Condition Based Maintenance for Offshore Wind Turbines: The Effects of False Alarms from Condition Monitoring Systems

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ABSTRACT: As wind turbines increase in size and move offshore, operations and maintenance procedures need to be optimised to increase reliability, safety and maximise cost effectiveness. The practice of installing condition monitoring systems to allow the real time monitoring of assets as a means to achieve these goals is becoming more wide-spread. This allows operators to adopt a condition based maintenance approach that theoretically allows reduced costs over both preventive and corrective maintenance strategies.
There have been several studies into the possible benefits and cost advantages of using a condition based maintenance strategy. However, few have examined the implications of system detection rates or false alarms. Many studies have assumed that condition monitoring systems will detect all the faults they are designed to observe. This will not be the case. Investigating false alarms or ignoring false positives in a remote offshore environment will incur costs that may alter the cost benefit of condition monitoring systems.
Probabilistic models are used in the paper to determine the possible benefits of using condition monitoring systems and the effect that system detection rates and false positives have on the reliability of the system. The methods used include Markov chains and time-series modelling.

1 INTRODUCTION

There has been growing support for the use of renewable energy. Of the different renewable technologies available, wind turbines have become the dominant technology in this area. The growth of the number and size of turbines installed worldwide has been large in recent years. In the UK, National Grid, the transmission operator, predict 26 GW of wind capacity in 2020 (Smith, Rimmer, Durk, & Wilkinson 2011). If British Government legislation is effective then offshore wind will provide 17 GW of this energy (DECC 2013).

The capital costs involved in the development and installation of wind farms have also increased. To ensure the maximum return on investment, operators are looking to maximise turbine availability and minimise Operation and Maintenance (O&M) costs. Condition Monitoring (CM) systems and Supervisory Control and Data Acquisition (SCADA) systems allow Condition Based Maintenance plans (CbM) to be used which offer possible O&M savings over both Failure based Maintenance (FbM) and Preventive Maintenance (PM) strategies (García Márquez, Tobias, Pinar Pérez, & Papaelias 2012).

To show if savings can be realised using CbM a cost benefit study must be completed. Cost benefit analyses for CbM have been produced for other industries including nuclear (March 1994), pharmaceuticals (Rajan & Roylance 1996), power transmission (Jones 2008) and railways (García Márquez, Lewis, Tobias, & Roberts 2008). These models rely heavily on reliability data and CM system detection rates. This is used in conjunction with information on component replacement costs, loss of revenue, environmental, safety and network performance. A particular concern to offshore wind turbines are sea states and weather which limit access for repair and inspection work.

Turbine reliability data has been collected from onshore wind farms since the late 1980s. The most popular databases are shown in Table 1. Offshore databases are smaller in number, size and duration. Information from the Dutch offshore farm, Egmond aan Zee (Noordzee Wind CV 2008, Noordzee Wind CV 2009, Noordzee Wind CV 2009), and several of the

UK offshore farms, including Scroby Sands (BERR 2007b) and Kentish Flats (BERR 2007a), have been used widely in literature (Faulstich, Hahn, & Tavner 2011, Dinwoodie, McMillan, & Quail 2012, Feng, Qiu, Crabtree, Long, & Tavner 2011).

Andrawus et al. (2006) examine the effect of CbM on 26 turbines of 600 kW. Asset life cycle analysis is used in conjunction with component failure rates to show a total saving in excess of £180,000 over 18 years. Byon and Ding (2010) demonstrated benefits from adopting a season-dependant dynamic CbM strategy using Markov states and Monte Carlo simulations. The results showed a reduction in O&M costs of £10,330 per annum. This was a further reduction from a static CbM strategy of £7,700. Many parameters are examined in these studies but there is no analysis for the effects of CM system detection rate or false alarms in these two studies.

Nilsson and Bertling (2007) model the effects of changing maintenance strategy on offshore turbines to include CbM, also using life cycle analysis. Their simulation model used cost information and reliability data obtained from Elsam (now DONG) Energy for offshore turbines. For an entire wind farm, the availability would need to increase by 0.43% to make the CM systems profitable. Also 47% of the corrective maintenance completed would need to have originally been PM. This figure shows the amount of work a CM system needs to complete to become an asset to a farm. It does not take into account the level of effectiveness a CM system must obtain to add value or examine the case of false alarms.

McMillan and Ault (2007) use Markov Chains to model the states of 5 MW offshore turbines and the effects that CbM has on O&M costs. They found that for an individual turbine cost savings of approximately £75,000 per annum when using CbM. This was for a CM system that is 100% effective at finding the desired fault modes. A parameter analysis was completed on CM system effectiveness and found that it needed to obtain a 60% effectiveness level to be cost effective on an optimistic model. This work does not examine the effect of false alarms on maintenance.

The CONMOW project run by the Energy Research Centre of the Netherlands (ECN) investigates condition monitoring systems for offshore turbines. As part of the project, a parameter analysis was completed looking at CM system effectiveness and false alarms (Wiggelinkhuizen, Verbruggen, Braam, Rademakers, Xiang, & Watson 2008). The paper added various amounts of additional false alarms to an existing CM alarm database. At a 60% CM fault detection rate, when the false alarm rate was increased from 10% to 50%, the reduction of repair costs changed from 13% to 10%. The study examines the addition of false alarm rates but does not treat them as intrinsic to the CM system itself.

The previous work shows that the benefit of CbM is affected by a wide range of parameters. Some of these parameters have been explored more than others and values such as CM system detection and false alarm rates have relatively unknown impacts on the cost effectiveness of CbM. Some basic information is becoming available about CM system detection rates for major subassembly. There is little information about actual false alarm rate of CM systems.

Table 1: Popular Onshore Failure Databases

Database	Information
LWK	A German database concerning wind farms installed in the Schleswig-Holstein region between 1993 and 2006.
WMEP	A long running German study that has been the framework for other studies. 1500 turbines were tracked between 1989 and 2006 with an average rating of 167 kW.
WindStats Germany	A German database updated quarterly between 1996 and 2008. 4924 turbines were tracked at its peak.

In this paper, a model is built to examine these parameters further. Some simple system detection rates are used as basis in the model. False alarms are generated independently for each sub assembly using a false alarm rate for different failure modes. These two parameters are varied to show the effect on the financial benefit of CM systems.

2 METHODOLOGY

The nature of failures in wind turbines can be modelled as both stochastic and deterministic processes. The wind is a stochastic process, leading to turbines having complex loading and failure patterns (Byon, Ntaimo, Singh, & Ding 2011). Markov chains have been used widely, as discussed previously, to represent such processes accurately.

In existing databases sub assemblies and components are often assigned a failure rate to show reliability. Failure rate is shown in Equation 1 where $f(t)$ is the number of failures over an observed time period and $N(t)$ is the duration of the time period.

A discrete time Markov chain has a finite number of states. After each time step, there is the chance of a change of state known as the transition probability. When discussing Markov chains with regards to reliability, the system begins in an operational state and has a chance to move to a deteriorated state. The transitional probability is based on the failure rate shown in Equation 2. The transitional probabilities are then grouped together into a state transition matrix. An example matrix is shown in Equation 3 for a two state Markov chain. The failure process in a wind turbine can be represented as both a two and three state Markov chain. Three state chains, used by McMillan and Ault and Abeygunawardane and Jirutitijaroen, have an intermediate state where a component is in a state of deterioration where repair is possible. It is in this deteriorated state that they measure the effectiveness of CM systems.

$$\lambda(t) = \frac{f(t)}{N(t)} \tag{1}$$

$$U(t) = 1 - e^{(-\lambda t)} \tag{2}$$

$$P = \begin{pmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \end{pmatrix} \tag{3}$$

Hidden Markov models (HMM) add a layer of complexity onto Markov chains. The core Markov chain is now unobserved and feedback from the system is given through an observation layer with its own statistical probabilities. Eddy (1996) states that they have been used in many fields including the generation of protein structural modelling. An example of a HMM is shown in Figure 1. In this example, when the system is in State 1, 'A' is most likely to be observed. When in State 2, a 'C' is most likely to be observed. When repeated multiple time, the output from the observable layer gives information about the hidden Markov chain. This is analogous to a CM system output which will attempt to predict the pending state of the sub assembly but will not be correct all the time.

It is this approach that Byon and Ding (2010) adopt in their work. Referred to as partially observed Markov decision process (POMDP), it is used to represent both the degradation of components and the ability of a condition monitoring system to derive a degraded state.

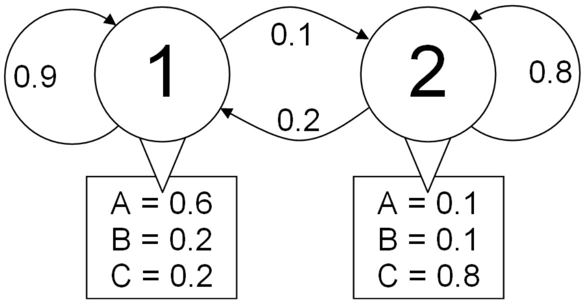

Figure 1: A simple HMM for a two state Markov chain

3 MODELLING

Throughout the remainder of this paper, CM system detection rate will refer to the ability of a CM system to detect a particular failure mode and flag this as an alarm. Likewise, CM system reliability will refer to the CM system's likelihood of showing alarms which are not present in the sub component or conversely, not alarming a state that requires action. Failure rates for both SCADA and CM sensors can be found for onshore turbines (Wilkinson & Hendriks 2007). However, the term CM system reliability is used to refer to errors within the system and that cannot be immediately cleared as a system fault.

Table 2: CM System Detection Rates

Sub Assembly	Detection Rate
Gearbox	50%
Generator	80%
Drive Train (incl. Main Bearing, High Speed and Low Speed Shaft)	40%

The model consists of wind turbine sub assemblies each represented by a two state Markov chains. These sub assemblies have been divided into the taxonomy suggested by Faulstich et al. (Faulstich, Durstewitz, Hahn, Knorr, & Rohrig 2008). This forms the hidden part of a HMM. An observable state transition matrix is used to represent the CM system output. This allows for the CM system detection rates for individual sub assemblies to be input. Further, it gives the possibilities of inserting false alarms, as an alarm can now be observed while the sub assembly is still in an operational state. It is assumed in the model that a false alarm allows causes 24 hours of lost production while the system is checked and the false alarm cleared. Figure 2 displays an example HMM used for each sub assembly.

Each sub assembly contains information on failure rates for major and minor faults, average downtime per fault, cost for component replacement, CM system detection rate and CM system reliability. The failure rates are based on NoordzeeWind reports (Noordzee Wind CV 2010), with the failure rates modified as suggested by Dinwoodie et al. (2012). These divide fault events into two categories. Major faults are those which exceed 24 hours of downtime. Minor faults are those that are cleared in less than that time. The CM system detection rates are based on those suggested by Weiss (2012) for the gearbox, generator and drive train. These numbers are shown in Table 2. No information could be found on likely CM system reliability and this was set initially to 99.99% reliable.

The component cost information was based on the work of Poore and Walford (Poore & Walford 2008). This gave 2004 onshore costs based on turbine size. The cost was adjusted to account for inflation to 2012 - set at 2.2% (CIA 2012). The additional cost of marinisation for offshore use was found using a factor of 1.27 (Dinwoodie, McMillan, & Quail 2012). Component costs were reduced for faults captured by CM system. It is assumed that CMS will allow the major component cost of the replacement to be saved. For example, a bearing failure in a generator may cause damage to the rotor and other components, leading to the replacement of the entire sub assembly. If the CM system detects the bearing fault early, then only

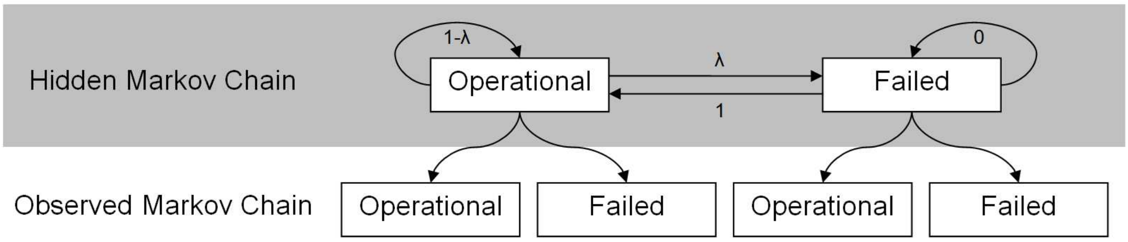

Figure 2: Example sub assembly hidden Markov chain used in the model

the bearings themselves may need to be replaced. Replacing the rotor and bearings in the generator of a 1500 kW onshore turbine in 2004 was \$52,850 while replacing the bearings alone cost \$3,300 (Poore and Walford 2008).

Other assumptions for the model include a cost of \$55 per MWh (Morton 2013) and a capacity factor of 33.3% based on the 2009 Egmond aan Zee value (Noordzee Wind CV 2010).

The model generates both hidden and observed states for the given number of Markov years for each sub assembly. It then counts and compares the observed and hidden states and notes any differences. Component costs and downtime hours for the year are then calculated and averaged out across the Markov years. A base line case is also computed where no CM system is used. As these failure rates are based on turbines that operate under regular inspection and maintenance, the base case is for a wind farm with a PM strategy. The cost formulae are given below in Equations 4, 5, 6 and 7. In the equations, C refers to component repair costs, $_{CMS}$ refers to a turbine with a CM system, $_{Base}$ refers to a turbine without a CM system, f refers to a failure not caught by the CM system, $_{CMf}$ represents a failure observed correctly, $_{fa}$ refers to a false alarm caused by the CM system and k refers to the number of failure modes for each component - in this model major and minor failures. When a failure is correctly identified by the CM system the downtime associated with the fault is reduced to 20%, a figure based on examples given by Morton (Morton 2013).

$$C_{CMS} = \sum_{i=1}^{k}(C_f + C_{CMf}) \tag{4}$$

$$C_{Base} = \sum_{i=1}^{k} C_f \tag{5}$$

$$DT_{CMS} = \sum_{i=1}^{k}(C_f + C_{CMf} + C_{fa} \tag{6}$$

$$DT_{Base} = \sum_{i=1}^{k} DT_f \tag{7}$$

This is done for each turbine in the farm and for each operational year. The annual downtime is multiplied by the cost of produced energy. This figure is added to the component cost to give an annual operational cost. Both baseline and CM system case costs are then levelised to represent net present value (NPV) and produce a wind farm availability figure. A discount rate of 4% is used.

3.1 *Convergence*

All models must produce results that are independent from the number of Markov years used in the simulation. Convergence refers to the point where the model produces the same result regardless of the number of years used. This is important for the accuracy of the model and to minimise the simulation run time. In Figure 3 the wind farm operational costs for the first year are plotted against the number of Markov years. Several techniques were employed to assess the convergence of the model based on Gelman and Shirley (2003). All simulations quoted in this paper use 2000 Markov years.

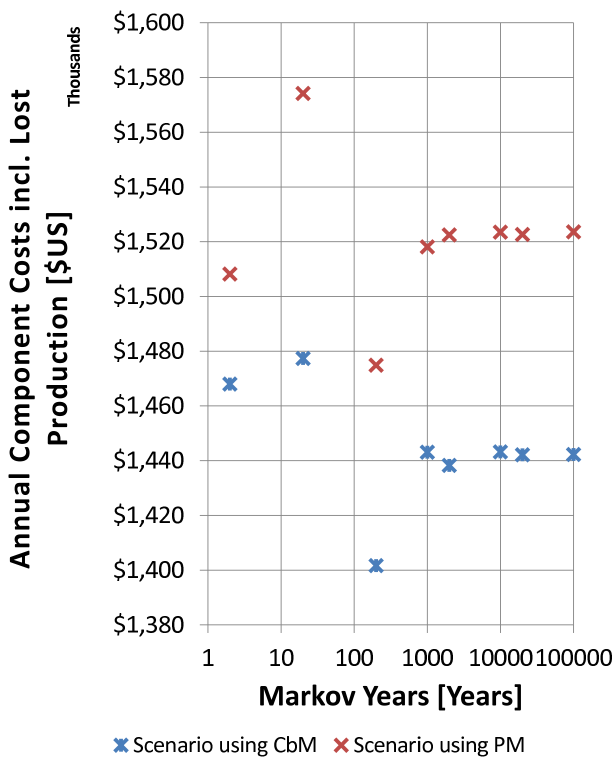

Figure 3: Convergence values of the simulation

4 RESULTS

4.1 *Basic validation against Scroby Sands*

In 2007, Scroby Sand wind farm spent approximately £1,634,000 on O&M costs (BERR 2007b). This number doesn't include the cost of lost production but does include labour costs. Scroby Sands is a UK offshore wind farm first commissioned in 2004 with 30 turbines of 2000 kW. This cost was adjusted for inflation to 2012 prices and converted into U.S. dollars based on the average foreign exchange rate for 2007 - $2.0012 (USD) to £1 (GBP) (X-Rates 2012).

This equates to a value of approximately $3,747,000. The model produced a component replacement cost (excluding the cost of lost production and labour) of approximately $4,378,000. This is a 17 % difference in costs.

A more direct comparison can be made for the farm availability. The average technical availability of Scroby Sands for 2007 was 83.83%. Technical availability is the time that the farm is available to generate 'expressed as a percentage of the theoretical maximum' (BERR 2007b), i.e. the 8760 hours in a year. The model produces a technical availability of 82.27%. This a 1.84% relative difference.

There are many other factors not included in the model such as turbine age or annual weather severity. So while this number may initially appear large the model is producing numbers that are in the correct order of magnitude. Additionally, the O&M cost is not broken down any further so the percentage of installation costs is unknown for Scroby Sands.

4.2 *Variation of CM System Detection Rate*

The remaining simulations in this paper use 30 turbines of 3000 kW for an operational life of 20 years. The CM system reliability rate is set at 99.99%. The known CM system detection rates as in Table 2 are applied throughout. The other sub assemblies have their detection rates varied from 90% to 50% in 10% increments. The results are shown in Figure 4. The figure shows that in each case, using a CbM strategy brings O&M cost savings over a PM strategy. The total operational costs over the lifetime of the wind farm for a PM strategy is approximately $132,100,000. At a 90% CM detection rate this reduces to $99,800,000 representing a saving of over 24%. At the lower CM system detection rate of 50% this reduces to 20.4%

The availability of the wind farm in the base case is 82%. This increases to over 90% with a CM detection rate of 50%.

4.3 *Variation of CM System Reliability*

The CM system detection rate was set to 50% for the unknown detection rates. The system reliability was then simulated as 99.99%, 99.9%, 99%, and 80%.

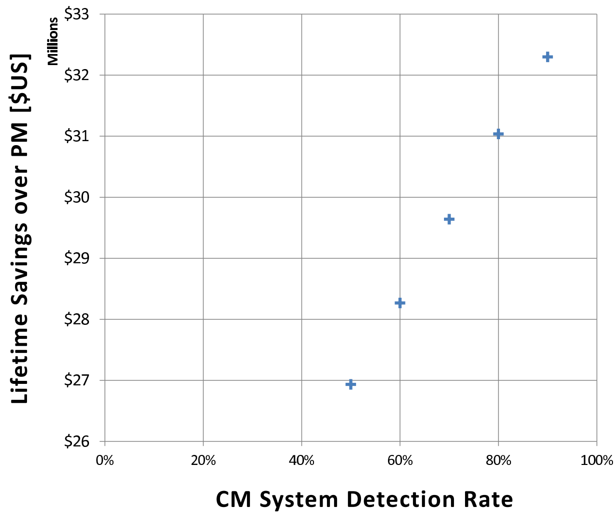

Figure 4: Lifetime savings compared to a PM strategy with different CM system detection rates

The life time wind farm availabilities are shown in Figure 5 against CM system reliability. In the figure the system reliability has been converted into an annual failure rate using Equation 2. A 99.99% reliable CM system gives an annual failure rate of 0.0001 and at 80% reliable this increases to 0.2231.

The availability drops from 90.0% to 88.9% as the reliability drops from 99.99% to 80%.

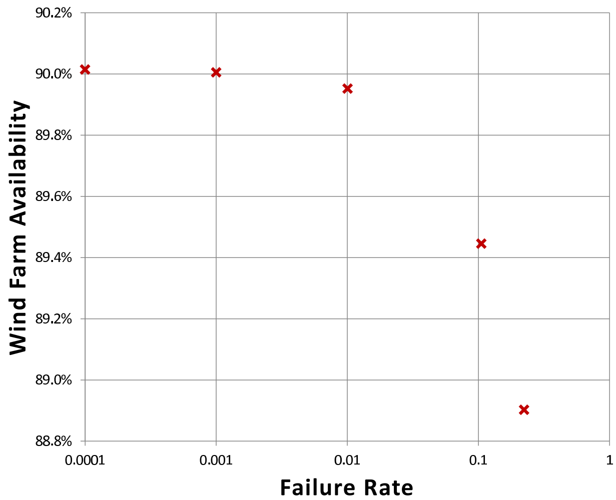

Figure 5: Wind farm lifetime availability plotted against 'failure rate'

Looking at the normalised lifetime costs associated for those reliabilities, for a decrease in system reliability from 99.99% to 90%, approximately an additional $282,000 is seen in lost production. When comparing the non levelised costs this figure is $322,223 which is the equivalent to 98.6 additional downtime hours per turbine per year.

5 CONCLUSIONS

A simulation model has been developed for use in the estimation of component costs - for both a PM and CbM strategy - using hidden Markov models. It shows that a CbM strategy has the ability to reduce operational lifetime costs by 20% over the PM equivalent when using some known detection rates.

With regards to the CM system reliability, a decrease in the reliability causes an increase in false alarms. These false alarms have an impact on the overall availability of the wind farm. The model has simulated this effect as reduction from 90.0% to 88.9% availability.

To improve the accuracy of the model, the cost model should be updated to include the installation and transport costs of the components. The securing of vessels and appropriate access windows also have an impact on availability and cost savings when analysing CbM (Dinwoodie & McMillan 2012). Adding the well documented effects of ageing on failure rates and annual weather variations effects on availability and capacity factor will go further to increase the accuracy of the model.

6 ACKNOWLEDGEMENTS

The work completed in this paper was made possible by the EPSRC funded Centre for Doctoral Training in Wind Energy Systems.

REFERENCES

Andrawus, J., J. Watson, M. Kishk, & A. Adam (2006). The selection of a suitable maintenance strategy for wind turbines. *Wind Engineering*, 1–18.

BERR (2007a). OFFSHORE WIND CAPITAL GRANTS SCHEME Kentish Flats Offshore Wind Farm. Technical Report December.

BERR (2007b). OFFSHORE WIND CAPITAL GRANTS SCHEME Scroby Sands Offshore Wind Farm. Technical Report December.

Byon, E. & Y. Ding (2010). Season-Dependent Condition-Based Maintenance for a Wind Turbine Using a Partially Observed. *IEEE Transactions on Power Systems 25*(4), 1823–1834.

Byon, E., L. Ntaimo, C. Singh, & Y. Ding (2011). Wind energy facility reliability and maintenance. *Handbook of Wind Power* ..., 1–31.

CIA (2012). Field Listing: Inflation Rate (Consumer Prices).

DECC (2013). Maintaining UK energy security.

Dinwoodie, I. & D. McMillan (2012). Sensitivity of Offshore Wind Turbine Operation & Maintenance Costs to Operational Parameters. In *42nd ESReDA Seminar*, Number May, Glasgow, pp. 11.

Dinwoodie, I., D. McMillan, & F. Quail (2012). Analysis of offshore wind turbine operation & maintenance using a novel time domain meteo-ocean modeling approach. *ASME Turbo Expo 2012*, 1–11.

Eddy, S. R. (1996, June). Hidden Markov models. *Current opinion in structural biology 6*(3), 361–5.

Faulstich, S., M. Durstewitz, B. Hahn, K. Knorr, & K. Rohrig (2008). Windenergy Report Germany 2008. Technical report, ISET.

Faulstich, S., B. Hahn, & P. J. Tavner (2011). Wind Turbine Downtime and Its Importance for Offshore Deployment. *Wind Energy 14*(July 2010), 327–337.

Feng, Y., Y. Qiu, C. J. Crabtree, H. Long, & P. J. Tavner (2011). Use of Scada and CMS Signals for Failure Detection and Diagnosis of a Wind Turbine Gearbox. In *Proceedings of EWEA 2011*, pp. 6.

García Márquez, F. P., R. W. Lewis, A. M. Tobias, & C. Roberts (2008, November). Life cycle costs for railway condition monitoring. *Transportation Research Part E: Logistics and Transportation Review 44*(6), 1175–1187.

García Márquez, F. P., A. M. Tobias, J. M. Pinar Pérez, & M. Papaelias (2012, October). Condition monitoring of wind turbines: Techniques and methods. *Renewable Energy 46*, 169–178.

Gelman, A. & K. Shirley (2003). Inference from Simulations and Monitoring Convergence. In S. Brooks, A. Gelman, G. Jones, and X.-L. Meng (Eds.), *Handbook of Makov Chain Monte Carlo*, Chapter 6, pp. 163–174. Chapmand & Hall.

Jones, D. (2008). The costs and benefits of condition monitoring in substations. *Transmission and Distribution and Distribution Conference and Exposition, 2008.*, 1–7.

March, R. (1994, July). Cost benefit analysis for condition monitoring. *Modern Power Systems 14*(7), 27.

McMillan, D. & G. Ault (2007). Quantification of condition monitoring benefit for offshore wind turbines. *Wind Engineering 44*(0).

Morton, B. (2013). The Value of Early Detection. *Wind Tech International*, 27–29.

Nilsson, J. & L. Bertling (2007). Maintenance management of wind power systems using condition monitoring systemsLife cycle cost analysis for two case studies. *Energy Conversion, IEEE Transactions ... 22*(1), 223–229.

Noordzee Wind CV (2008). Operations Report 2007. Technical Report October.

Noordzee Wind CV (2009). Operations Report 2008. Technical Report August.

Noordzee Wind CV (2010). Operations Report 2009. Technical Report November.

Poore, R. & C. Walford (2008). Development of an Operations and Maintenance Cost Model to Identify Cost of Energy Savings for Low Wind Speed Turbines. Technical Report January, NREL.

Rajan, B. S. & B. J. Roylance (1996). The development of a cost benefit analysis method for monitoring the condition of batch process plant machinery. In *Technology Showcase: Integrated Monitoring, Diagnostics and Failure Prevention*, Mobile, Alabama, pp. 13. US Department of Defense.

Smith, R., D. Rimmer, S. Durk, & E. Wilkinson (2011). Gone Green 2011 - Key Facts and Figures. Technical report, National Grid.

Weiss, A. (2012). Condition Monitoring - Case Histories. In *AWEA 2012*, pp. 9. AWEA.

Wiggelinkhuizen, E., T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, & S. Watson (2008). Assessment of Condition Monitoring Techniques for Offshore Wind Farms. *Journal of Solar Energy Engineering 130*(3), 031004.

Wilkinson, M. & B. Hendriks (2007). Report on Wind Turbine Reliability Profiles. Technical Report 212966, Reliawind.

X-Rates (2012). Exchange Rate Average (British Pound, US Dollar - X-Rates.