Towards Quantification of Condition Monitoring Benefit for Wind Turbine Generators

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Abstract

Condition monitoring systems are increasingly installed in wind turbine generators with the goal of providing component-specific information to the wind farm operator and hence increase equipment availability through maintenance and operating actions based on this information. In some cases, however, the economic benefits of such systems are unclear. A quantitative measure of these benefits may therefore be of value to utilities and O&M groups involved in planning and operating wind farm installations. The development of a probabilistic model based on discrete-time Markov Chain solved via Monte Carlo methods to meet these requirements is illustrated. Potential value is demonstrated through case study simulations.

1 Introduction

Wind power is currently regarded by many policy makers and utilities as the renewable energy source most suited to delivering desired targets on carbon emission reductions and diversity of supply. For this reason major utilities are driving forward with planning and construction of wind farms, with over 10GW wind capacity currently in the UK planning system alone [1]. Additionally, recent UK policy documents have re-iterated government support for the wind industry in the form of the renewables obligation until at least 2027 [2]. If these trends continue, future utilities will have generation portfolios comprising a substantial proportion of wind power.

This recent rapid construction of wind farm capacity has also resulted in widespread installation of condition monitoring (CM) systems for wind turbine generators (WTGs). These systems provide information to the wind farm operator, with the goal of improving operational efficiency via more informed decision-making. As the number of operational wind farms increases, more focus will be placed on effective and efficient use of these systems, which has not been a priority to date. Wind farm operators are keen to manage their plant as economically as possible: therefore they will select a maintenance policy which reflects this. Any prospective maintenance policy based on condition information must have clear financial benefits: else the initial outlay for the CM system and associated costs cannot be justified.

This paper argues that via modelling a WTG and its sub-components in a Markov Chain solved via Monte Carlo simulation (MCS), it is possible to evaluate the impact of a CM system on the performance of an onshore wind turbine over its operational lifetime. This impact is based on how the condition information is used: for example it may be used to manage and optimise maintenance. By comparing various output metrics with those obtained via other maintenance policies (i.e. scheduled), the value of such a system may be quantitatively evaluated. The set of models being developed for this purpose are presented in this paper, and will begin to address the following questions related to WTG CM:

- What is the value of WTG CM?
- Are WTG CM systems currently cost-effective for onshore conditions?
- What are the necessary conditions for cost-effective WTG CM?

These questions are interesting for several reasons: perhaps the most insightful is that few wind farm operators would be able to give a definitive answer. This paper aims to move towards these answers based on a combination of mathematical models which aim to capture the nuances and subtleties of this problem. A variety of data sources are used and operational experience from industry is taken advantage of.

2 Overview of WTG CM Systems and their Modelling

Most modern WTGs are now manufactured with some form of integrated CM system: such systems are commonly based on vibration monitoring of the WTG drive-train [3] as well as temperature of bearings, machine windings etc. Additionally, several emerging systems are commercially available based on technologies such as lubrication oil particulate content and optical strain measurements [4], [5].

Figure 1 illustrates four WTG 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.

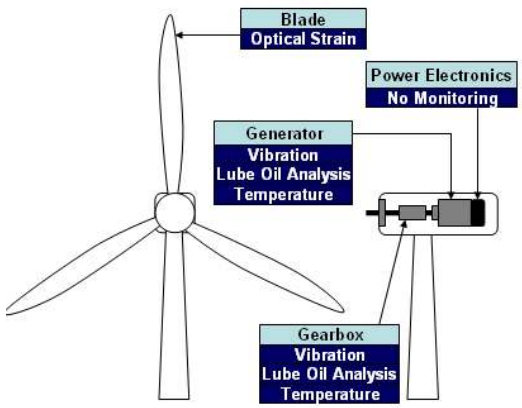


Figure 1: Selection of WTG Monitoring Options

[6] and [7] provide particularly insightful reviews of the state of the art in WTG CM systems. Several other systems have been developed, such as the blade monitoring system presented in [8], and the holistic set of intelligent models developed in [9]: however temperature and vibration are the main tools used in commercially available systems.

Given that the CM system is monitoring the status of a set of components, capturing the deterioration process of those components is vital. When this process is adequately represented, condition monitoring can be simply modelled as knowledge of the current state. A myriad of research related to this area of ‘deterioration modelling’ and maintenance modelling exists in literature, with many interesting applications, providing useful insight for this work. References [10] and [11] 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 [11] uses sensitivity studies, Marseguerra [10] 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 [12] and [13]. Sayas and Billinton [14], [15] 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 notable contributions in the fields of oil-filled circuit breakers [16], water infrastructure [17], and road networks [18], [19].

Continuous- time models with analytical solution are favoured by most authors: however this can be problematic when representing more complex systems and processes. In this sense, discrete-time models solved via simulation provide a degree of insight and flexibility which is essential to capture the nuances of operational activities. Therefore, a discrete-time simulation-solved model is adopted in these studies.

3 WTG Asset Management Modelling

In order to represent the various facets of the complex problem of quantifying the effects of CM on WTGs, a multi-level modelling approach is being adopted, as shown in figure 2.

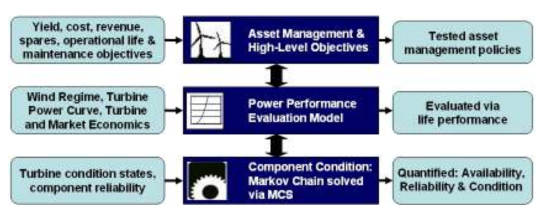


Figure 2: Multi-level WTG Representation

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.

3.1 WTG Sub-Component Models

The sub-component representation of a physical system has been implemented in several different ways in literature, as shown in Figure 3.

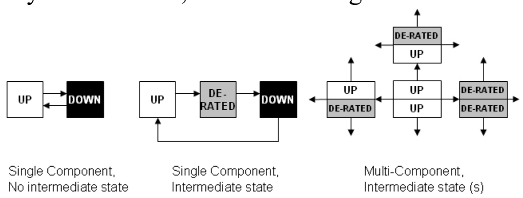


Figure 3: Sub-Component Models

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 intermediate states and thus the CM aspect cannot be captured. 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 these studies.

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. Once these issues are addressed, the state-space of the Markov model is effectively defined.

3.2 Modelled Components

Two main sources of information were used to determine which of the WTG sub-components should be included in the modelling: published sub-component reliability data; and wind farm operational experience.

3.2.1 WTG Sub-Component Reliability Data

Reliability data for wind turbine sub-components is readily available. This is primarily due to the significant (and growing) number of wind farms of various age, type and location in existence across the world. This information represents a useful starting point for modelling of the wind turbine sub-components, ultimately for use in the condition monitoring evaluation study. A summary plot of three studies containing WTG sub-component reliability data are shown in figure 4: these have been taken from various published sources (Top-left, clockwise: [21], [22] and [23]).

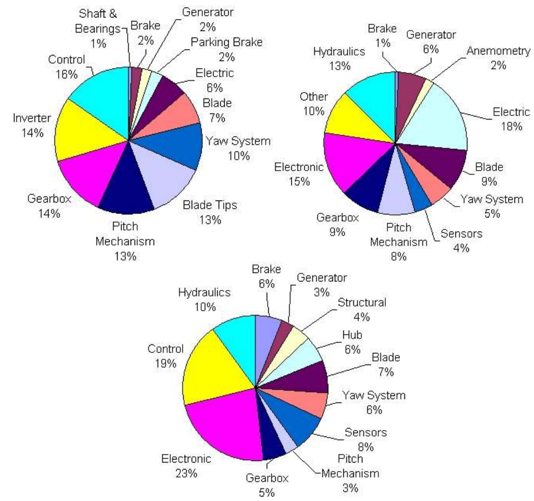


Figure 4: A Selection of Wind Turbine Reliability Studies

The data plotted in figure 4 is predominantly characteristic of the experiences of Danish and German utilities. A sizable chunk of failures are electronic related, corresponding to small downtime and relatively convenient replacement. Indeed, it is important to note that these results reflect only relative failure frequency: not duration of downtime, or cost of components. Hence, it is been recognised that other factors beyond the failure rate should be considered.

3.2.2 Operational Experience

Dialogue with a UK utility engaged in wind farm O&M yields interesting contrast with published results as outlined in the previous section. Although it is not possible to quantify the various relative WTG failures without access to the data, it is clear through this dialogue that the most significant operational failures are associated with the gearbox and generator components. The reasons for this high significance can be summarized:

- 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 a gearbox replacement is of the order of 700 hours. A recent report detailing operational activities at the Scroby Sands offshore wind farm [24] appears to back up the conclusions above, with gearbox bearing problems the most prevalent.

For the studies conducted in this paper, a 4–component model comprising generator, gearbox, blades and power electronics system was chosen (see figure 1). The gearbox and generator were included for the reasons outlined above. Blades were also included as there are emerging methods of monitoring these, and although logistical problems of transporting such awkward components are not explicitly modelled, it is expected this will be a factor in later iterations of this model. Finally, in order to accurately re-create the overall wind turbine failure rate, the power electronics was included even though monitoring capability is not modelled.

3.2.3 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 [25]) 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 [26]. 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.

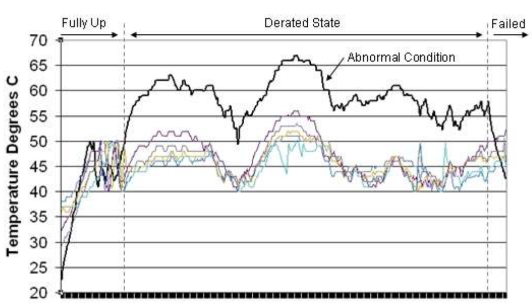


Figure 5: CM System Categorisation

Figure 5 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 then, how the physical state of the WTG component corresponds to its modelled state in the Markov chain.

Recall that the components to be modelled are those shown in figure 1: the states of those components may be categorised in the manner shown in figure 5, using the various CM methods available. Finally the state-space must be defined based on this information, and the transition probabilities between states deduced.

3.3 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 6 shows a sub-set of the state space and a key indicating the identity of the components.

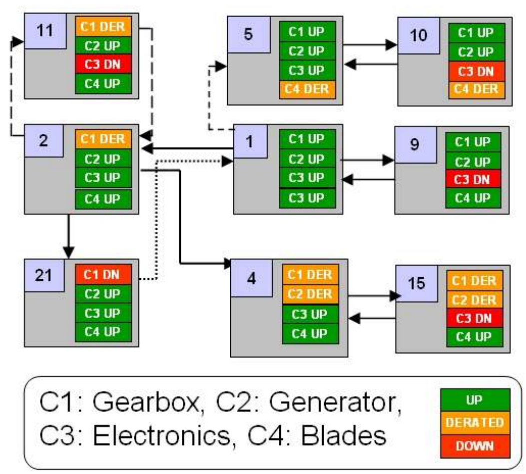


Figure 6: Sub-Set of WTG State-Space

The total possible state space is 52 states: however this was reduced to 28 via simplifying assumptions, the most influential being:

- The probability of simultaneous failure events is considered insignificant
- Components must transit to derated state before outright failure (except electronics)

Validity of these assumptions increases as the time resolution of the model approaches continuous time i.e. small discrete time periods.

3.4 Transition Probabilities

Ideally the transition probability matrix (TPM) which governs the behaviour of the system over the discrete time periods 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 3.2.1) 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 output metrics. Additionally, the probabilities can be influenced by comparing the model condition trajectory to that of a monitored turbine in operation. 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 is providing a direct input into shaping the behaviour of the model.

3.5 Turbine Yield Modelling

The yield model consists of two parts: a power curve model and a wind model. The power curve used in these studies, shown in figure 7, is a 2MW rated machine – although any curve could be used. It has characteristic cut in, rated and cut out wind speeds of 4, 14 and 25m/s respectively.

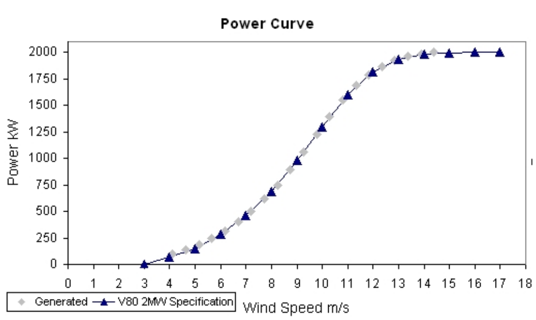


Figure 7: 2MW Turbine Power Curve

The wind speed is sampled at each simulation trial, from a probability-partitioned data set at intervals of roughly 0.5m/s, giving a capacity factor of 0.22. The sampling is based exclusively on the probability of the partitioned sample, with no correlation between the samples. This is an aspect of the model which is currently being reviewed: it is anticipated that a time-series model will be implemented in the near future. This will enable realistic auto-correlations to be captured, which is especially relevant at high model resolution (i.e. hours rather than weeks).

3.5.1 Yield Revenue Calculation

Turbine revenue is calculated from the volume of energy (MWh) generated, and is dependent on the following equation:

$$\mathrm{Re}\,venue = \sum_{T=1}^{Trials} MWh_T \times \left[MP_{Elec} + MP_{ROC}\right]$$

Where MP_{Elec} and MP_{ROC} the market price of electricity and ROCs is 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.

3.6 Maintenance Models

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

- Scheduled – Perform maintenance at set intervals (~Every 6 months)
- Risk/Condition Based – Maintain according to condition rule policy

It is noted that both approaches will inevitably involve some amount of reactive maintenance. Additionally, some maintenance and repair actions are subject to weather constraints (see table 1): these are typically set by the owner/ operator for health and safety reasons.

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 (NEG Micon turbines)
10	No lifting roof of nacelle
7	No blade removal
5	No climbing met masts

Table 1: Maintenance Weather Constraints

It is assumed that downtime for unplanned outages involving nacelle components is highly variable and uncontrolled, whereas planned maintenance actions are carried out with certainty if weather conditions are favourable: reflecting the benefit of a more pre-emptive approach to maintenance. The modelling of downtime is dependent only on the transition probabilities: alternative methods using 'downtime distributions' derived from SCADA data will be investigated in future work. The Markov model has the flexibility to handle different behaviour both short-term (in-maintenance, weather-constrained, operational) and long-term (modelling life-cycle stages). A TPM with suitably adjusted transition probabilities can be used for these situations.

3.6.1 Maintenance Costs

The baseline maintenance costs for a 2MW WTG were taken as £10K per year. If 6-monthly maintenance is adopted, this corresponds to £5K per maintenance action. Therefore the (planned) maintenance costs of a Risk/ CBM policy can be calculated as a yearly proportion, depending on the frequency of maintenance actions. Table 2 illustrates the rules used to model these maintenance costs.

Policy	Frequency/ Year	Cost per Turbine
Scheduled	2	£5K per 6-month interval
Condition-Based	As required (F)	£(F x 5K) per year

Table 2: Planned Maintenance Costs

In addition to scheduled maintenance costs, unplanned costs for replacement or repair of major WTG 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 WTG revenue stream (of course any potential yield revenue is also lost while in the down state). Replacement and repair costs for the key WTG components are shown in table 3.

WTG Component	£K Replacement Cost	£K Repair Cost
Gearbox	100	10
Generator	50	5
Blade	70	7
Electronics Sub	5	0.5

Table 3: Component Replacement & Repair Cost

The repair costs are modelled deterministically, but this is another area of the model where increased detail could be accommodated. 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.

3.6.2 Scheduled Maintenance Regime

The most widely practiced maintenance paradigm in any industry is scheduled 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. 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 (see table 1) and are assumed to be carried out every 6 months.

3.6.3 Risk/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 WTG operator would observe (manually or through an automated system) the trajectory of various instrumented WTG 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 8 for a simple illustration of this concept.

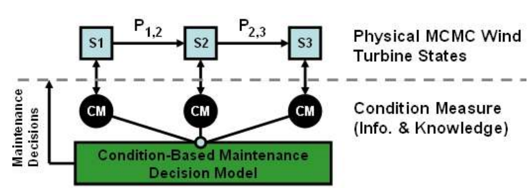


Figure 8: Markov Model Captures CM Info.

An implicit assumption in this approach is that the CM system can infer the current equipment condition with certainty. Therefore, the model as it stands does not address the issue of possible spurious CM diagnosis: for the analysis presented in this paper the assumption is held.

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:

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

Where 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 9. The reason only states 2-8 are included is that these are the intermediate operational states where the CM knowledge can be taken advantage of.

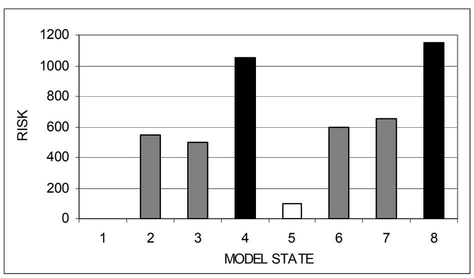


Figure 9: Risk Associated with Each State

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 WTG. 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 very clear due to large differences between risk values.

Table 4 shows the wait time in days for each risk interval corresponding to the values in figure 9: the time values in table 4 were determined by conducting a simple sensitivity study. As with scheduled policies, when the wait time has elapsed, the maintenance will only be carried out if weather conditions are favourable. Using the equipment state and wait times, the 6-monthly scheduled maintenance policy can be replaced with a risk/ condition based policy.

States	Risk Threshold	Risk Level	Wait Time Days
4,8	RISK>1000	HIGH	7
2,3,6,7	200>RISK>800	MED	28
5	150>RISK	LOW	168

Table 4: Wait Times- Linking Condition Information to Maintenance Actions

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

3.7 Model Flexibility

One of the main reasons that a discrete-time Markov chain solved via simulation was used in these studies was the flexibility of that approach. This flexibility enables many aspects of this problem to be captured, detail which is essential to the adequate representation of the system. One aspect of particular interest is how time (or other variable!)-dependence can be achieved with a multi-stage model: how the failure behaviour of the system sub-components evolves in time, or as recently hypothesised, with respect to the on-site weather conditions [27]. For the moment this is not considered, and the case studies presented are based on the models as described.

3.8 Statistical Significance

The program was developed to include a flexible approach to the number of trials to be run. Essentially the program can be run either in order to generate a 'real' condition history (20 simulated years~7000 trials), or in order to obtain statistically sound values (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 28 possible 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 WTG 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 WTG 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:

$$L = \pm \frac{Z \times SDev}{\sqrt{N}}$$

Where *SDev* 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 is equal to 1.65. Using this statistical tool 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.

4 Case Studies

A number of case study simulations are presented to illustrate the capabilities of the set of models as described in previous sections. The models were implemented in Fortran code and solved within five minutes in all cases. These studies are run at a time resolution of 1 day.

4.1 Model Metric Benchmarking

A short study was conducted to confirm that the models produce output metrics with a sufficient level of accuracy as compared with real figures. Table 5 shows a summary of the output, which is visualised in figure 10.

	Annual Metric	Average	SDev	Confidence Limits	
	Availability %	97.51419	0.80723	97.75737	97.27102
	Yield MWh	3728.513	31.1716	3737.904	3719.123
	Revenue £	159747	13629.97	163853	155641
Failure Rates	Overall Turbine	2.013333	0.219102	2.079337	1.947329
	Gearbox	1.31	0.155216	1.353425	1.259908
	Generator	0.21	0.056452	0.223673	0.189661
	Electronics	0.43	0.082911	0.45081	0.400857
	Blade	0.07	0.041773	0.086751	0.061583

Table 5: Model Metrics for Scheduled 6-Monthly Maintenance

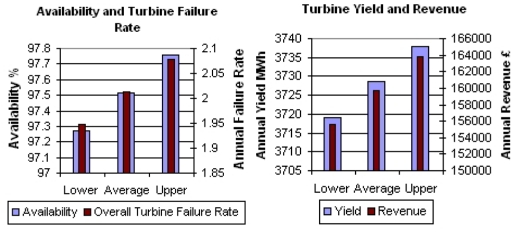


Figure 10: Availability, Failure Rate, Yield and Turbine Revenue with Confidence Limits

A figure of 98% is often quoted for wind turbine availability, which compares fairly well with the 97.5% mean value produced by the model: although the upper confidence limit is only 97.76 and so perhaps this requires slight adjustment.

The annual yield in MWh can be estimated by using a simple calculation:

$$MWh_{YEAR} = Hrs_{YEAR} \times Rating_{MW} \times CF \times A_{\%}$$

Assuming a capacity factor (*CF*) of 0.22 (see section 3.5) and availability ($A_{\%}$) of 98%:

$$MWh_{YEAR} = 8760 \times 2 \times 0.22 \times 0.98 = 3777$$

This can be considered adequately close to the simulated mean value of 3728MWh (see above). Based on this yield, the annual revenue can be calculated:

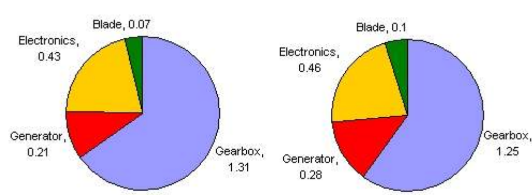
$$\mathrm{Re}\,venue_{YEAR} = MWh_{YEAR} \times (MP_{ROC} + MP_{ELEC}) - C_{O\&M}$$

Annual O&M cost ($C_{O\&M}$) is taken as £10,000 per turbine. MP_{Elec} and MP_{ROC} are the market price of electricity and ROCs taken as £36/MWh and £40/MWh respectively, giving:

$$\mathrm{Re}\,venue_{YEAR} = 3777 \times (40 + 36) - 10{,}000 = £277{,}052$$

The large disparity between this value and the simulated £159,747 can be attributed to real $C_{O\&M}$ being very much larger than the assumed £10,000 in the above calculation. Indeed, replacement of major components can have a large impact on the revenue stream, and this feature is captured in the models. Thus, while for individual years the turbine may reach high levels of revenue, these may be offset by years where a major unplanned outage occurs.

Figure 11 shows the individual component failure rates. A comparison is made between the desired annual failure rates (based on reliability data and industry information: 'Input values') and simulated values obtained from the program.



Simulated Values Input Values

Figure 11: Key Component Annual Failure Rate

In conclusion, it can be seen that the presented model simulations provide realistic outputs for WTG and sub-component reliability, energy yield, revenue and availability. With this established, an evaluation of condition monitoring can be conducted.

4.2 Condition Monitoring Evaluation

In this section a comparison is made between a 6-monthly scheduled maintenance policy and a condition based policy. The goal is to begin to answer the questions posed in the introduction.

Each simulation was run 30 times, in order that statistical tests can be made. Figure 12 shows the annual turbine revenue for the individual simulations. This first result is interesting as it shows immediately that in some cases the scheduled maintenance policy will out-perform the condition-based one, in roughly one third of the cases.

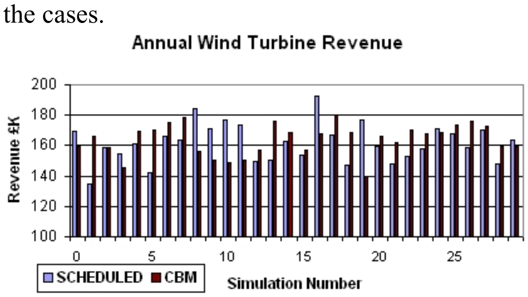


Figure 12: Simulated WTG Revenue

Considering the turbine failure rate for each case in figure 13 it can be seen in all simulation cases that the overall turbine failure rate is lower for the condition-based maintenance policy. This is fairly intuitive since in the CBM cases wait times are shorter and correspond to the needs of the equipment.

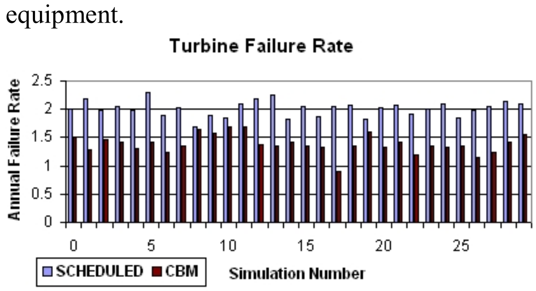


Figure 13: Simulated WTG Failure Rate

Equally intuitive is the fact that the maintenance effort for the condition-based results varies over the sample: this can be clearly seen in figure 14. The overall mean annual CBM frequency of 4.3 is more than double the scheduled value of 2 actions per year. Since the CBM policy is dependent on the condition of the monitored components, the frequency of maintenance actions is strongly coupled with the number of potential failures experienced by the WTG over its operational lifetime. In general, more reliable components mean less maintenance effort.

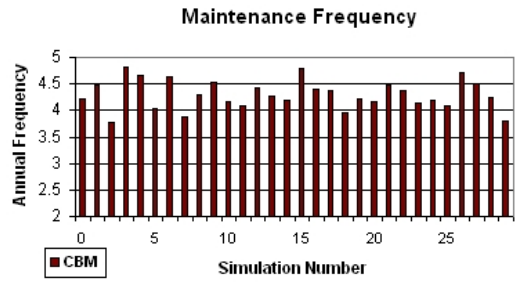


Figure 14: CBM Maintenance Frequency

Table 6 summarises the average values taken from the 30 simulations, directly comparing the outputs of the different maintenance policies.

Metrics (Annual)		6-Monthly Scheduled	Condition-Based
Availability %		97.22	97.02
Yield MWh		3718	3699
Revenue £		161738	164021
Maint. Freq./ Year		2	4.30
Failure Rate	Overall Turbine	2.01	1.39
	Gearbox	1.27	0.78
	Generator	0.20	0.08
	Electronics	0.46	0.47
	Blades	0.08	0.06

Table 6: Annual Mean Values for Simulation Output Metrics

One of the central points of interest is how the revenue streams of the two approaches compare. Figure 15 shows a mean annual value of just over £2000 for the condition-based maintenance, relative to the widely-used scheduled maintenance policy. Over the 20 year life of the WTG this represents a saving of £40,000 per turbine, so for a medium sized wind farm of 20 turbines this equates to significant additional revenue.

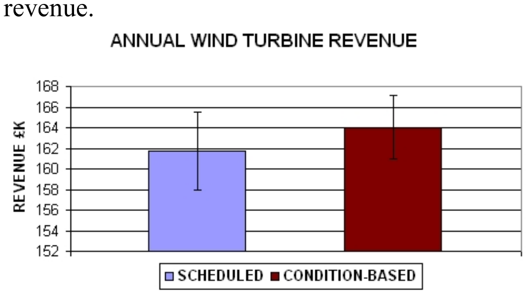


Figure 15: Comparison of Annual WTG Revenue with Confidence Level

It should be noted however that the possible ancillary costs of the monitoring, i.e. a human expert or extended automated interpretation system, have not been included in the model. In addition, the monitoring system itself is made up of components, especially transducers, which will have to be replaced during the operational lifetime of the wind turbine. This, coupled with figure 15, seems to conclude that the case for onshore condition monitoring systems for wind turbines is currently borderline cost-effective.

5 Conclusions

A set of models to quantify the benefits of condition monitoring systems for wind turbines has been presented in this paper. The results, especially figure 15, indicate that the benefit of onshore WTG CM is marginal for the conditions evaluated here. This is a fairly intuitive result given the low-economic margin of wind plant in general: however it has been backed up through the detailed modelling presented in this paper. This conclusion appears to be in keeping with the opinion of electric power industry utilities, understandably reluctant to change their maintenance strategies unless clear economic benefits of condition-based maintenance for WTGs can be demonstrated. It must be noted however that the value of the information provided by WTG CM systems may have some benefit beyond informing maintenance, such as information regarding how turbines react to specific operating conditions.

This paper has demonstrated that the value of a WTG CM system can indeed be quantified. Future work will be geared towards increasing model accuracy via less simplifying assumptions and better characterisation of the subcomponent deterioration behaviour. In addition, further model simulations with different conditions may yield interesting results. The effects of wind regime, turbine ratings, and reliability of the CM system itself are issues which will be tackled in future work, along with an evaluation of WTG CM in the offshore environment.

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