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Economic analysis of condition monitoring systems for offshore wind turbine sub-systems

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Abstract:

The use of condition monitoring systems on wind turbines has increased dramatically in recent times. However, their use is mostly restricted to vibration based monitoring systems for the gearbox, generator and drive train. There are many forms and types of condition monitoring systems now available for wind turbines. A survey of commercially available condition monitoring systems and their associated costs has been undertaken for the blades, drive train and tower. This paper considers what value can be obtained from these systems if they are used correctly. This is achieved by running simulations on an operations and maintenance model for a 20 year life cycle wind farm. The model uses Hidden Markov Models to represent both the actual system state and the observed state. The costs for system failures are derived, as are possible reductions in these costs due to early detection. Various scenarios are simulated including the addition of condition monitoring systems to the drive train and blade and tower monitoring. Finally, the efficacy of these systems is examined and its effect on operation costs.

Keywords: Condition monitoring, structural health, operations and maintenance.

1 Introduction

Wind energy has enjoyed a large growth in recent years as countries around the world seek to exploit renewable resources. Offshore wind projects have been part of this expansion but access related issues such as remote locations, specialist access equipment and extreme weather has led to operation and maintenance (O&M) costs which are up to five times that of onshore [23]. O&M costs are a sizeable part of the total costs associated with an offshore wind project - up to 30% of the energy generation cost [30].

As such, there has been many investigations to discover ways of reducing O&M costs. Increased utilisation of SCADA data and condition monitoring (CM) systems have allowed for a shift in maintenance pattern.

Maintenance plans can be divided generally into preventative and corrective maintenance. Corrective maintenance occurs after a failure has occurred. Preventative maintenance is used to minimise down time by servicing or component replacement. This can be in the form of scheduled maintenance, where servicing occurs based on calendar intervals, or condition based maintenance (CBM), where maintenance actions are triggered based on the actual condition of a component.

CBM theoretically allows for a reduction in both downtime and maintenance operations. The majority of CM systems are vibration based and focused on the drive train of wind turbines - the generator, gearbox and associated bearings - as these components historically have large amounts of downtime per failure[19].

Several studies examine the possible benefit of CM drive train systems and the majority of these show a return on investment (ROI) of the monitoring equipment [1, 15, 2]. These studies assume that the CM system installed is perfect and will always inform the user ahead of any impending failure mode. However, this is not the case and false alarms and missed failures will incur costs.

These imperfections and their effects on O&M costs have been examined [14, 30, 28]. The ROI periods for the systems increase in these studies and in some cases the use of CM systems cease to be economically valid. These named studies almost all exclusively use only a vibration based condition monitoring system.

CM systems analysing parts of the wind turbine other than the drive train are available commercially and some experimental CM techniques show promise [9]. These include systems for monitoring foundations, offshore foundation areas (to examine scour) and blades.

There has been limited work examining the economic benefit of CM systems other than vibration drive train CM systems. The work of McMillan and Thöns [27] examines the use of CM systems on offshore foundations and May and McMillan [13] take a broad approach to the use of CM systems for all subsystems.

This paper will look at extending the studies of economic benefit conducted for vibration drivetrain CM studies to other CM systems by examining the capital expenditure (CAPEX) and operational expenditure (OPEX) of these devices against any reductions in O&M costs.

2 Condition Monitoring Systems

The condition monitoring systems noted below have been selected due to the possibility of them delivering real-time information to a turbine operator and being included in a regular SCADA or existing CM system data stream. The majority of these technologies have been chosen from the studies of CM systems by Ciang, Lee and Bang [3], Crabtree [4] and of Sørensen et al. [21].

2.1 Oil Analysis

By analysing the quality and the debris suspended within lubricating oil much can be learned about a component's condition. This can be used to ascertain further information about a gearbox, generator or bearing. There have been many approaches of analysing oil suggested. However, the majority of these methods are offline and as such cannot be conducted in real time [12].

Dielectric current sensors can monitor a change in the electromagnetic properties of oil and can detect both types (ferrous and non-ferrous) and an estimation of the amount of debris. Another technique uses magnets to attract ferrous particles onto a screen. Once the screen is full it is then flushed. The time between flushes are recorded to give an indication of oil debris content. Examples of online sensors that are commercially available include: the HYDAClab from HYDAC and the TechAlert 20 from Macom.

2.2 Vibration

Vibration based CM systems have been widely adopted for monitoring wind turbine drive trains. Accelerometers are used to measure the forces being applied to the component and these are trended over time with frequency. Techniques on how to analyse this vibration data for wind turbines are given by Hameed et al. [11].

However, vibration systems have also been utilised for other applications including blade and tower monitoring. The monitoring techniques and methods are similar to that of drive train CM systems but are sampled at lower frequencies. The vibration data can be further used to assess changes in the natural frequency of the structure and foundation. Mode shapes and modal frequencies change as cracks or weld damage occur. The low frequency structural vibration data can be used to calculate a real time mode shape and compare this to that of a known health configuration.

Some commercial examples of these systems include: BLADEControl from Bosch Rexroth to monitor blade loadings and ice detection; and XY CANopen from Gram & Juhl to monitor tower sway.

2.3 Optical Fibre

Optical fibre systems have been demonstrated on wind turbine blades to measure strain using two distinct methods. In one method, the attenuation of light as it travels through the fibre is measured. It is from measuring this deviation that strain can be determined. The second method uses fibre Graff gratings. A Graff grating is an etching in a optical fibre that reflects a certain wavelength of light. If the grating is subject to strain then the wavelength returned to the measuring point alters. As multiple gratings can be used on the same fibre and are highly sensitive, FBG allow for blade impacts to be detected.

Some optical systems are available for retrofitting onto an existing turbines with minimal modification to the turbine. However, some systems require that the fibres are impregnated into the blades during the curing phase. This obviously requires special blades be manufactured. One study suggests that having fibres impregnated may actually be advantageous to ensure that the curing of blades is completed properly [20]. There is the possibility to realise time and energy savings in the manufacturing process using this technique.

Optical systems are available commercially include SmartScan from Smart Fibre Ltd. and windMETER from FiberSensing.

2.4 Acoustic Emission

Acoustic emission (AE) involves the use of piezo-electric sensors to record the release of stored elastic energy during cracking and deformation. This energy release is in the form of high energy waves and are outside the audible range. The signals can be categorised by their amplitude into the type of damage occurring and when several sensors are used a location can be determined. AE events have been shown to 'cluster' around the ultimate failure point.

Systems have been developed for monitoring both the structural health of blades and the drive train. The WinTur system is an AE blade health monitoring system being developed principally by TWI and SWANwind from Curtiss Wright Flow Control is a drive train monitoring product.

3 Operation Modelling

3.1 Markov Processes

The wind is a stochastic process and complex loadings lead to complex component failure patterns. Various methodologies have been implemented to examine the failure process and the effectiveness of various O&M plans. Gamma processes [10], P-F Curves [28] and Markov chains have been widely used to represent wind turbine failure patterns. Simulations are used instead of analytical expressions to account for these wind complexities.

Failure rates are commonly used to express the number of failures, f, expected to occur over a given time period, N. These can be converted into a percentage chance of failure, U, for a given period of time, t. These are shown in Equations 1 and 2. Failure rates can be used to populate a state transition matrix, P, used in Markov processes as in Equation 3. In this Equation, the ability of the system to transition from a failed state to a repaired one is given as a percentage, μ.

$$\lambda = \frac{f}{N} \tag{1}$$

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

$$P = \begin{pmatrix} 1-U & U \\ \mu & 1-\mu \end{pmatrix} \tag{3}$$

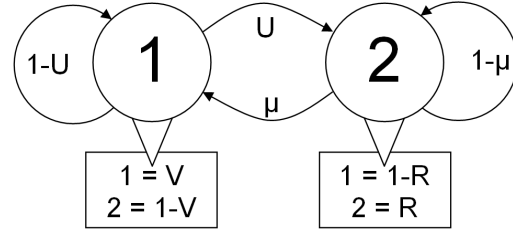$$E = \begin{pmatrix} V & 1-V \\ 1-R & R \end{pmatrix} \tag{4}$$

Figure 1: Example of a Hidden Markov Process

3.2 Condition Monitoring System

Hidden Markov Models (HMM) have the ability to hide the actual state of the system. The observable state of the system can be different to the actual condition of the system. This is shown graphically in Figure 1. In HMM, it is the emissions matrix, E, that contains the probabilities of what is observed by the operator and is shown in Equation 4. The emissions matrix is used to define how accurately the condition monitoring system reports failures and how frequently it returns false results.

The effectiveness of the condition monitoring system to detect a failure before it occurs is stored as a percentage, R, in E. The higher the value of R then the increased likelihood of the system detecting failures before they occur. Weiss [29] gives detection rates for the GE Bentley Nevada ADAPT wind system and these are shown in Table 1.

In this paper, multiple CM systems that observe different properties are added to the same sub-system. These have been modelled as parallel systems and are shown in Equation 5 [25]. In this equation, R_p is the overall chance of detection and R_i is the individual system detection rate.

$$R_p = 1 - \Pi R_i \tag{5}$$

The reliability of the system is defined as V. This is the ability of the CM system to correctly return an operational state. The lower the percentage, the greater chance of the system showing an erroneous failed state. The effects of reliability have been investigated [13] for this paper the reliability has been fixed and kept at 99.99%.

These two properties, V and R, allow for false positives, false negatives, faults that can't be detected using CM systems and CM system failures to be accounted for.

Sub Assembly	Detection Rate
Gearbox	50%
Generator	80%
Drive Train (incl. Main Bearing and Coupling)	40%

Table 1: CM System Detection Rates

3.3 Model

A model has been constructed that represents turbines as structures with 13 sub assemblies and is shown in Figure 2. This follows the taxonomy as used in Faustlich, Hahn and Tavner [8]. A notable exception to this taxonomy is the addition of a sub system representing the offshore foundation.

Each subsystem contains the information as shown in Figure 3. A wind farm is constructed from multiple independent turbine structures. Failure modes are divided into 'Major' and 'Minor' and populated with failure rates from Egmond aan Zee offshore wind farm [16] as modified by Dinwoodie, Quail and McMillan [7].

In 2009, Egmond aan Zee noted that the connection between the transition piece and the foundation was exhibiting greater settlement than expected [17]. The grout in the connection had failed and the tower was resting on temporary support brackets [24]. While no immediate safety issues were discovered, some work was promptly undertaken on 3 turbines to secure the long term operation of the assets. The foundation subsystem in this paper will be used to represent the grouted connection and a SHM will be used to monitor it.

The model is solved by simulation. The model generates an operational and observed state for every turbine subsystem. This is repeated for each turbine in the farm and for each operational year. An algorithm then compares the operational and observed states and notes any differences. O&M costs for both a PM and CBM are calculated from the subsystem failures.

In the model, each turbine is simulated independently for 3000 Markov years. The resulting total failures are then averaged. This gives the failure rate for that operational year.

4 Cost Modelling

The annual operating and maintenance costs are calculated from adding the costs incurred from replacing spare parts, the lost production, the crew and
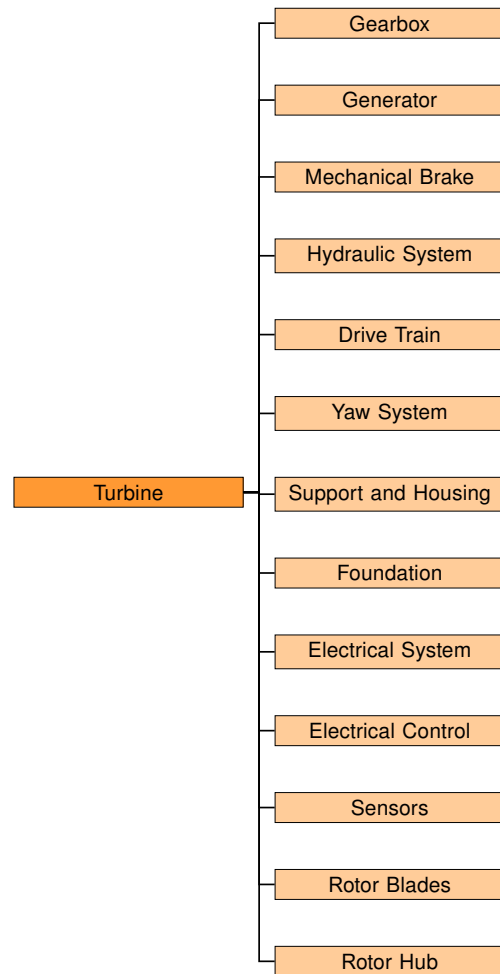
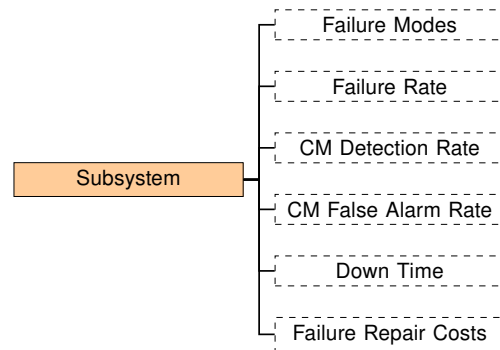Figure 2: Model structure of an individual wind turbine

Figure 3: Information contained within each subsystem

vessel hire and the installation and use of CM systems.

The costs for each year are levelised to represent the Net Present Value (NPV) of the lifetime operating costs. NPV is shown in Equation 6 where a discount rate, r of 4% is used and cost of year i is defined by C_{OP}.

$$NPV = \sum_{i=1}^{y} \frac{C(i)_{OP}}{(1+r)^i} \qquad (6)$$

4.1 Spare Parts

A failure in a subsystem will incur a cost for part replacement. The cost depends on the severity of the failure and damage caused by the failure, C_f. The cost of replacement parts, C_{RP}, are summed for each subsystem, k, as seen in 7.

If the failure is detected in advance by the CM system then in some cases the replacement costs, C_{CMf}, can be lowered if the damage isn't as severe. This alternate cost, C_{RPC}, is shown in Equation 8.

The costs for turbine spare parts are compiled from Poore and Walford [18]. This gave 2004 onshore costs based on turbine size. The cost was adjusted to account for inflation to 2012 - set at 2.2%. The additional cost of marinisation for offshore use was found using a factor of 1.27 [7].

The cost of the repairs are taken from two articles reporting on the possible costs of the connection repair [5, 22].

$$C_{RP} = \sum_{i=1}^{k} C(i)_f \qquad (7)$$

$$C_{RPC} = \sum_{i=1}^{k} (C(i)_f + C(i)_{CMf}) \qquad (8)$$

4.2 Lost Production

A turbine cannot produce energy while it is not operational or offline during maintenance. The longer the down time (DT) associated with a failure then the greater the lost production (LP). In a cost benefit analysis this number is used to represent income that could have otherwise been earned.

The cost of lost production, C_{LP}, is sum of the DT from all subsystem failures multiplied by the energy production cost, C_P, shown in Equation 11. This is the cost of energy in the market (including obligation

tariffs prices per unit) multiplied by the capacity factor, CF. This is shown in Equation 9. The capacity factor used in the model is 33.3% is based on the value from Egmond aan Zee [16].

If a CM system can detect a failure in advance then the DT will be reduced. Logistic operations can be started before the failure occurs, C_{CMf}. However, when using a CM system the possibility of a false alarm occurs. A critical subsystem alarm will result in a turbine shut down until a trained technician can inspect the component. This time for false alarms, T_{fa}, is added to the DT in Equation 11. No average down time associated with false alarms was available so therefore 24 hours is used to represent the DT in the model as an approximation.

$$C_{LP} = C_P \times \sum_{i=1}^{k} T(i)_f \qquad (9)$$

$$C_{LPC} = C_P \times \sum_{i=1}^{k} (T(i)_f + ... \qquad (10)$$

$$...T(i)_{CMf} + T(i)_{fa})$$

$$C_P = CF \times (C_{ROC} + C_{EP}) \qquad (11)$$

4.3 Installation Costs

To complete resets and to replace spare parts, technicians and appropriate vessels need to be used. Each failure mode is assigned a failure category. This category relates to the severity of the failure.

A high category failure indicates that large parts will need to be replaced requiring an crew access vessel and a crane vessel. It also requires a large logistics time and a crew in excess of 7. Conversely, a false alarm is classed as a low category failure, requiring inspection only. This can be organised quickly utilising only a crew access vessel and a small crew.

The installation costs, C_I, are given in Equation 12. The costs of vessel hire, C_E, are based on Dinwoodie, Quail and McMillan [6] as are the labour costs per hour, per crew member. The total number of work hours per job are estimated from a commercial report.

$$C_I = \sum_{i=1}^{k} (C(i)_E + C(i)_L) \qquad (12)$$

4.4 Monitoring Systems

The majority of condition monitoring systems incur costs for the procurement and installation of the CM

system and annual costs associated with maintenance, analysis and software. Generic costs have been anonymised from an array of vendors and averaged to produce the values shown in Table 2. The capital cost of the system is added to the O&M costs for the first operation year. The annual costs are added to the costs for each year of operation.

5 Cost Benefit Analysis

The simulations in this paper use a wind farm consisting of 30 turbines of 3 MW size for an operational life of 20 years. The costs for turbine spare parts, installation costs, lost production (including false alarms) and costs for monitoring systems are summed. A base case demonstrating only preventative maintenance is used to compare the results of a CBM plan. Unless otherwise stated, every CM system has a detection rate of 80%, excluding the system for the vibration drive train which is as noted in Table 1.

5.1 Drive Train CM Systems

As noted earlier, most studies find that vibration based CM systems for the drive train offer return on investment (ROI). Of the other CM methods discussed, both oil sensors and AE systems can be used on drive trains. The effects of these systems on the operating costs are examined in Table 3. As shown in Table 1, a system defined for a drive train detects failures on the gearbox, generator and drive train - which includes the main bearing and output shafts.

Drive Train CMS	Lifetime Saving Over PM
Vibration	£4,266,000
Vibration & Oil Sensor	£4,157,000
Vibration & AE	£4,160,000
Vibration, Oil & AE	£3,984,000

Table 3: Drive Train CM Systems

The model produces annual costs for both competing maintenance strategies. The first year O&M costs for the CbM strategy is £6,102,000, consisting of £2.41m in spare parts, £3.30m in lost production and £0.28m including CM annual operating fees. This compares to £6.43m for the PM strategy.

In the model, a vibration CM system offers potential lifetime savings of approximately £4m over a PM strategy. The addition of either oil sensors or an AE

system reduce the lifetime savings. This indicates that the additional O&M cost reductions found from adding CM systems are outstripped by the cost of the CM systems themselves.

The probability of detection increases from 40% for the drive train with only a vibration CM system to 97.6% for one with all three drive train systems. However, this results in an increase of capital costs for a 30 turbine wind farm from £135,000 to £493,000.

5.2 Structural Monitoring

Blade, tower and foundation SHM systems were added to a standard vibration based drive train CM system. The effects of these systems on operating costs are shown in Table 4.

SHM System & Drive Train Vib CM	Lifetime Saving Over PM
Blades (Optical)	£7,858,000
Blades (Vib)	£7,665,000
Blades (AE)	£7,537,000
Tower	£4,139,000
Tower & Blades (Vib)	£7,569,000
Tower & Foundation	£4,155,000
Tower, Foundation & Blades (Vib)	£7,554,000
Foundation	£4,264,000

Table 4: SHM Systems on Blades and Tower

Blade SHM systems offer further savings over a drive train monitoring system alone. The largest saving over a PM strategy was when using the optical blade SHM system at £7,858,000 an increase of 84%. Adding a SHM system to monitor the tower increases lifetime costs over solely using a drive train CM by 2.5%. Utilising a tower, foundation and blade SHM system as well as a drive train CM results in an increase of 77%.

The ability of the CM and SHM systems to detect failures has a direct influence on the ROI of the systems. This is investigated in Figure 4. In this figure a monitoring system consisting of a vibration system placed on the drive train, blades and tower is shown. The detection rates for both SHM systems started at 60% and was increased in increments to 99% and the resulting levelised lifetimes savings recorded.

Subsystem	Drive Train			Blades			Tower	Foundation
CM Type	Vibration	Oil	Acoustic	Vibration	Acoustic	Optical	Vibration	Vibration
Capital Costs [€]	8,040	11,310	10,000	13,360	34,850	15,080	5,300	18,000
Annual Costs [€]	700	0	0	950	0	0	100	5000

Table 2: Anonymised Generic Costs of Commercially Available CM and SHM Systems

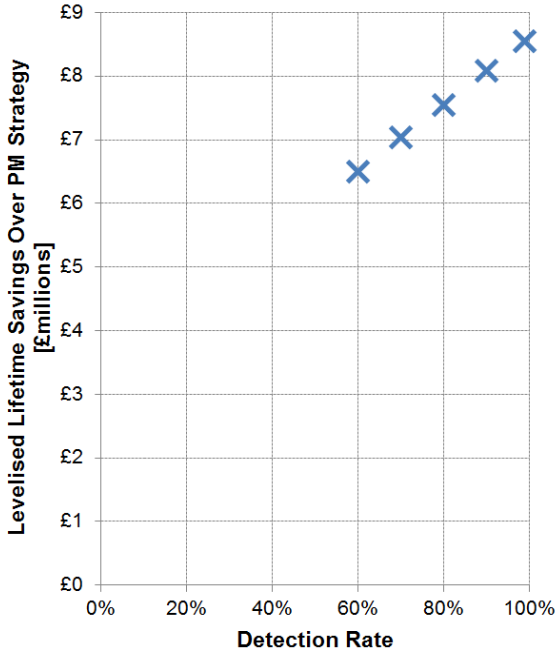Figure 4: Detection rate of Blade, Tower and Foundation CM systems versus potential levelised lifetime savings

Figure 5: Detection rate of only Tower and Foundation SHM systems versus potential levelised lifetime savings

At 60% the lifetime O&M saving was £6,500,000. This increased to £8,552,000, an increase of 32%, when the fault detection rate was set at 99% and followed a linear pattern for detection rates in between. If a system with a better detection rate can be found then it is likely to decrease the O&M costs for a wind farm.

The detection rates of the tower and foundation SHM systems were also examined in a similar manner and are shown in Figure 5. Increasing the detection rate from 60% to 99%, yields an increase in savings of 4% from £4.06m to £4.22m.

6 Discussion

Monitoring the gearbox and generator subsystems appear to offer the largest benefits to O&M costs. These systems have large down times associated with major failures (> 3000 hours), high repair costs
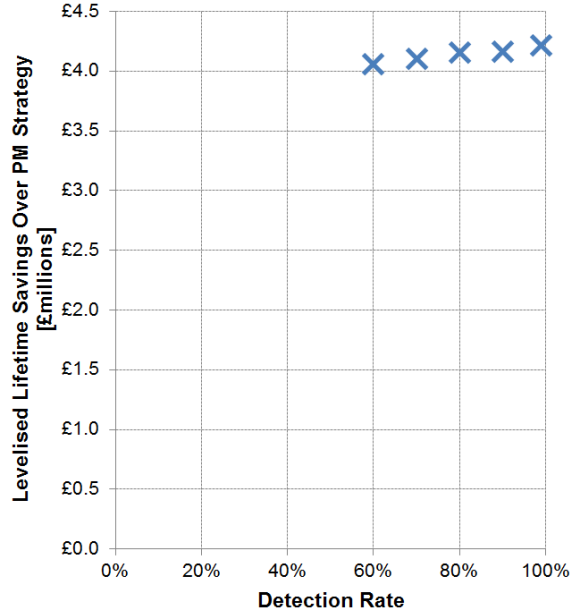
($> £100,000$) and not insignificant failure rates (> 0.1 annually). Drive train Vibration CM have the advantages of monitoring these subsystems and the main shaft at a relatively low cost. Acoustic emission can monitor all these subsystems but at larger cost. Arguably, AE system may have a greater detection rate than their vibration based counterparts but the additional cost appears to out-weigh these benefits. Oil sensors can diagnose a wide range faults, some out with the capabilities of either an AE or vibration CM, but the higher cost may not have a large ROI. The model is not capable of defining the different failure modes where one sensor type is better than another so both systems may have larger ROI than initially indicated. Rotor blades and hub systems also have similar failure characteristics that allow for monitoring to reduce O&M costs.

Due to the high reliability (failure rates of 0.01 annually for major [7]) and the small down time associated with tower faults (approximately 600 hours for a major fault) a SHM system appears to increase some running costs as seen in Section 5.2.

The model may not appropriately derive the cost saving from a SHM system for the tower. The cost benefits for SHM systems are normally defined by reduction of risk and reduction of the structural integrity management efforts [26]. Further development of the model would achieve this distinction and may show a better ROI for tower monitoring systems. Additionally, the model fails to examine some of the additional benefits of these systems such as ice detection and importantly reduction in insurance premiums. Insurance premiums can be reduced by a significant amount over the lifetime by the use of CM/SHM systems and by avoiding scheduled maintenance that is stipulated by the insurer if no CM is present.

7 Conclusions

A model has been produced that examines the effects of condition monitoring and structural health monitoring systems on the operation and maintenance costs of an offshore wind farm. A cost study of commercially available real time operating CM/SHM systems has been completed and the results used in the model. CM/SHM systems were added to various subsystems of a wind turbine and in some cases, multiple CM systems were used on the same subsystem to increase the chance of fault detection.

It was found that adding additional CM systems to the drive train, gearbox and generator increased the chance of fault detection but this had little effect on the O&M costs due to the expense of the additional monitoring systems. The addition of a SHM system to monitor the tower also has little effect on the O&M cost. Blade monitoring systems increased O&M savings by 95% over using just a drive train CM system.

The detection rate of the system had significant impact on the possible O&M savings if the cost for the system did not increase. As the detection rate for a monitoring system for the blades, drive train, tower and grout increased from 60% to 99% then the lifetime levelised savings increased by 32%.

Acknowledgements

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