understood that typical downtime for an unscheduled gearbox replacement is of the order of 700 hours [24], though this is dependent on availability of the component from the manufacturer. A recent report detailing operational activities at the Scroby Sands offshore wind farm [25] appears to back up the conclusions above, with gearbox bearing problems the most prevalent. Published data available from windstats [26], and plotted in Figure 4, shows the significance of operational failures in terms of downtime per component failure. This data reinforces the conclusions above, since the generator and gearbox failures account for 42% of the total downtime.

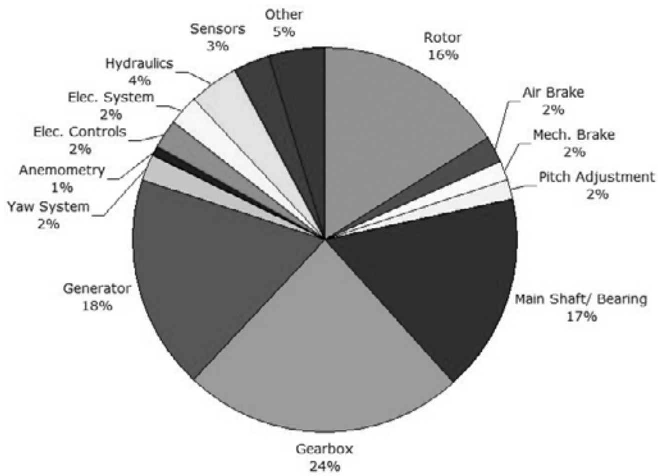

Figure 4. WT Downtime Distribution [26]

Taking this information into account, the studies conducted in this paper feature a 4-component model comprising generator, gearbox, blades and power electronics system. The gearbox and generator were included for the reasons outlined above by the industrial project partners. Blades were also included as there are emerging methods of monitoring these, and while they have low probability of failure, the impact of a blade replacement is very significant from an operational and economic viewpoint. Finally, in order to accurately re-create the overall wind turbine failure rate, power electronics was included even though monitoring capability is not modelled.

Figure 5 illustrates the four WT sub-components and a sub-set of monitoring options. The quality of information provided by each of these measurements, as well as the data interpretation, determines the accuracy of the overall 'system picture', as inferred by the CM system.

3.4 Mapping of CM Information to Markov States

The crux of condition monitoring effectiveness lies in the ability of the CM system to reliably diagnose the status of the components and hence the overall system. There are of course many methods of achieving this, some more simple than others. This ability to diagnose and categorise (whether achieved via human expert or automated systems) is the basis of any CM system and its subsequent mathematical representation. Indeed, the practicalities of quantifying condition as a mathematical index have been investigated elsewhere: a particularly comprehensive and succinct summary is provided in [27]. For this work, a simple example of the possible mapping between the monitored system variables and Markov state space is sufficient to illustrate the concept.

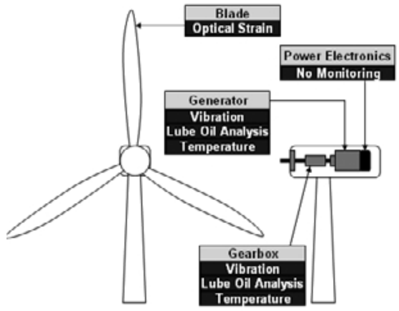

Figure 5. Selection of WTG Monitoring Options

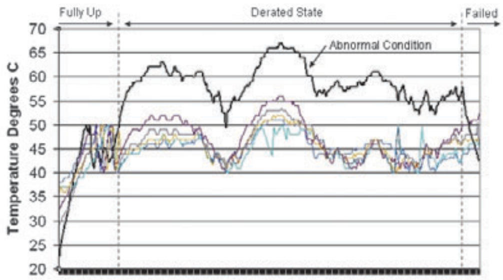

Figure 6. CM System Categorisation

Figure 6 shows a set of wind turbine gearbox lubrication oil temperature traces, along with possible state categorisation. Since deterioration is essentially random, Monte Carlo methods can be used to represent this process adequately. It can be seen that the physical state of the WT component corresponds to its modelled state in the Markov chain (e.g. fully up, derated, failed). The components to be modelled are those shown in Figure 5: the states of those components may be categorised in the manner shown in Figure 6, using the various CM methods available. Finally, the state-space must be defined based on this information, and the transition probabilities between states deduced.

3.5 Markov Chain State Space

In the state space diagram, each box represents the condition of the overall wind turbine, i.e. the status of the 4 modelled components. Figure 7 shows the full state space where C1, C2, C3 and C4 represent the modelled components and their various possible condition states. The total possible state space is 52 states: however this was reduced to 28 via simplifying assumptions, the most influential being that probability of simultaneous failure events is considered insignificant and that components will transit to a derated state before outright failure (except electronics). The model time resolution is 1 day, which does represent a highly optimistic picture of the ability of the CM system to catch failures before they occur. The validity of these assumptions increases as the time resolution of the model approaches continuous time i.e. small discrete intervals of minutes rather than days. Future studies will take account of near-instantaneous failure events as these are not currently explicitly modelled, though the framework is amenable to such changes. A deeper study of the early warning capability of WT CM systems and the nature of offshore WT faults (i.e. time periods involved) would be the next step in refining the approach. For the results contained in this paper, however, the 1 day time resolution model is used.

3.6 Transition Probability Matrix

Ideally the transition probability matrix which governs the behaviour of the system over the discrete intervals would be defined by taking a long-run turbine history and calculating transitions based on this history alone. The main issue is that such data sets may not exist in reality, and may not capture a wide range of turbine faults: therefore other approaches must be considered.

The sub-component failure probabilities (see 3.2) are known quantities over large populations of turbines, and therefore the model should reproduce these faithfully (if sampled sufficiently to reach steady-state values). The transition probabilities can be at least partially deduced by using sensitivity studies to observe the effect on these model output metrics compared with actual sub-component failure rate values. Additionally, the probabilities can be influenced by comparing the model condition trajectory to that of a real monitored turbine in operation (see Figure 6). For example, it is possible to deduce the probability of failure in the next time period if it is known that the current state is a de-rated state: in this sense the turbine condition data provides direct input into shaping the behaviour of the model. It should be noted however that minor outages are often not recorded in the available statistical data: therefore in reality the failure rate may be higher than suggested in such publications. This may be a significant factor offshore, since even a minor shutdown may necessitate an inspection and associated costs, which may be substantial.

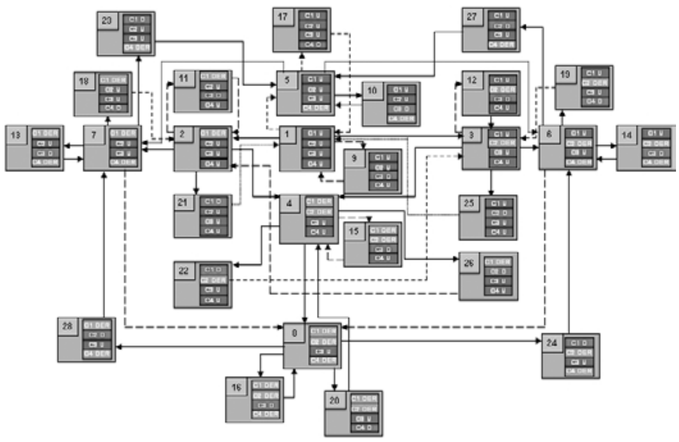

Figure 7. WT Condition State Space Diagram

3.7 Turbine Yield Model

The yield model consists of two parts: a power curve model and a wind speed model. The wind model is based on an autoregressive time series model with a single parameter (also known as an AR(1) model). This has been developed using raw SCADA data from an *onshore* WT at Black Law wind farm with a strong wind profile (mean wind speed, μ, 7m/s), to reproduce offshore performance as closely as possible, given the limited data available offshore. Although offshore locations may have significantly stronger wind regimes, this profile represents the best case with the data available. The single parameter autoregressive model has the form:

$$WS_t - \mu = \phi\,(WS_{t-1} - \mu) + \varepsilon_t \qquad (1)$$

If the wind speed in the previous period, WS_{t-1}, is known, then the next time series value, WS_t, can be calculated from equation (1). Classification was achieved through inspection of the autocorrelation and partial autocorrelation functions [28], and the model was fitted using the ordinary least squares fitting technique. A statistical programming language was used to estimate model parameter ϕ and variance σ^2 of the Gaussian noise term ε_t. This approach enables day to day correlation between wind speed values to be captured within the model. Simulated wind speed values can thus be plugged into the relevant power curve, as shown in Figure 8. This is a 5 MW rated machine [29], specifically developed for offshore applications. It has characteristic cut in, rated and cut out wind speeds of 3.5, 13 and 30 m/s respectively.

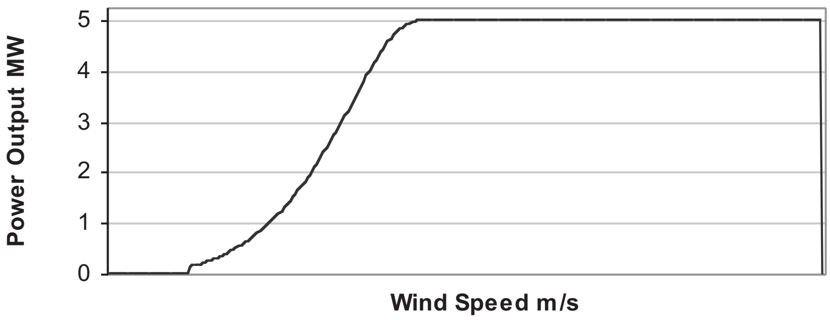

Figure 8. 5 MW Offshore Wind Turbine

Turbine revenue, R, is calculated from the energy (MWh) generated, and is calculated as shown in eq'n (2), where MP_{Elec} and MP_{ROC}, the market price of electricity and renewables obligation certificates, are taken as £36/MWh and £40/MWh respectively. These costs are currently fixed in the model, although their variability could easily be modelled deterministically or probabilistically in future studies. Operations and maintenance costs, described in the next section, are subtracted from the revenue stream to calculate income from each turbine.

$$R = \sum_{T=1}^{Trials} MWh_T \times [MP_{Elec} + MP_{ROC}] \tag{2}$$

3.8 Maintenance Models

Two contrasting maintenance approaches were implemented in the model: periodic and risk/condition based maintenance.

- Periodic – Perform maintenance at set intervals (~Every 12 months)
- Risk/Condition Based – Maintain according to condition rule policy

It is noted that both approaches will inevitably involve some reactive maintenance, especially in the offshore case where frequent periodic maintenance is often impractical. Additionally, many maintenance and repair actions will be subject to weather constraints for offshore installations. Table 1 illustrates a set of maintenance restrictions as applied onshore, set by the owner/ operator for health and safety reasons: these restrictions are built into the program. Until data for offshore access and working arrangements is available, Table 1 will be adopted for use in the offshore analysis. Although wave height is the dominant access factor offshore, this is coupled strongly with wind speed and so inclusion of wind speed constraints is valid, though clearly this represents an approximation which may have an effect on the results of the analysis.

Table 1. Maintenance Weather Constraints (related also to sea state)	
Wind Speed (m/s)	**Restrictions**
>30	No access to site
>20	No climbing turbines
>18	No opening roof doors fully
>15	No working on roof of nacelle
>12	No going into hub
>10	No lifting roof of nacelle
>7	No blade removal
>5	No climbing MET masts

It is assumed that downtime for an unplanned outage is a deterministic constant. For this work, assumed values for onshore downtimes were adjusted to reflect the problems encountered in the offshore environment: these are displayed in Table 2. The downtime increase is due to two factors. The first is significant lead time for a suitable jack-up crane vessel (needed for generator, gearbox and blade), which has been quantified as 10 days in [30]. The second part is the logistics time from the upload point to the wind farm (which may be as much as 20km from shore [31]) and is considered to be 1 day. It is emphasised that the Table 2 values represent typical downtime values, but these values are modified depending on environmental factors – in the case of this work, excessive wind speed may delay the maintenance actions, over and above Table 2 values.

Table 2. Major Component Outage, typical Downtimes		
Component Outage	**Days Downtime Onshore**	**Days Downtime Offshore**
Gearbox	30	41
Generator	21	32
Blade	30	41
Electronics Sub.	1	2

In contrast, planned maintenance actions are carried out with certainty if weather conditions are favourable, reflecting the benefit of a more pre-emptive approach to maintenance (components and installation equipment can be purchased/ hired in advance). Alternative methods for downtime modelling using 'downtime distributions' derived from wind farm SCADA data will be investigated in future work.

3.8.1 Maintenance Costs

The baseline maintenance costs for a 2 MW onshore WT were taken as £10 K per year in previous studies [10, 33]. While it is difficult to put a figure on annual offshore O&M cost, dialogue with WT operators has put the offshore figure at between 3 and 5 times the equivalent onshore cost. For offshore conditions, if an annual maintenance period is adopted, this corresponds to £10K, 30K and 50K per maintenance action respectively. Therefore, the (planned) maintenance costs of a CBM policy can be calculated as a yearly proportion, depending on the frequency of maintenance actions, F. Table 3 illustrates the rules used to model these maintenance costs.

Table 3. Planned Maintenance Cost Range			
Maintenance Policy	**Annual Frequency**	**Cost Multipler**	**Annual Cost/Turbine**
Periodic	1	1X	10K
Periodic	1	3X	30K
Periodic	1	5X	50K
CBM	As required (F)	1X	£(F x 10K)
CBM	F	3X	£(F x 30K)
CBM	F	5X	£(F x 50K)

In addition to scheduled maintenance costs, unplanned costs for replacement of major WT components should also be modelled, as they are significant. To capture this, every time the Markov model transits to a failure state, the failed component is identified and repair or replacement cost deducted from the WT revenue stream (of course any potential yield revenue is also lost while in the down state). Estimated replacement costs for the key components of an offshore 5MW WT are shown in Table 4, and are calculated using the 'percentage of capital cost' method proposed in [32]. Capital cost of £600,000 per MW of installed capacity was assumed for the purposes of deriving component cost estimates [33]: overall capital cost of offshore projects is currently closer to £1M per MW capacity. Repair costs are taken as a 10% proportion of the offshore component replacement values.

Table 4. 5MW WT Component Replacement Cost

Gearbox	£402,000
Generator	£201,000
Blade	£166,000
Electronics Sub.	£10,000

These costs are modelled deterministically, but this is another area of the model where increased detail could be accommodated in future developments of the model. Likewise, the probability of repair or replacement of a failed component is equally likely: further study into the robustness and 'reparability' of the components may lend more accuracy to these assumptions.

3.8.2 Periodic Maintenance Regime

The most widely practiced maintenance paradigm in any industry is periodic maintenance, and maintenance of wind farms is no different. Despite the various monitoring options available, most owner/ operators tend to keep to methods they are familiar with in maintenance of their assets. In the model it is assumed that maintenance actions are 100% successful, and have only a small impact on yield, being scheduled during periods of low wind. The actions are weather constrained and are assumed to be carried out once every 12 months.

3.8.3 Condition Based Maintenance Regime

As previously discussed, one of the chief advantages of the Markov approach is its ability to model condition monitoring knowledge capture. In reality, the WT operator would observe (manually or through an automated system) the trajectory of various instrumented WT components via measurements delivered by the CM system, as previously discussed. In the Markov model this can be replicated by allowing the maintenance actions to be informed by the current state of the system (Physical Markov condition model): see Figure 9 for a simple illustration of this concept.

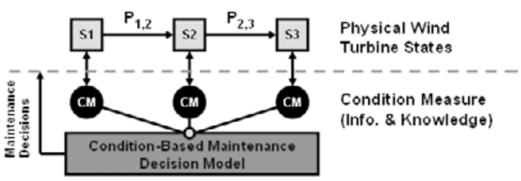

Figure 9. Markov Model Captures Condition Monitoring Information

An implicit assumption in this approach is that the CM system can infer the current equipment condition with certainty. Therefore, the model as defined so far does not address the issue of possible spurious CM diagnosis. This shortcoming is addressed in section 4.3, where a further refinement is added which allows possible unreliability of the CM system to be modelled, and will be explored further in future work.

The next challenge is the development and specification of a suitable condition-based decision model, coupling condition and maintenance. An operator of any plant or system desires some signal regarding the risk that their plant is subject to. Risk is defined as the product of probability and impact of an event or compound event: the Markov model is again particularly suited to the expression of such metrics. The risk in any system state can be expressed specifically as:

$$Risk(state) = \sum \Pr(event)_N \times \mathrm{Im}(event)_N \tag{3}$$

Where N failure events are possible, $Pr(event)$ is the probability of transition to a failure state and $Im(event)$ is the impact of that particular component failure should it occur, which could comprise a number of economic terms, but is currently simply the component replacement cost. By using the equation above, all states with probability paths to failure can have an associated risk calculated for them, as displayed in Figure 10. The reason only states 2-8 are included is that these are the intermediate operational states where the CM knowledge can be utilised.

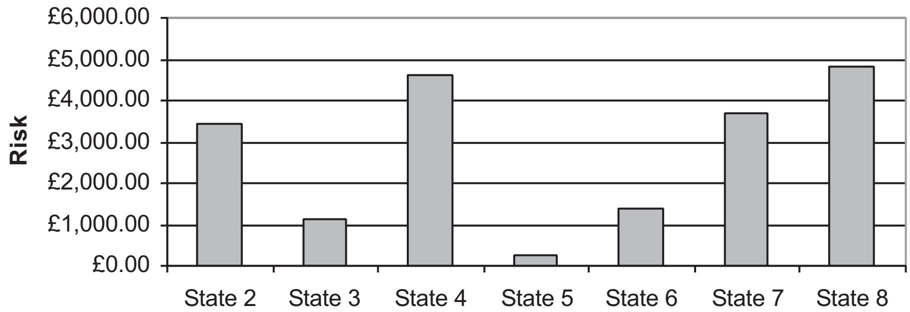

Figure 10. Risk Associated with Each State

Once calculated, the magnitude of risk for each state can be used as an indicator to determine how urgently repair work should be scheduled by the operator of the WT. In this work the risk measure is used to set a maintenance time delay. The states are grouped into intervals depending on their risk values: at this point there is no formal framework for how these intervals are formed, although in previous model iterations these divisions were clear due to large differences between risk values.

Table 5 shows the wait time in weeks for each risk interval corresponding to the values in Figure 10: the time values in Table 5 were determined by conducting a simple sensitivity study, and represent the cost-optimal maintenance interval. When the wait time has elapsed the maintenance will only be carried out if weather conditions are favourable, which depends on recent wind speed but also has an element of randomness, see eq'n. (2). Using the equipment state and wait times, the 12-monthly periodic maintenance policy can be replaced with a risk/condition based policy.

Table 5. Wait Times Linking Condition Information to Maintenance Actions			
States	Risk Threshold	Risk Level	Wait Time Days
4,8	>£4000	HIGH	7
2,3,6,7	£4,000>RISK>£1,000	MED	28
5	<£1,000	LOW	140

The maintenance policies have been presented, along with the representations of the wind turbine and associated modelling. Some general issues concerning the model and its probabilistic nature are now discussed.

3.9 Statistical Significance

The program was developed in order to obtain statistically sound results (14,000 trial simulation run 30 times: 420,000 trials). When 14,000 trials were run, this almost always resulted in the turbine residing in each of the possible component failure states at least once. In fact, in order for the sample to be statistically credible, all possible failure modes should occur: so an upper limit of 14,000 trials seems adequate. Of course in a real situation this may not be the case: a WT may only experience a sub-set of the failures possible (since conditions and equipment vary from site to site). The spread of this sub-set of failures and frequency of failures experienced by the WT may be a contributing factor to the perceived effectiveness of any maintenance policy. To increase statistical confidence, multiple simulation runs are conducted and average values taken. For direct comparisons of individual cases, correlated sampling was used. A simple statistical calculation can be carried out in order to establish confidence limits (L) of the simulation results:

$$L = \pm \frac{Z \times s}{\sqrt{N}} \tag{4}$$

Where s is the standard deviation of the samples, and N is the number of samples taken. If the degree of confidence in the result is set to 95%, then the Z score (a quantity reflecting the accuracy of the simulations) is equal to 1.65. Using this statistical technique it is possible to assert that the real mean value is 95% certain to lie within the bounds of the upper and lower confidence limits [34].

4. CASE STUDIES FOR OFFSHORE WT CM EVALUATION

Previously published case studies using the models presented in this paper have been at least partially validated in an existing publication [10]. The changes required to this model which have been implemented in this work are as follows:

- Larger turbine rating and stronger wind profile for offshore case
- Longer downtimes for repair and replacement for offshore case
- Higher cost O&M and component repair/ replacement (c.f. onshore WT)

Since these correspond to the assumptions regarding offshore WT CM as outlined in the introduction, the output from the following simulations should be capable of providing insightful information regarding cost-effectiveness of offshore WT CM systems.

4.1 Offshore Base Case

O&M costs for the base case are taken as the optimistic figure of 3 times the assumed onshore value of £10K per annum. The most notable assumption in the base case is that the CM system is assumed to be 100% reliable when diagnosing if a component has deteriorated. Figure 11 shows the annual revenue for all 30 simulation runs: this illustrates that the condition-based policy out-performs the periodic policy in the vast majority of cases. The physical effect of the two different maintenance approaches can be clearly seen in Figure 12, where the CBM policy improves the reliability performance of the WT in almost every case. Figure 13 compares the constant periodic maintenance frequency to that of the variable CBM policy.

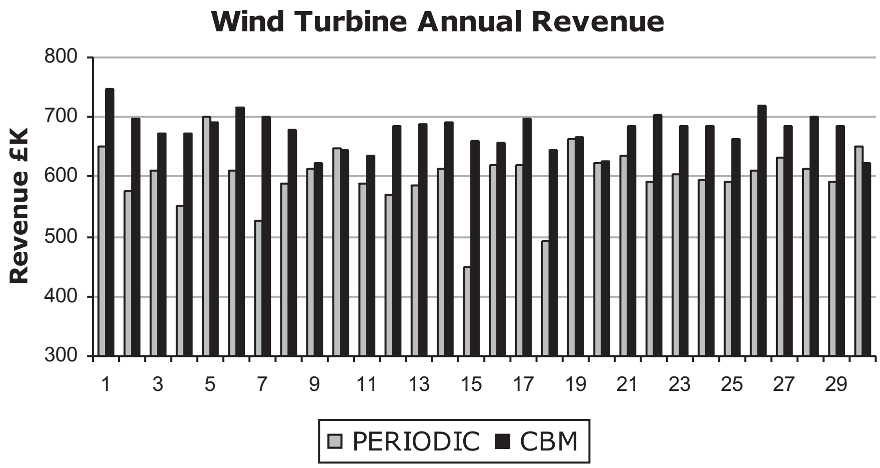

Figure 11. Simulated WT Revenue

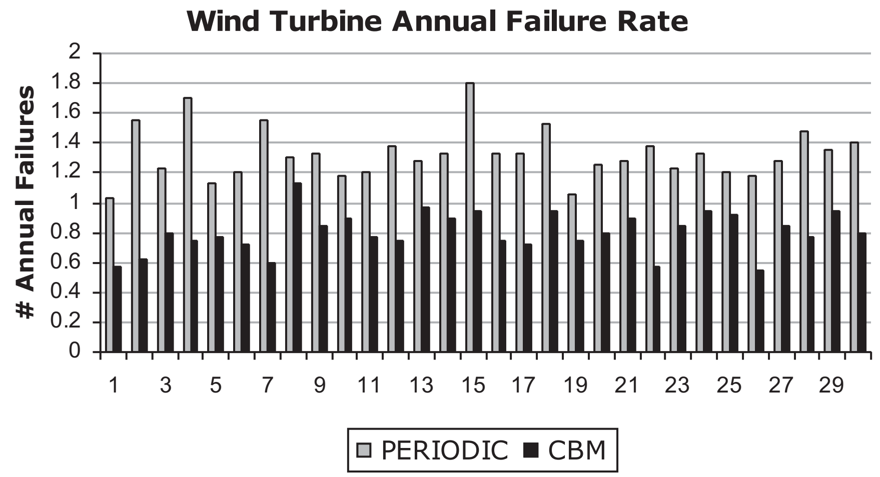

Figure 12. Simulated WT Failure Rate

Table 6 summarises the average values taken over the 30 simulations, directly comparing the output metrics of the two maintenance approaches. Using eq'n (4) to calculate the confidence limits, Figure 14 shows an extremely clear economic benefit for condition-based maintenance of offshore WTs. This benefit is quantified as £76,784 for an individual WT per annum for the conditions evaluated, i.e. assuming the CM system is 100% accurate as regards successful diagnosis of WT sub-component status. This result appears to back up the widely held view that WT CM systems could become cost-effective in the offshore environment: however, note from the confidence limits that the result could be as little as £53K or as much as £100K.

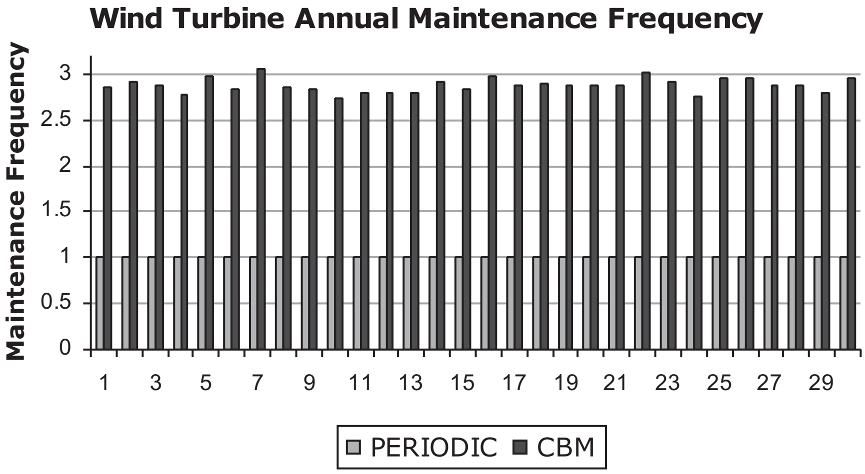

Figure 13. Simulated WT Maintenance Frequency

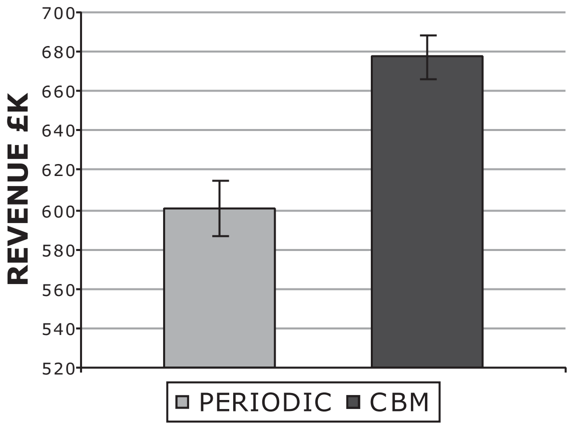

Figure 14. Comparison of WT Revenue

Table 6. Base Case Summary

Annual Metric	Periodic	CBM
Availability %	94.75	96.99
Yield MWh	11918	12207
Revenue £	600543	677327
Maintenance Freq.	1.000	2.877
Failure Rates		
Overall Turbine	1.32	0.81
Gearbox	0.40	0.11
Generator	0.24	0.07
Electronics	0.39	0.42
Blade	0.30	0.21
CM Annual Benefit		£76,784

4.2 Offshore Condition Based Maintenance Benefit Sensitivity to Variations in Operations and Maintenance Cost

As discussed in section 3.8.1, the offshore WT operations and maintenance cost was estimated by industrial collaborators at between 3 times and 5 times the cost onshore (which is assumed to be £10,000 per year). Figure 15 shows the impact of variation of this cost on the annual economic benefit of the CM system, within the assumed boundaries. This second result illustrates diminishing cost-effectiveness of CBM as O&M cost increases. It should be noted that in all cases evaluated, the theoretical net benefit of a condition-based maintenance policy is over £35,000 per annum, and indeed the maximum benefit level would result in a lifetime benefit of around £1.5M per turbine, assuming a 20-year life cycle. Needless to say, this represents a significant benefit over a WT large population making up an offshore wind farm. It is important to note, however, that the assumption of a highly reliable CM system may be unrealistic and therefore consideration of this aspect is crucial to the understanding of the economic case for offshore WT CM.

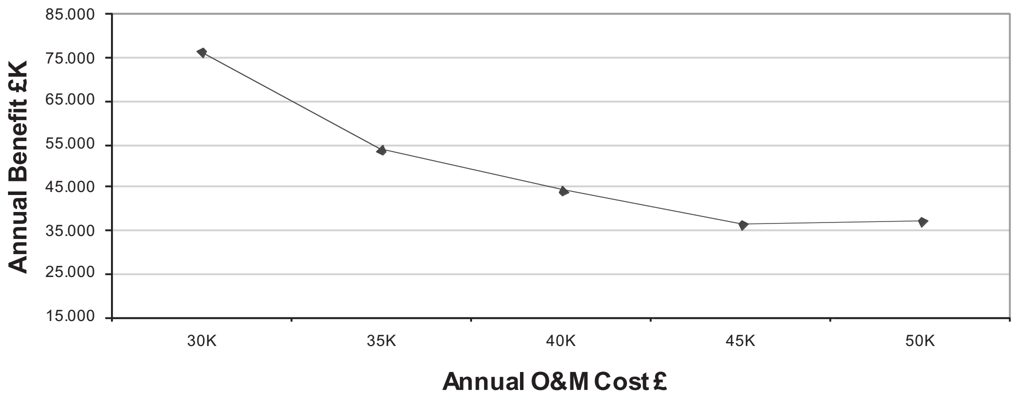

Figure 15. Impact of O&M Cost Variation on Offshore WT CM System Benefit

4.3 Impact of Condition Monitoring System Effectiveness on Economic Benefit

All the previously evaluated cases have assumed that the CM system is 100% effective in diagnosing the WT sub-component status. Practical difficulties encountered with CM systems in the field indicate that this assumption does not hold true. Therefore it is beneficial to obtain an indication of how the economic benefit of WT CBM is influenced by the ability of the CM system to reliably diagnose future failures. This is achieved by introducing a CM effectiveness probability: a measure of how likely the CM system is to successfully detect and diagnose (and hence successfully repair) an incipient fault. This is modelled by introducing uncertainty into condition-based repair of the sub-components: instead of this procedure being carried out with certainty, there is a probability that the condition-based repair is unsuccessful. Figure 16 illustrates the impact of this CM effectiveness on the economic benefits of CM. The pessimistic (£50K per annum) and optimistic (30K per annum) case for O & M actions are plotted in order to establish the envelope of values for which the CM system is economically justified.

This final result reflects the difficulties in practical implementation of WT CM systems, cited in many circles as a hurdle to cost-effectiveness, not least by wind farm operators themselves. To some extent the results are intuitive, with the calculated CM benefit generally reducing with respect to reduced CM reliability. Figure 16 indicates that in order for condition-based maintenance to be more cost-effective than periodic maintenance for the conditions evaluated, the condition monitoring system should diagnose problems accurately in over 60% of cases (for optimistic O & M costs), and 80% or more for pessimistic O & M costs. If the accuracy of the system falls below these benchmarks, the system is no longer economically justified. The more expensive maintenance actions become, the better the performance of the

CM system needs to be to justify itself economically. The fact that the benchmark for cost-effectiveness changes so significantly in relation to O & M cost indicates that the result may be sensitive to other key assumptions, such as sub-component reliability. It would be of interest, in future work, to establish the most influential variables, in order to assess the 'conditions for success' for an offshore WT CM system.

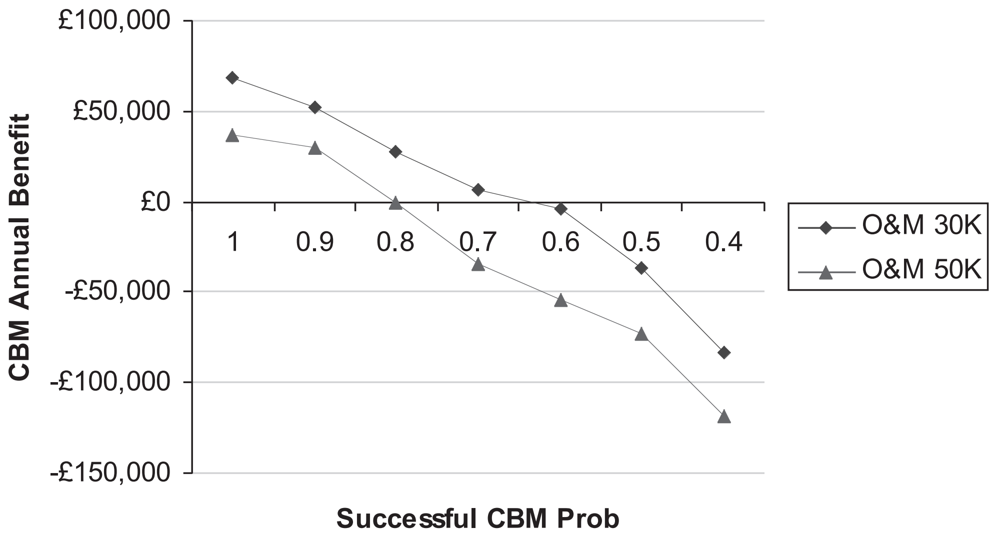

Figure 16. Offshore Wind Turbine Condition Monitoring Benefit

6. CONCLUSIONS

A set of models able to quantify the economic benefit of condition monitoring systems for 5 MW offshore wind turbines has been presented in this paper. The models were derived using methods from different research areas and data from various available sources. A base case showed that the economic case for offshore WT CM is clear if the O&M costs are fairly optimistic (three times onshore) and the CM system is 100% effective. The possible dependence of the measured benefit on the O&M cost was investigated within bounds suggested by an industrial collaborator: this showed significant coupling between the two quantities. Nevertheless, in theory an economic case for CBM could be established: however this is based on the premise that the CM system can detect every incipient failure. Finally, the capability of the CM system to perform its function was explored in order to evaluate the possible impact on the cost-effectiveness of offshore WT CM. The results show that in order to be cost-effective, the CM system must provide accurate diagnosis in around 60% – 80% of cases, depending on the cost of maintenance actions. It remains to be seen if offshore WT CM systems are able to deliver the reliability and robustness necessary in order to fulfil the significant potential of such systems.

Future work will challenge the assumptions made in the models, particularly as regards modelling of spurious CM-informed diagnosis. Changes in maintenance practice, condition monitoring equipment, cost functions, detailed modelling of equipment life stages and optimisation of maintenance under uncertainty will also be addressed. Multiple WTs dependant on a common resource such as maintenance crews or spare parts could be more explicitly included as constraints. It is acknowledged that although useful, the conclusions reached in this paper may be highly dependent upon the input assumptions and, as such, should be interpreted with care. Finally, this approach could be extended to quantify CM benefit for any plant item where the economic case for such systems is unclear.

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