Condition monitoring data in the study of offshore wind turbines' risk of failure

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Abstract

Unplanned maintenance actions entail a period of inactivity of wind turbines and therefore a loss of revenues. This is even more pronounced in the case of offshore wind farms because of difficulties in access. To this end, condition monitoring (or health monitoring) systems have been implemented on wind turbines by manufacturer to support maintenance decision making by operators. However, a major concern with using condition monitoring is the creation of false positives.

In this paper, we have considered how SCADA data may be used to support reliability and maintainability models. We have taken into account SCADA data to assess the level of degradation of a gearbox at any instant of time. Workshops with offshore engineers suggested that degradation is dependent on a small number of variables, e.g. turbulence intensity, wind speed, temperature, etc., and as such, these information sources have been considered in our model to support maintenance decision making.

Dynamic Bayesian Belief Networks allows for modelling multiple information sources (including expert judgement) and dynamic phenomena, e.g. system deterioration. They are also capable of representing dependencies between variables of interest. For these reasons, we developed a Dynamic Bayesian Belief Network to assess the risk of failure of the component under study at any instant of time. We considered the information provided by SCADA about the factors affecting the degradation of the system. In this way, we obtained an estimation of the risk of failure of the system.

1. Motivation

The wind power industry has grown considerably over the past 15 years. By the end of 2011 it was able to produce 204 TWh of electricity and meet 6.3% of the EU's total electricity demand (Arapogianni et al., 2012). The European Wind Energy Association (EWEA) expects 230 GW of installed capacity in 2020 and 400 GW by 2030. As a result, wind power is establishing itself as the main power technology in the EU (Arapogianni et al., 2012). Additionally, in 2010 2,965 MW of wind capacity was operational offshore, equating to 3.5% of the total installed wind energy capacity. This share is expected to increase to 17.4% by 2020 (40 GW) and 37.5% by 2030 (150 GW) (Arapogianni et al., 2012).

Offshore wind farms pose different challenges to onshore wind farms with respect to reliability and maintenance. Due to operating in harsher climates, the need to use specialised vessels, large losses associated with down time and greater technical uncertainty from using wind turbines without a significant operating history, offshore operation and maintenance costs are greater; in some cases as much as 25%-30% of the cost of the energy, (Nielsen and Sørensen (2010)). For this reason, it is of paramount importance to prevent failure and reduce the unavailability of the wind turbines. To this end, condition monitoring (or health monitoring) systems are currently being used by the wind industry.

The core of a condition monitoring system (CMS) are fault diagnosis algorithms that provide early warnings about the occurrence of mechanical and electrical faults. The aim of CMSs is to predict the failure of major components and from this, repairs actions can be planned prior to failure. This is particularly important in offshore wind farms, where weather constraints can delay a repair action for several weeks. The information provided by CMSs is starting to be considered to support reliability, maintainability and logistic models, however, as yet, it not clear what the economic benefit of these systems are (McMillan and Ault, 2008).

The aim of this paper is to explore how a particular methodology, Dynamic Bayesian Networks, can be used to model reliability and maintenance decisions taken during the lifetime of a wind farm. The typical decisions we wish to support are what kind of maintenance action we should perform, i.e. inspection, repair, replace, and when it should be done, i.e. best scheduled of the intervention.

Bayesian Belief Networks (BBNs) are frequently used to model systems subject to uncertainty. BBNs are probabilistic graphical models that are able to represent the dependencies between the variables of interest. BBNs have been applied extensively in system reliability and maintenance modelling, (Pearl (1988), Neil et al. (2001), Sigurdsson et al. (2001), Langseth and Lindqvist (2003), Weidl et al. (2003) and Langseth and Portinale (2006). For a detailed description of BBNs, both theoretical and applied, see, for example, Pearl (1988), Lauritzen (1996), Cowell et al. (1999), Jensen (2001).

One drawback of BBNs is that they are static models that represent the joint probability distribution at a fixed point or interval of time. As such, they are unable to capture the dynamic behaviour of a system degrading through time due to usage. When modelling systems' reliability, whose nature is dynamic, Dynamic Bayesian Belief Networks (DBBNs) are more suitable. DBBNs are an extension of BBNs that allow for the modelling of dynamic phenomena, i.e. the system deterioration and the weather, and allow us to consider temporal dependencies. DBBNs are, in this way, a useful tool to support temporal-decision making. Recently, McNaught and Zagorecki (2009) applied DBBNs for prognostic modelling of equipment in order to better inform maintenance decision-making. They consider CMS to infer the true condition of the system and also external factors that accelerate the wear-out of the system.

In this paper, we consider how DBBNs can be used to model the external factors affecting the deterioration of the system by taking into account the information provided by SCADA systems. We anticipate using this model to support maintenance decision making and to measure the impact of these decisions on the reliability of the system. We focus in assessing the risk of failure of one of the major components of the wind turbine, i.e. the gearbox. The gearbox is a critical component whose failure implies the longest downtime compared to other components, (Ribrant et al., 2007).

In spite of the similarities to the paper of McNaught and Zagorecki (2009) there are some important differences. While they consider just discrete variables, we have developed a hybrid DBBN, with continuous and discrete variables. In addition, for the purposes of this research, we restrict ourselves to modelling using a Kalman Filter (KF). The KF can be seen as a special kind of DBBN where the joint probability distribution is Normal. The aim of our model is to estimate the deterioration state of the system.

This paper is organized as follows: Section 2 provides an overview of DBBNs and the KF. In Section 3 we describe the structure of the DBBN adopted in this problem, i.e. the selected factors specified by experts. The population of the model is discussed in Section 4. In Section 5 the output of the analysis is illustrated. Conclusions and future work are provided in Section 6.

2. Methodology

2.1 *Dynamic Bayesian Networks*

BBNs were introduced in the 1980s, (Pearl (1988)), as a flexible and powerful probabilistic modelling framework that makes them suitable for applications in the field of reliability and maintenance. They are a tool for reasoning under uncertainty and allow dependencies between variables of interest to be modelled. Furthermore, as the statistical methodology is Bayesian, data can be combined with expert opinion, e.g. considering how different environmental factors or design considerations will affect reliability.

A BBN is a compact representation of a multivariate statistical distribution. It encodes the probability density function governing a set of n random variables $X=(X_1,X_2,\ldots,X_n)$ by specifying a set of conditional independent statements together with a set of conditional probability functions, (Langseth and Portinale (2006)). More specifically, a BBN can be seen as a static graphical model, in which the nodes represent random variables (continuous or discrete), and the edges imply direct dependencies between the linked variables (see Figure 1). The strength of these dependencies is quantified by conditional probabilities.

The joint probability distribution of the variables is determined taking into account the BBN structure (Figure 1), using the chain rule, and considering the conditional independence assumptions. The joint distribution of a set of variables $X_1,X_2,\ldots,X_n$ is given by the following expression,

$$f(x_1,x_2,\ldots,x_n)=\prod_{i=1}^{n} f\left(x_i \middle| pa(X_i)\right) \qquad (1)$$

where $pa(X_i)$ denotes the set of all the parents of node X_i.

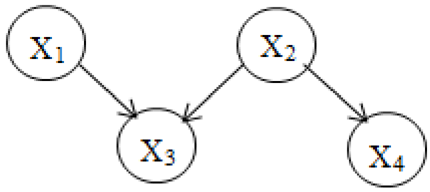

Figure 1: A simple Bayesian Belief Network

Nevertheless, BBNs are static models that represent the joint probability distribution at a fixed point or interval of time. To account for temporal dependencies, we need an explicit representation of time in a BBN. DBBNs extend BBNs to allow for reasoning in a dynamic world where changes occur over the time. In a DBBN, we consider successive time instants and a random variable, i.e. a node, is associated with each time instant. A DBBN captures the evolution of a system over time by interconnecting static BBNs over time slices (Wang et al., 2010). For more information, see Dean and Kanazawa (1989) and Murphy (2002).

Assuming that, $X_t = (X_1(t), X_2(t), \ldots, X_n(t))$ represents the set of random variables at time t, we have that the joint distribution in a DBBN is given by the following expression,

$$f(x_{1:T}) = \prod_{t=1}^{T} f\left(x_1(t), \ldots, x_n(t)\right) = \prod_{t=1}^{T}\prod_{i=1}^{n} f\left(x_i(t) \middle| pa\left(X_i(t)\right)\right) \quad (2)$$

where $X_{1:T}$ denotes the corresponding variables in each time slice, for some $T > 0$,see Zitrou et al. (2010).

2.2 *Kalman Filter*

The KF can be seen as a DBBN where the Conditional probability distributions and the joint distribution are Gaussian (Murphy (2002)). The KF is an optimal recursive data processing algorithm that uses a series of measurements observed over the time and produces estimations of unknown variables. The KF uses (1) the knowledge of the system and measurements device dynamics (2) the uncertainty in the dynamics models and (3) any initial conditions of the variables of interest (Maybeck (1979)). The algorithm works in a 2 step process. First, the KF produces estimations of the current state of the variables of interest along with their uncertainties. Second, once a measurement is observed, the previous estimations are updated using a weighted average, with more weight being given to estimations with higher certainty.

Formally, we can define the KF in the following way (Welch and Bishop(2001)):

The Kalman filter addresses the general problem of trying to estimate the state $X_t \in \Re^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation

$$X_t = AX_{t-1} + BU_t + V_t \quad (3)$$

with a measurement $Z_t \in \Re^m$. That is

$$Z_t = HX_t + W_t$$

The random variables V_t and W_t represent the process and measurement noise (respectively). The matrix A relates the state at the previous time step $(t-1)$ to the state at the current step t, in the absence of either a driving function or process noise. The matrix B relates the optional control input U_t to the state X_t. The matrix H in the measurement equation relates the state X_t to the measurement Z_t.

KF has been broadly applied. In particular, Qu and Hahn (2009) compare different kinds of KF for detection of abnormal operating conditions in industry.

3. Model approach

Mechanical systems are subject to aging, which entails sooner or later to the deterioration of their performances and ultimately their failure. External conditions can accelerate this degradation and cause unexpected failures. For an offshore wind farm, an unplanned maintenance action can suppose a considerable loss of revenues. CMS can help us to prevent the failure; however, a major concern when using CMS is the creation of false positives.

3.1 *DBBN structure*

As a first approach to understand how the gearbox of an offshore wind turbine deteriorates, several interviews with engineers were conducted. During these interviews factors influencing the deterioration of the system were discussed. From this, the variables that were considered to have the biggest impact on the reliability of the gearbox were *Turbulence intensity,* defined as the ratio of the Wind Speed Standard deviation and the mean wind speed determined from the same set of measured data samples of wind speed, and taken over a specified period of time (IEC 61400-1 (1999))*, Generator rpm* and the *Maintenance decisions*.

In our approach, the deterioration of the gearbox is measured in terms of a variable called *Cumulated Effective Number of Rotations of the Generator (CENRG).* We use *CENRG* as we believe that the measurement of the deterioration through the usage of the gearbox is a more accurate representation of the deterioration than the calendar age. The variable *CENRG* depends on the *Generator rpm,* which is an indicator of the usage of the generator, and on the *Turbulence intensity*, which provides the conditions of usage. The latter variable corresponds to the external conditions accelerating the deterioration on the gearbox. For wind turbines exposed to high turbulence intensity, it is expected that the gearbox will deteriorate much faster than when this intensity is low.

We also consider the impact of *Maintenance decision*s. While the first two variables, *Generator rpm* and *Turbulence intensity,* increase the deterioration on the gearbox, the maintenance action has an opposite impact on the deterioration.

We expand *Turbulence Intensity* and *Generator rpm* to include *Observed Turbulence Intensity* and *Observed Generator rpm*. The reason is that the SCADA system is providing evidence of the *True Turbulence Intensity* and the *True Generator rpm* every 10 minutes. Applying KF, we are able to infer the *True Turbulence Intensity* and the *True Generator rpm*. Therefore, in our DBBN, the time slices correspond to 10 minutes intervals. The DBBN can also predict the evolution of the system considering the previous history of the gearbox.

The dynamic evolution of the system is represented by means of a DBBN given by Figure 2. The arcs on the figure correspond to direct probabilistic dependencies between the different variables. Straight arrows indicate relationships within the same time slice. Circular arrows indicate a dependence across time slices, in this case from one time slice to the next one, as it is indicated by the number 1.

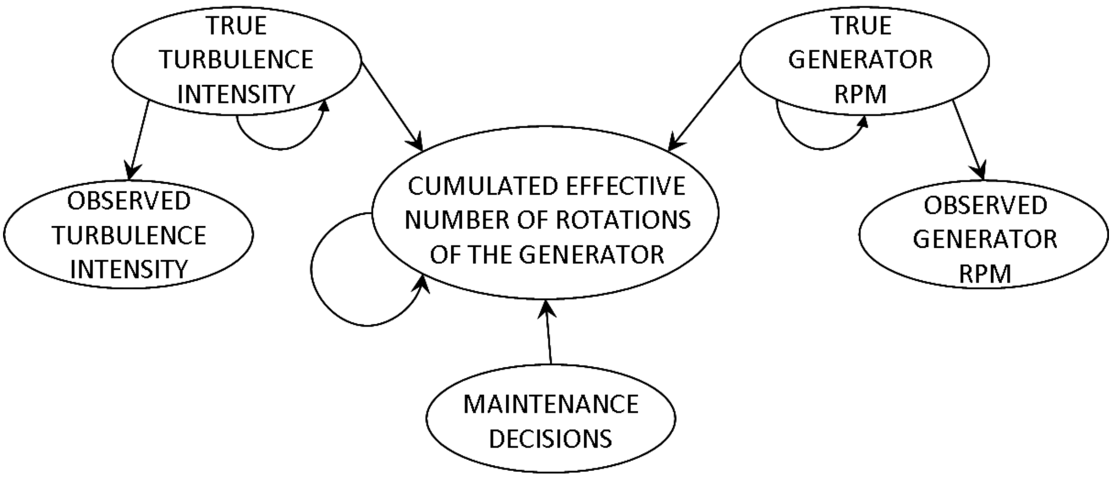

Figure 2. DBBN for the deterioration of the gearbox

3.2 *Obtaining the gearbox deterioration*

Considering the structure of the DBBN, we are able to infer the deterioration level of the gearbox in the following way. First, we consider how the *True Turbulence Intensity* is inferred by the *Observed Turbulence Intensity* through the KF*,*

- *KF for Turbulence Intensity*

$$TI_{t+1} = A_{TI} TI_t + VTI_{t+1} \quad (4)$$

$$O_{TI_{t+1}} = H_{TI} TI_t + WTI_{t+1}$$

$O_{TI_{t+1}}$ is the observation at time slice $t+1$ of the *True Turbulence Intensity*, TI_{t+1}, this is obtained through the SCADA system, being A_{TI}, H_{TI} matrices. VTI_{t+1} and WTI_{t+1} represent the process and measurement noise respectively (see Section 2.2).

We do the same for *True Generator rpm* and the *Observed Generator rpm*

- KF for Generator rpm

$$Grpm_{t+1} = A_G Gprm_t + VG_{t+1} \qquad (5)$$

$$O_{Grpm_{t+1}} = H_G Grpm_t + WG_{t+1}$$

$O_{Grpm_{t+1}}$ is the observation of the *True Generator rpm*, $Grpm_{t+1}$, provided by SCADA at time slice $t+1$. A_G, H_G are matrices. VG_{t+1} and WG_{t+1} represent the process and measurement noise respectively (see Section 2.2).

Taking this into account we can estimate the *CENRG* as follows*:*

$$CErpm_{t+1} = (CErpm_t + \gamma_{t+1} Grpm_{t+1})(1-(\rho_{t+1}) \qquad (6)$$

Where,

- $CErpm_{t+1}$ and $CErpm_t$ represent the *CENRG* at time slices $t+1$ and t respectively.
- $Grpm_{t+1}$ is the *Generator rpm* between the time slices t and $t+1$.
- $\gamma_{t+1} \geq 1$ is the *True Turbulence Intens*ity between time slices t and $t+1$. This parameter corresponds to the impact of the turbulence on the deterioration of the gearbox. If the *True Turbulence intensity* in that interval exceeds a threshold, γ_{t+1} is greater than 1, so the number of *Generator rpm* in that interval is multiplied, accelerating the deterioration of the gearbox. The impact value and the different thresholds are elicited from engineers.
- $0 \leq \rho_{t+1} \leq 1$ represents the effectiveness of the maintenance action performed, if any, at time slice $t+1$. When no maintenance action takes place, this value is 0. If there is an intervention, then $\rho_{t+1} > 0$. This value depends on the intervention carried out, e.g. if we replace the gearbox ρ_{t+1} is 1, i.e. we reset the CENRG to 0. The different values of ρ_{t+1} depend on the maintenance action. As we can see, maintenance actions remove partially or completely the cumulated damage on the system during its whole life. Our approach is inspired on the Effective age models known as *Arithmetic Reduction of the Age (ARA models).* For a detailed explanation of these models see Doyen and Gaudoin (2004).

Once the *CENRG* is calculated, the probability of failure is estimated using a Weibull distribution, this was decided after discussion with engineers. The probability of failure is given in terms of the *CENRG*. The probability of failure at time slice *t* becomes:

$$F\left(CErpm_t\right)=1-e^{-\left(\frac{CErpm_t}{\lambda}\right)^k},\quad CErpm_t\geq 0 \qquad (7)$$

where $k>0$ is the shape parameter and $\lambda>0$ is the scale parameter. We have estimated the parameter using experts elicitation

4. Validation and population of the DBBN

4.1 Gathering some data

As explained in previous sections, we have historical SCADA observations. In particular we have observations of *Wind Speed average, Standard deviation of the Wind Speed.* From these observations, we obtain the *Observed Turbulence Intensity.* We have also observations of *Generator rpm.* In order to populate the model, we must specify the joint probability distribution across all the variables. These values have been elicited from engineers.

4.2 Quantitative Elicitation

We define expert judgement as “any structured method of acquiring knowledge from experts” (Bedford et al, 2006). There are numerous examples of risk and reliability projects where expert judgement has been adopted.

We use expert judgement to structure and populate the model in this project due to the lack of available data. The model of the deterioration of the gearbox has been developed after discussion with engineers. During these interviews other variables were suggested, e.g. Wind Speed, Humidity, Dust, Load, Power output, Wind direction, Downtime, etc. Some of these variables will be included in a future version of the model.

Due to the lack of data, the distribution of the lifetime of the gearbox in terms of the CENRG was elicited from experts and fit to a Weibull distribution. The *Turbulence intensity impact* on the deterioration, the thresholds related and the *Maintenance actions impact*s were also elicited. We have considered three categories for the turbulence intensity, ‘*Normal*’, ‘*Medium*’ and ‘*High*’, and we have associated different impacts to each category. For the Maintenance actions, we have distinguished between ‘*Inspection/Small repair*’, ‘*Repair*’, ‘*Replacement of the gearbox*’, ‘*De-rating*’ and ‘*No action*’. We have historical data of failures and repairs available so they have been used to partially validate the values obtained through a questionnaire.

5. Outputs and decision support

Once the model was populated, the data was used to forecast future deterioration beyond time step t. From the proposed DBBN we obtain a probability of failure at any instant of time. To do this, we use the historical dataset of observations and apply the KF to update our beliefs, i.e. to estimate the true value of these two variables. From this, we can then use the DBBN to infer the *CENRG*. This allows us to estimate the current probability of failure of the gearbox. We can also use the KF to predict the *Turbulence Intensity* and the *Generator rpm* over the next time steps. By doing so, we can predict the future probability of failure over those time steps.

If we do not take into account CMS' evidence, the DBBN offers interesting outputs, i.e. the level of deterioration at any instant of time considering external factors and maintenance actions impact. In this way a maintenance action can be advised even before the CMS indicates a problem in the system. The understanding of the deterioration mechanisms of the gearbox can be used to review the company's policy concerning scheduled preventive maintenance actions and replacements, and in this way, to reduce costs.

5.1 *Illustration of outputs*

Due to the confidentiality of the data used during the development of the model, we use fictional data to illustrate the performance of the DBBN. Let us suppose that the distribution of the of the lifetime of the gearbox in terms of the *CERNG* is gven by a Weibull distribution with the shape parameter $k = 1.5$ and the scale parameter $\lambda = 1800000000$. Consider prior distributions over the *True Turbulence Intensity* and *Generator rpm* as Normal distributions with parameters $\mu_{TI} = 0.2, \sigma_{TI} = 0.5$ and $\mu_G = 1000$, $\sigma_G = 100$ respectively. In addition, we elicit $A_{TI} = 1.001, H_{TI} = 1, A_G = 1, \text{ and } H_G = 1.001$. We also provide the noises distributions for each KF, however, due to space restrictions, they are not provided here.

Suppose that we have SCADA data of *Turbulence intensity* and *Generator rpm* since the wind turbine started its operation as new. Taking into account the previous distributions and the structure of our DBBN, we are able to infer the survival probability at the present moment and also in the near future, as we can see in Figure 3.

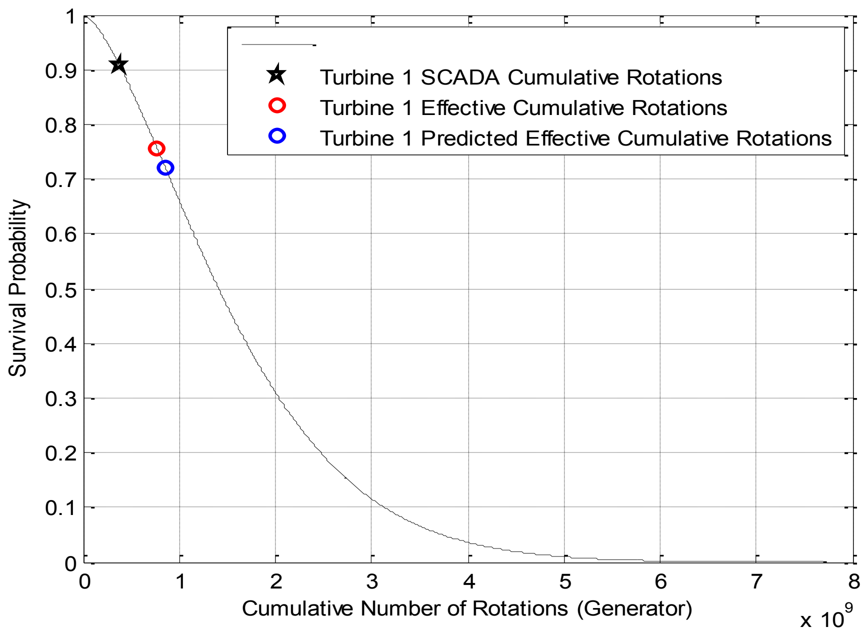

Figure 3. Survival probabilities for Turbine 1

In Figure 3, the black star represents the survival probability if we do not consider the impact of the *Turbulence Intensity* over the system. The red circle is the Survival probability if we consider the impact of the external factors, i.e. the Turbulence Intensity. The blue circle is the prediction of the survival probability in 90 days. This modelling allows operators of wind turbines to compare the 'health' of multiple wind turbines.

We also can estimate the impact on the Survival probability function after the different maintenance actions that can be performed on the gearbox. We assume that the repair action recovers the system 50%, i.e. the *CENRG* decreases 50%. Replacement recovers the system 100%, The rest of the maintenance actions considered, i.e. 'Inspection/Small repair', 'De-rating' and 'None', keep the same level of degradation.

In Figure 4 we consider a degrade gearbox and estimate the effect of the different maintenance actions over the Survival probability of the system.

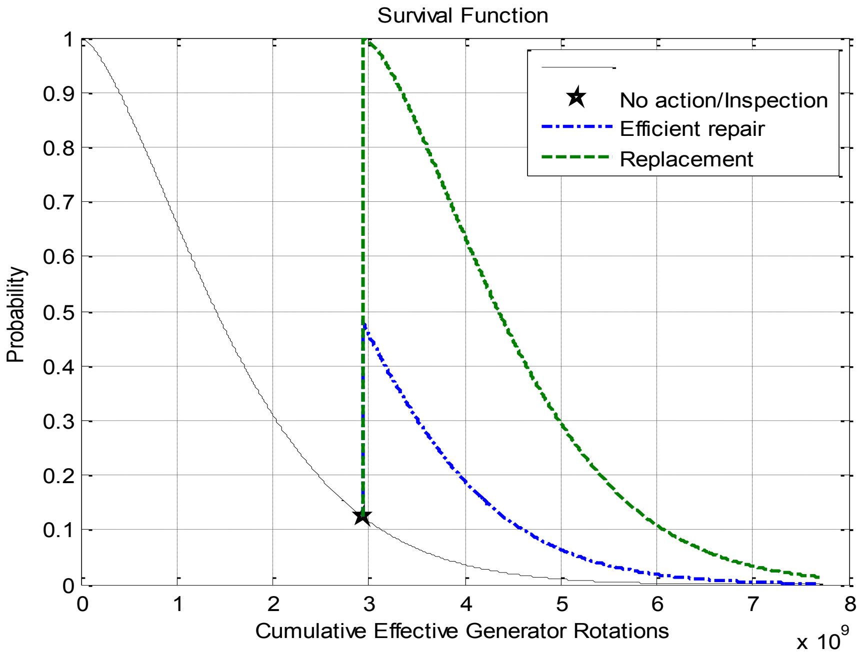

Figure 4: Maintenance actions' effects on the Gearbox's Survival probability

6. Conclusions and future work

In the present paper we propose a DBBN for the estimation of the degradation of the gearbox of an offshore wind turbine. As we mentioned, the model can bring some benefits by its own, such as reduction of the maintenance costs and downtime with a better understanding of the deterioration process. This model constitutes a first approach and in the future, additional variables will be included. We will also consider the main components on the gearbox, the dependencies between those components and the dependencies between the different wind turbines within the wind farm.

In addition, we wish to include information provided by CMSs. Currently, machine learning algorithms are being applied to historical data to develop diagnostic and prognostic models. In future, this information will be incorporated within the DBBN to estimate the deterioration level of the gearbox. Besides, using the CMS data, we can estimate the impact of the maintenance action over the system, i.e. if the maintenance action is not performed as expected, the failure rate will increase quicker after the intervention. CMSs can help us to reduce the uncertainty on the maintenance action impact as new data are available.

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