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Wind Turbine Gearbox Ice Sensing and Condition Monitoring for Fault Prognosis and Diagnosis

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Abstract

The gearbox is seen as one of the most important assets of a wind turbine, so a major concern is how to keep it running smoothly to maximise its service time and reduce the cost. However, wind turbines are often located at remote locations where icing is possible and likely, e.g. high altitudes or cold regions. This challenges the wind turbine stability and causes a variety of problems. Furthermore, rapid expansion of wind energy, along with high operation and maintenance costs, all lead to the need for a condition monitoring system which can offer diagnostics of present condition and prognostics of future condition to improve the reliability of wind turbine and reduce the cost of unscheduled maintenances and unexpected failures. The proposed approach is demonstrated by using a Bayesian Belief Network and Dynamic Bayesian Network under LabVIEW and GeNIe respectively. The proposed procedure is applied on a wind turbine gearbox model to show its feasibility.

1. Introduction

The UK government has set a target for 20% of electricity generation from renewable sources by 2020 (Soni and Ozveren 2007). Among all the various renewable energy technologies, the environmental benefits and cost-competitiveness have driven the rapid expansion of wind power as a significant green source in recent decades.

Often the best locations for wind turbines are in severely exposed locations. Critical to meeting the target, large numbers of offshore wind turbines are being considered, but the excessive wind speeds can cause significant forces on gearbox and torsion strain on the tower. The remote site of wind turbines, where icing is possible and likely, challenges the wind turbine stability and causes a variety of problems. Remote sites, harsh weather conditions lead to the need for a condition monitoring system which can offer the diagnostics of present condition and the prognostics of future condtion to improve the reliability of wind turbines (Parent and Ilinca 2011).

The gearbox is vital to the operation of the wind turbine. As shown in Graph 1, the gearbox is one of the most problematic components of the wind turbine for many reasons, including high maintenance costs and long downtimes. Therefore, it is critical that it operates smoothly to maximum its service time. Given the high risk associated with the gearbox, many methods are used to monitor its condition, e.g. lubricant condition, external vibration testing and contaminants testing. In this paper, the lubrication oil of the wind turbine gearbox and icing are considered as the on-line condition monitoring factors. We use the output of sensors to monitor the gearbox condition and analyze the data by using statistical methods.
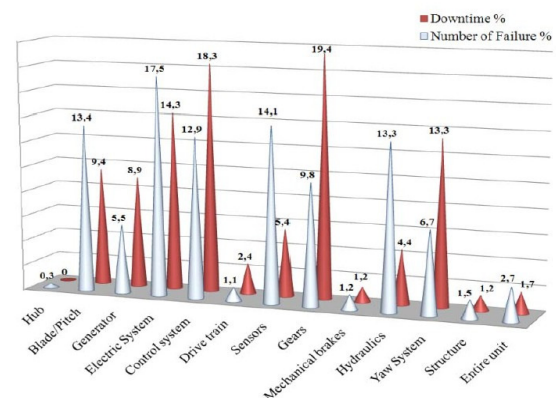
Graph 1: Failure frequency and downtime for wind turbine component (Daneshi-Far, Capolino et al. 2010)

Diagnostic and prognostic methods offer a way to assess an asset's current and future condition. Good use of these is meant to reduce maintenance costs, operation downtime and safety hazards for the high-value assets (Leader and Friend 2000). Diagnosis is a post-event activity and prognosis is to predict the next failure which is also closely related to condition

monitoring (Lybeck, Marble et al. 2007; DeOrio, Khudia et al. 2011). Here, Bayesian Belief Networks (BBN) (Pearl 1988) are applied to perform the diagnostics of gearbox condition based on the on-line sensors results, while a Dynamic Bayesian Network (DBN) (Murphy 2002) is used to perform prognosis of the gearbox condition. In this work, the diagnostics are processed by a LabVIEW model, while GeNIe (Druzdel 1999) is used to model a DBN to obtain the prognostic modeling of the gearbox condition.

The paper is organized as follows: Section 2 motivates the problem and offers a review of related work in ice-sensing technologies. Section 3 presents the lubricant oil condition testing and LabVIEW implementation. In section 4, the prognostics process of gearbox condition are investigated. Section 5 considers avenues for future work and summarises the findings of the paper.

2. Problem Motivation and Related Work in Ice Sensing

2.1 Reason for ice detector

The icing of wind turbines causes a variety of problems.

Loss of production: Ice on the leading edge of the aerofoils reduces the aerodynamic properties of the blade and hence cuts down the power production (Parent and Ilinca 2011). Studies have proven that ice accretion on the blades can lead to up to 30% decrease in the lift coefficient and 50% increase of the drag coefficient (Yan, Fang et al. 2010). Apart from the loss of production due to the disrupted aerodynamics, improper ice sensors in a harsh environment may give false alarms and increase the downtime.

Extra loading: The icing event possibly adds hundreds of kilograms extra weight to the wind turbine blades. Ice accretions considerably increase the load because the unbalanced loading of the blades can lead to additional drive train loads and vibration (Xing, Cui et al. 2012). Furthermore, the increased failures of the gearbox due to the increased fatigue caused by the unbalanced ice loading result in significant downtime and incur costly repairs. Extreme loads with icing events have been recorded many times (Dimitrova, Ibrahim et al. 2011). Picture 1 shows a case of ice accretion on the wind turbines.
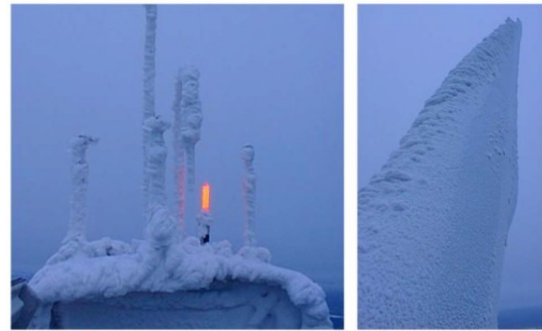
Picture 1: Icing conditions of wind turbine (Dimitrova, Ibrahim et al. 2011)

Safety hazard: The uncontrolled shedding of ice may cause harm and damage to buildings and people near the wind turbine (Homola, Nicklasson et al. 2006). Previous studies proved that large icing accumulation on blades can be thrown to a distance of up to 150% the combined height of the turbine and the rotor diameter (Parent and Ilinca 2011). In addition, a safe area is not always possible.

One example is a wind turbine in southern Sweden which was stopped for over seven weeks during the best operating period because of icing (Kolousek 1986). As mentioned above, icing causes many problems to wind turbines: increased noise, ice throw, extra loading and O&M aspects. Icing affects the operation and the accuracy of the controller system as well. Also, large ice accretions may stop the entire anemometer and result in a total stop of the wind turbine. So an ice detection mechanism should be included in the condition monitoring system. But the ice detection is a more complex and extensive task due to the factors like temperature, wind speed, wind direction, radiation and height etc (Yan, Fang et al. 2010). It is known that icing can be detected by both direct and indirect methods. Direct ways are to detect the direct changes caused by the accretion of ice, e.g. thermal conductivity, inductance, resistance, mass properties. Weather conditions can be used to detect the icing indirectly.

2.2 Existing and proposed methods for ice detection

It's known that there are mainly three types of icing conditions: In-cloud icing including *glaze*, *hard rime* and *soft rime*; Precipitation icing including wet snow, freezing rain and frost (Farzaneh 2008). The air temperature, wind speed, the humidity and storm duration are some of the factors which affecting the icing and deciding the type of ice.

2.2.1 Direct detection

Temperature rise with heat: By using an effective heat-capacity approach, this technology can easily calculate the time to reach equilibrium given an induced heat. There are already many commercial products, one of which is carbon nanotube (CNT) Ice Detection of metis design. However, this method has trouble of detecting very thin layers of ice.

Infrared spectroscopy: This method is optical in nature. Firstly, the sensor emits a beam of infrared light that hits an extended area. Light is partially absorbed by ice or water on that area, and light reflected back to the detector is sensed (Kobayashi, Karaki et al. 2012). Presence or absence of ice or water is then calculated by using the optical properties of the retro reflected infrared light. It is also found that one of the most useful benefits is its ability to detect black ice, which often is near invisible to the human eye. Furthermore, there are no extra conductors out to the blades as all the components can be mounted in the hub, as a consequence, there are no additional lightning risks (Kobayashi, Karaki et al. 2012).

Ultrasound system inside the blade: This method has been simulated to measure ice accretion on aircraft and shown to detect to an accuracy of ± 0.5 mm of ice thickness. The device can also be mounted on any ice accreting surface of the wind turbine. Ultrasonic pulse-echo ice thickness measurements emit a brief compressive pulse from the ultrasound transducer. Then the pulse travels through the ice, reflected by the ice interface, and returns to the ultrasound transducer as an echo signal. The ice thickness can be calculated by the following equation:

$$D = CT_{p-e}/2 \qquad (1)$$

where C is the speed of propagation of the pulse-echo signal in ice and time elapsed is between the emission of the pulse from the transducer and the return of the echo from the ice interface (Bekker and Seliverstov 1996).

Surface acoustic wave sensor: This sensor is a class of microelectromechanical systems which modulate the surface acoustic waves (Peng, Greve et al. 2012). The input electrical signal is changed to the corresponding mechanical signal which is susceptible to the physical phenomena, and acts as a band pass filter in both the radio frequency and intermediate frequency sections. It has shown that it's an effective dew point and humidity sensor if the surface acoustic wave sensor is temperature controlled and exposed to the ambient atmosphere (Drafts 2001). The

respective advantage is that the sensor can detect both ice and water as well as distinguish between them (Farzaneh 2008).

2.2.2 Indirect detection

Dew point and temperature: A dew point detector is to measure the air temperature as well as the relative humidity. It indicates the amount of moisture in the air. On many occasions, the temperature is below 0°C and the relative humidity is above 95% when there is an ice event (Parent and Ilinca 2011) (Parent and Ilinca 2011). In addition, it has a relatively low cost. The disadvantage is that the dew point detector need to be mounted on the wind turbine nacelle.

Actual power output vs. predicted from wind speed: Power curve analysis is a cornerstone of the wind turbine condition monitoring. Power generated from the turbine is roughly proportional to the cube of the wind speed, so comparisons between the normal operation curve and the actual power output can provide a hint on icing condition. For stall regulated wind turbines, a 50% power drop is used as the reference for an icing event (Parent and Ilinca 2011). Normally, the analysis is used along with other temperature and air pressure measurements since it cannot provide accurate indication.

Change in blade resonant frequency: The method of detecting the resonant frequency is based on the fact that ice changes the blade natural frequency. The disadvantage is the low sensitivity as the blade resonant frequency will not change for a thin ice layer.

Another method is detecting increased noise from the blades caused by the layer of ice. Also for wind turbine application it's possible to use anemometers with and without heating and compare the differences of wind speed to detect ice. In addition, a rain detector with a temperature sensor and visual detection are also considered as potential ways to detect the ice accretion.

In general, many methods are not designed for the purpose of detecting ice accretion of wind turbines. There are some basic requirements for successful ice detection. The blade tip is the most probable component to have ice accretion, so it is the best position for ice detection. As a consequence, lightning protection is needed for the sensors which are mounted on the blade tip. Therefore, placing the ice sensors on the gearbox offers major benefits.In addition, a high sensitivity sensor with the ability to detect the ice over a large area is required. A common major icing event in the UK is in-cloud icing due to super

cooled water droplets. If the temperature is below 0°C and relative ambient humidity is above 95%, there is a high possibility of icing events. And this work investigates how combining measurements of ambient humidity and ambient temperature can be used to detect icing events on the gearbox. Additionally, by also monitoring the lubricant oil condition it becomes possible to enable diagnosis of the overall gearbox condition.

3. Diagnostics

3.1 Ice detector and lubricant condition testing

The ambient humidity and temperature are monitored here as the method to detect the icing. Previous study shows that lubricant monitoring includes: particle counting, identification, viscosity, water content, acid content, temperature and oil degradation monitoring (Kostandyan and Sorensen 2012). In this study, lubricant condition is monitored to quantify the oil condition by measuring oil particle count and oil temperature. The application of LabVIEW provides a vibration monitoring and intelligent fault diagnosis system. The detailed oil sensors are as follows:

Oil particle counter is used to find out the amount of wear present in a lubrication channel. Particulate contamination has a negative influence on gearbox performance. Particle size is slightly larger than the oil film which damages contact surfaces and causes extra fatigue. Also, metallic contamination will reduce the lubricant oil life time by accelerating oil degradation. Iron content is used to present the particle contents index. And the oil temperature which may affects oil lubrication performance, making the oil more acidic and accelerating thermal degradation, is monitored here as well.

All the sensors including ice detectors and llubricant condition detectors have been installed and tested by using LabVIEW on the rig.


Picture 2: Physical rig for the lab testing

3.2 BBN diagnostics

In many cases, diagnostic methods rely on undocumented knowledge of a few experts which sometimes cost unnecessary down time and repair expenses. This is practical but has some shortcomings (Kolousek 1986). A more promising method is to use an artificial intelligence method to address these problems. In this study a BBN is applied to the wind turbine gearbox diagnosis problem.

BBNs (Pearl 1988) are statistical models used for knowledge representation, reasoning under uncertainty, taking the form of a directed acyclic graph (DAG) in which each node is annotated with quantitative probability information among variables to learn causes-effect relationship among variables. A BBN model normally contains several random variables which are divided roughly into two classes: evidence and root causes. The BBN topology is comprised of nodes and links or arrows representing variables and assertions of conditional independence respectively. If a node has no arcs, the single prior distribution of itself needs to be defined. However, for the nodes with parent nodes, the construction of conditional probability tables (CPT) is needed for each possible state of the parent variable.

The LabVIEW BBN diagnostic system is shown in Picture 3. Four sensors (oil temperature sensor, oil particle count, ambient temperature and ambient humidity) are available. There are three states for the gearbox condition: *good*, *poor* and *bad*. The conditional probability curves for the sensors are obtained from expert knowledge. By feeding live data into the BBN, the currently state of the gearbox is inferred. The probability of ice is determined through the ambient temperature and ambient humidity. It is found through test that as the temperature gets lower and humidity gets higher, the probability of ice increases. Also, high oil temperature and high particle count result in a high probability of bad gearbox condition. The diagnostics model shows a good agreement with the previous assumption.
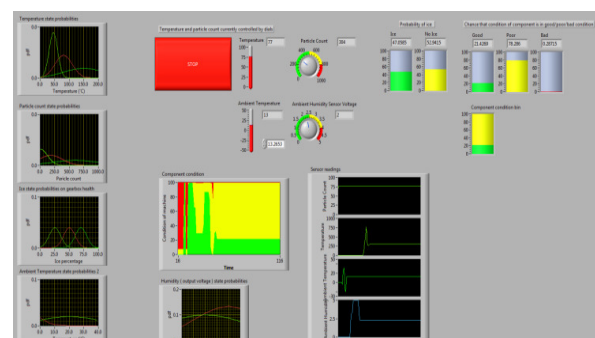
Picture 3: BBN diagnostics network by LabVIEW

4. Prognostics

Prognostics are used to accurately predict the remaining useful life of wind turbine gearbox (Zhigang 2009). Predicting future condition is becoming a useful tool in the optimisation of maintenance scheduling. In this work we use DBNs (Murphy 2002) to model the prognostic problem. While a BBN is a static model representing a joint probability distribution at a fixed point of time, a DBN can represent probability distributions across time. The different temporal dependencies are represented by the arcs with certain time indices.

An example of DBN, representing the probabilies of taking an umbrella depending on whether it is raining or not, is presented below (Stuart J. Russell 2003). For each day t, the set of evidence contains a single variable "Umbrella" and a single unobservable variable, "Rain". The dependencies reflect that weather today depends on the previous day's weather (Kontkanen, Myllymäki et al. 2000).

Graph 2: An example of a simple DBN

P (Rain)	
True	0.7
False	0.3

| P(Rain$_t$)			P(Umbrella$_t$)		
Rain$_{t-1}$	true	false	Rain$_t$	true	false
true	0.7	0.3	true	0.9	0.2
false	0.3	0.1	false	0.1	0.8

Table 1: DBN condition probability tables

GeNIe is a environment for building graphical decision models and performing classification and inference. In this work, GeNIe is used to study ice cycles and gearbox condition cycles over long time-periods. In GeNIe, there are two ways to determine the predictive distribution: posteriori and evidence approach.

The first method uses the training data and a prior probabilistic distribution to obtain the predictive distribution using the highest posterior probability (Kontkanen, Myllymäki et al. 2000). The normal approach is to firstly define a model to represent the system, use prior beliefs to build the prior distribution over the parameters and then observe the data to compute the posterior probability distribution. The posteriori results then can be used to make prediction by finding the highest

posterior probability or to account for the uncertainties of the model (Kontkanen, Myllymäki et al. 2000). The posterior distribution can be accomplished using Bayes' Rule to derive values prior for the given data, where S is the current state of the component and O is the data observed:

$$P(S|O) = \frac{P(O|S) * P(S)}{P(O)} \qquad (2)$$

The second one involves computing the evidence in order to draw the inference to some hypothesis. Once all the observed evidence has been propagated through the conditional probability among the nodes which weights the relationship of the network, the state of the nodes can be valued. Previous work has proven that the second method gives a more accurate predictive distribution which is applied here. The DBN shown in Graph 3 is concerned with the condition of a gearbox over two years using a monthly time step. The probability of ice depends on the ambient temperature and ambient humidiy which is shown by the arcs. If there is no number with the arc, it means the relationship is within the same time step. Conversely, a value, x, means the time t is influenced by the state at t-x.
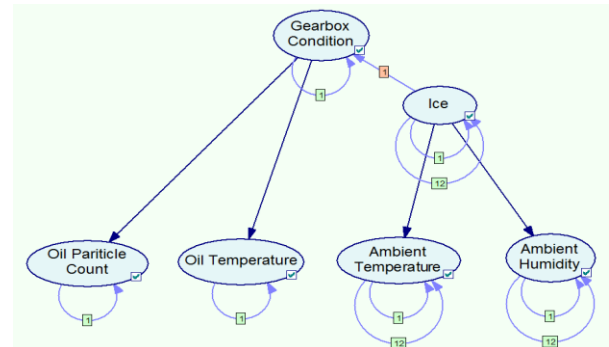
Graph 3: GeNIe DBN model. Labels on self-arcs indicate a number of preceding timesteps. For instance, Ambient Temperature is dependent upon the previous temperature, and that of 12 months previous.

An understanding of the unexplained natural variability of past climate is an essential pre-requisite to increase confidence in predictions of long-term change (Hulst). Therefore, ice condition at the current time is dependent upon this value at the previous timestep (1 month), and 12 months previous, due to the seasonal pattern of climate variation. Ambient temperature and ambient humidity work on the same principle. There are two states of the ice condition, ICE and NO_ICE. The probability of ice (and therefore computing the value of ICE) increases with lower ambient temperature and higher ambient humidity. The behavior of the gearbox condition can be identified as: good, poor (partial loss of the normal

condition) and *bad*. Here, the condition of gearbox is related to the load which is created by the ice accretion. Table 2 is an example of the CPTs of the GeNIe model. The conditional probabilities are obtained through expert knowledge.

P(ICE)	
Ice	0.1
No_ice	0.9

Self(*t-1*)	ICE	NO_ICE
Ice	0.75	0.2
No_ice	0.25	0.8

Self(t-1)	ICE	NO_ICE
Ice	0.75	0.2
No_ice	0.25	0.8

Self(*t-1*)	ICE		NO_ICE	
Self(*t-12*)	ICE	NO_ICE	ICE	NO_ICE
Ice	0.95	0.1	0.85	0.05
No_ice	0.05	0.9	0.15	0.95

Table 2: DBN CPTs for ice condition

4.1 Case study: without oil evidence

In order to predict the probability of ice in future timesteps/months, training data or *evidence* is needed to improve the understanding of the processes. In this case, 12 months evidence of ambient temperature and humidity are given based on the seasonal pattern. Graph 4 shows the prediction of ice, where the top area represents the *ICE* probability and the bottom is *NO_ICE* probability. The inferred year shows a clear correlation with the previous year.
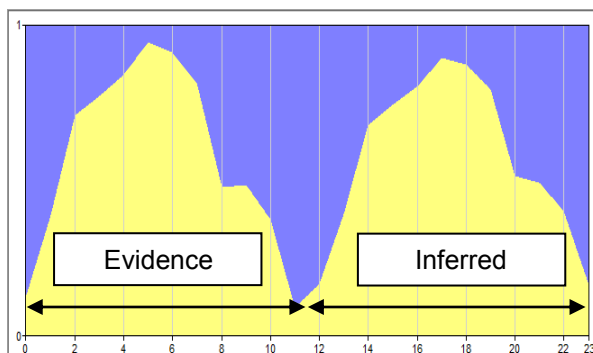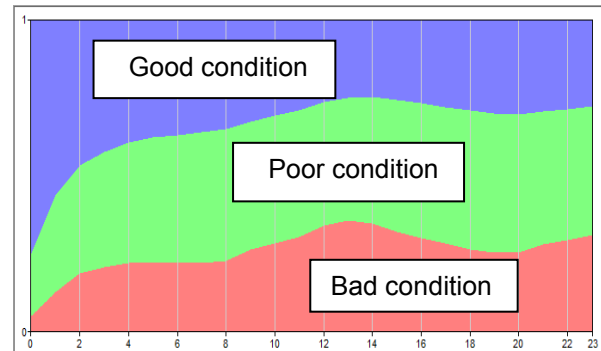

Graph 4: Ice temporal probability distribution

Graph 5 shows the temporal probability distribution of gearbox condition with no oil information (that is, oil condition is unobserved) and same evidence of ambient temperature as Graph 4. In this case, it is clear that the poor and bad condition follows the undulation of the seasonal pattern of ice due to the absence of evidence from the oil. The same trend is achieved with longer inferred time, shown in Graph 6 which adds confidence to the results.

4.2 Case study: good oil condition

Here, the potential effects of good oil scenarios on gearbox condition are investigated. If there is a good oil condition scenario for the first 12 months of observations, there is a high probability of good gearbox condition at *t=12*. Beyond this, the increase in probability of bad condition corresponds to unknown anomalies and follows the seasonal pattern again. The gearbox condition is modelled as a first-order Markov process, wherein the current state depends only upon the previous state (rather than the previous *n* states).


Graph 5: Gearbox temporal probability distribution
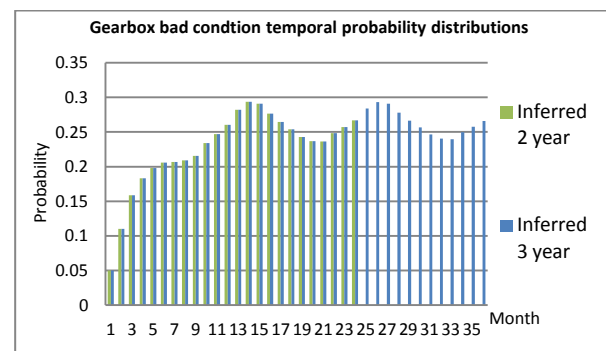
Graph 6: Gearbox bad condition inferred curve comparison

The results in Graph 7 and 8 indicate that it takes 4 or 5 months to recover to the no observation condition. By using the Markov assumption, the transition probabilities are only related to the current state which is fine with most cases but it does not map well this model.
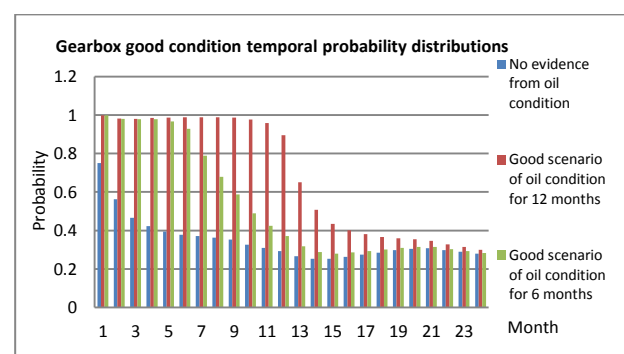
Graph 7: Comparison of inferred gearbox

condition under various observations of "good" oil condition
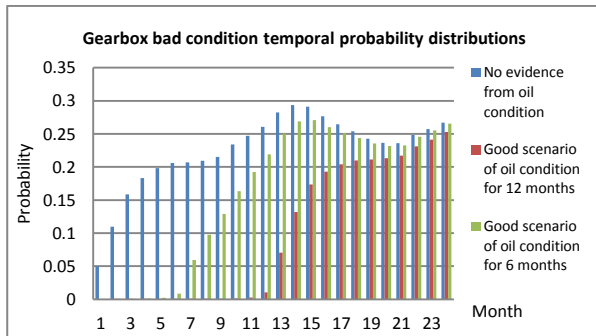
Graph 8: Gearbox bad condition with good oil scenario comparison

4.3 Case study: degrading oil condition

Degrading oil condition is investigated through a case where the first 6 months have good oil condition followed by 6 month poor oil condition, under the same evidence of ice scenario. As mentioned above, the evidence includes only sufficient baseline data of good and poor oil condition and no fault data. In Graph 9, for the inferred year, the data set of the degrading oil leading up to bad gearbox condition is achievable. This illustrates how the prognostic model functions in practice.
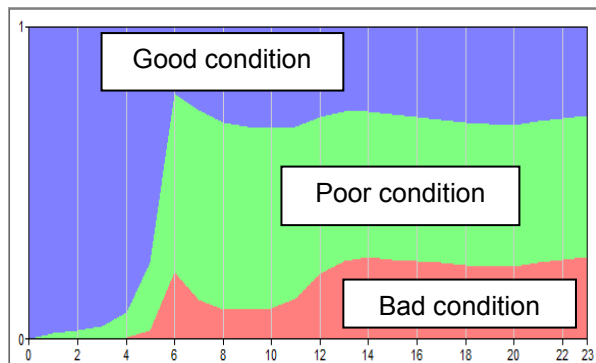
Graph 9: Gearbox temporal probability distribution
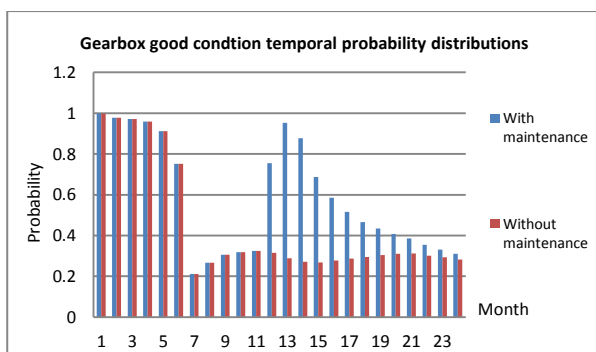
Graph 10: Gearbox good condition with maintenance scenario comparison

4.4 Case study: maintenance

In this study, a maintenance inspection is performed at *t=12* which means the oil condition is returned to *good* after the maintenance. As can be seen from Graph 10, after the maintenance, the probability of the gearbox being in a good state is higher than the previous one which proves that evidence-based approaches are robust that they predict well on the whole.

5. Conclusions

This paper has proposed an approach for diagnostics and prognostics of the wind turbine gearbox condition monitoring. A BBN is applied here to provide the online diagnostic condition of gearbox. All the sensors have been installed, tested and inspected under the LabVIEW environment. For prognostics, the GeNIe model utilizes a DBN to predict the temporal probabilistic distribution of the future condition given the evidence of prior condition. The proposed model is found to be successful in dealing with prediction of the future condition of a wind turbine gearbox and can simulate different scenarios. The reliability and flexibility have been tested and verified. The results show the effectiveness of the principle, and show that the both BBNs and DBNs are useful for assessing wind turbine performance. In future work, for the BBN part, once the interface of LabVIEW is connected to the physical rig, the real online diagnostic of the gearbox condition can apply a decision problem as well. The GeNIe model can be extended to gain more accuracy by finding how many essential pre-requisite time steps are suitable for gearbox condition node and improving the maintenance case.

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