Anomaly Detection and Explanation of Wind Turbine Main Bearings using Autoencoder and Bayesian Network Models

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Abstract

The installation of wind turbines presents several challenges and difficulties for operators. Indeed, wind turbines often face harsh environmental conditions and complex operational requirements, leading to high costs for operation and maintenance (O&M). Unexpected component failures can result in unscheduled maintenance that can be expensive to achieve. To address these issues, we propose an approach for anomaly detection and explanation based on Supervisory Control and Data Acquisition (SCADA) data. In this study, we focus our attention on a critical component of the wind turbine system called the main bearing. The approach involves two main steps: training an autoencoder model to detect anomalies in main bearing observations and using a probabilistic graphical model to gain insights into the relationships between system components and the main causes of failures. The robustness and benefits of this method compared to other fault detection techniques are demonstrated through numerical experiments.

Keywords: Anomaly, main bearing, autoencoder, explainable AI, Bayesian models

1. Introduction

Providing green and economical energy is quickly becoming one of the main goals in the energy sector. Renewable energy refers to the energy obtained from alternative sources (free of CO2 emissions) such as wind, solar, hydroelectric, etc. The high demand for renewable energy can present several control and maintenance challenges. In fact, wind turbines are often subject to harsh operating conditions that increase the risk of various faults. The wind turbine, although quite adapted to its particular task and environment, it remains very brittle to extreme climate conditions. Unscheduled maintenance caused by unexpected faults can be very costly due to the maintenance support and the lost production time. According to [1], the operating and maintenance (O&M) costs lie between 20% and 25% of the overall levelized (LCOE) cost of electricity of current wind power systems. To further extend the installation of wind turbines, the improvement of wind energy performance as well as the reduction of operating and maintenance costs are crucial. To do so, a meticulous evaluation of the reliability of the different components of the wind turbine during the whole life cycle is required. In the last decade, numerous efforts have been devoted to overcome the limitation of current maintenance strategies, which are mainly based on preventive and corrective maintenance. These approaches allow real-time monitoring rather than costly time interval intervention and performance tune-ups. Feedback from various industries shows that condition monitoring techniques can detect anomalies before they turn into system-critical faults, allowing therefore maintenance to be well scheduled. The wind industry nowadays employs various condition-monitoring techniques to detect a failure at a sufficiently early stage. These techniques include acoustic monitoring [2], oil monitoring [3], thermal monitoring [4], etc. However, the widespread implementation of these methods is often infeasible due to the high cost of installing custom sensors and the complex communication infrastructure and protocols needed to manage their data. To address these limitations, numerous data-driven approaches based on SCADA data have been provided. In [5], an unsupervised
main bearing fault prognosis approach is presented. In this approach, only healthy SCADA is collected and an artificial neural network is used to predict the low-speed shaft temperature. An anomaly detection threshold is then established based on the residuals between the predicted and real values. Authors in [6] proposed a semi-supervised method based on a one-class support vector machine classifier. The method detects anomalies in the main bearing by using a decision function that categorizes real-time data as similar or dissimilar to the safe data. Other unsupervised anomaly detection approaches have been proposed in [7–9]. While these methods are efficient, they cannot point out the sensor observations responsible for the failure. Note that this information is required in the planning of diagnosis and maintenance actions. In [10] a supervised machine learning approach is proposed to detect failures on the gearbox component. Unfortunately, the training process of the anomaly model needs historical faulty data to be tagged, which is a time-consuming and error-prone task. Additionally, the highly imbalanced nature of gearbox fault observations in the SCADA data may lead to other performance issues. In this study, we shall focus our discussion on the main bearing component. According to the European Academy of Wind Energy, main bearing failures have been identified as a critical issue in terms of increasing wind turbine reliability [11]. Therefore, a special attention should be given to this component in order to prevent severe consequences. We propose a two-phase anomaly detection algorithm. The first phase aims to train an autoencoder model using only safe SCADA data. In the second phase, we propose an algorithm based on the Bayesian network (BN) model to interpret and explain the anomaly results returned by the autoencoder. In this context, beyond the wish of using the BN to identify the main sources of the anomaly, there is also the will to understand and validate the already detected failure in the main-bearing component. The rest of the paper is organized as follows: Section 2 introduces the wind turbine system. Then, the main bearing failure modes are reviewed in section 3. We discuss the used SCADA data in section 4. In section 5, we present a new approach based on an autoencoder and a BN for detecting and explaining main bearing failures. Its effectiveness is proven through experiments in section 6. Finally, some concluding remarks are given.

2. Wind turbine overview

A wind turbine is a device that converts the kinetic energy of wind into mechanical energy. The mechanical energy is then transformed into electrical energy by a generator. The electrical energy produced by a wind turbine depends mainly on three factors: the design and size of the blades, wind speed, and outdoor temperature, which directly affect the density of the air. The wind power $P$ (in Watts) is computed as follows: $P = \frac{1}{2} \rho A w^3$, where $A$ is the rotor swept area in $m^2$, $\rho$ is the air density in $Kg/m^3$ and $w$ is the wind speed in $m/s$. The wind turbine consists of three major parts: a tower, a nacelle, and rotor blades. It is also equipped with a pitch control system to reduce failures while improving safety and reliability. In fact, the pitch control is used to adjust the angle of the blades by rotating them to achieve specific rotor speeds and power output. Moreover, it serves as a protective mechanism by ensuring the safety of the wind turbine during high winds, loss of electrical load, or other extreme conditions.

The wind farm SCADA data provides a rich source of continuous-time observations about

![Figure 1](https://example.com/figure1.png)

*Figure 1.* (a) Fatigue failure (subsurface-initiated) (b) Fatigue failure (surface-initiated) (c) Corrosion failure (Moisture) (d) Corrosion failure (fretting).
different components of the system, as well as the environmental conditions. Together with the pitch system, the SCADA data can be used to ensure wind turbine performance.

3. Main bearing failures

The main bearing is a critical component inside the wind turbine that can be damaged in a variety of ways. The Svenska KullagerFabriken (SKF) classified the main bearing failure into 6 main modes: fatigue, wear, corrosion, electrical erosion, plastic deformation, and fracture and cracking\(^1\). These modes are divided into sub-modes.

For fatigue failure, there are two sub-modes: subsurface-initiated fatigue and surface-initiated fatigue (see Fig.1 (a) and (b)). The subsurface-initiated phenomenon is characterized by the buildup of residual stresses that alter the material at the contact surface, transforming its structure from a randomly oriented grain to a fracture plane. It occurs beneath contact surfaces of the raceways and rolling elements. The surface-initiated fatigue occurs as a result of indentations on the rolling contact surface asperities, which are typically caused by inadequate lubrication.

The wear failures can be divided into two sub-modes: abrasive wear and adhesive wear. Abrasive wear refers to the gradual removal of surface material caused by poor lubrication or the entry of solid contaminants. Adhesive wear is a form of damage that takes place between two mating surfaces due to a lubrication issue. It is characterized by the transfer of material from one surface to the other. This mode of failure is often accompanied by friction-generated heat, which can occasionally temper or re-harden the mating surfaces.

In the category of corrosion failures, there are three types: moisture corrosion, fretting corrosion, and false brinelling. Moisture corrosion occurs when water and aggressive liquid contaminants penetrate the bearing, resulting in the formation of rust (as seen in Fig.1(d)). Fretting corrosion is caused by repeated sliding between bearing surfaces, while false brinelling, which occurs in the contact area, is the result of prolonged absence of relative movement, vibrations, or small oscillations.

Regarding the electrical erosion failure mode, there are two sub-modes: excessive current erosion and current leakage erosion. Excessive current erosion occurs due to electric current flowing from one ring to the other through the rolling elements. At the contact surfaces, the process is similar to electric arc welding. In that case, the material is heated to temperatures ranging from tempering to melting levels. This process leads in the generation of discolored regions where the material has been tempered, rehardened, or melted. Conversely, the damage caused by current-leakage erosion occurs when the current intensity is comparatively low. It is characterized by shallow craters that are closely spaced on the surface and have a smaller size compared to those caused by excessive current erosion. Fifth, plastic deformation occurs due to an overload or indentations caused by the debris. The overload deformation is basically caused by one of the following events: (i) static overloading, (ii) shock loads, or (iii) improper handling. In all cases, the resulting damage is the same. Regarding the indentations from debris, solid contaminants can enter a bearing through the seals and/or lubricant. In some cases, they can result from wear or damage that affects an adjacent component to the main bearing. Finally, the bearing can be affected by a fracture and cracking which results from forced fracture, fatigue fracture, or thermal cracking. The forced fracture occurs when the stress concentrations exceed the material’s resistance strength. The fatigue fracture appears when the fatigue capacity of a material is exceeded under cyclic bending. Repeated bending movements causes a hairline crack which propagates until the ring or cage develops through the crack. Finally, thermal cracking happens due to the heat generated by the sliding of two surfaces against each other. If the sliding is important, the heat can lead to cracks, and eventually, the ring will crack through.

\(^1\)https://www.skf.com
4. Available data

The SCADA data provides a rich source of continuous-time observations about several of condition variables. The wind turbines considered in this study are located on a wind farm situated in the northeast region of France. The datasets consist of environmental, electrical, component temperature, hydraulic, and control variables. The environmental-related variables include ambient temperature (°C), nacelle temperature (°C), wind speed (m/s), and turbulence index. These variables are highly correlated with the electrical and component temperature variables. For instance, the distribution of the main bearing temperature changes significantly between winter and summer. Among all environmental variables, it is important to emphasize that the wind speed variable is considered the most influential variable on the wind turbine subsystems. When the wind speed is below its rated speed (13 m/s), an increase in rotor speed due to higher wind speeds will raise the output power and the temperature of all mechanical components.

The electrical variables group encompasses active power (kW), phase voltage (V), power factor, reactive power (kW), and electric network frequency (Hz). These variables describe the power generated by the wind turbine before it enters the distribution grid. The active power curve is very sensitive to small variations in the wind speed output of the nacelle anemometer. Electrical network frequency and phase voltage measurements are obtained to control potential fluctuations, while reactive power and power factor measurements provide insight into the efficiency of electric power utilization. The goal for wind turbine control is to maintain a power factor as close to 1 as possible.

The component temperature variables correspond to temperature signals (in °C) from several key locations in the nacelle, such as the gearbox, generator, and main bearing. Component temperatures are one of the main condition parameters that are closely related to the performance of the wind turbine. In this study, we will focus our discussion on detecting anomalies in the main bearing. Hence, the rotor bearing temperature is considered the most important variable as it is the closest sensor to the component under study. Note that the temperature of the main bearing is strongly influenced by the temperatures of components located near it, as well as environmental conditions. Additionally, control variables such as rotor speed can be a reliable indicator of the main bearing’s operating regime.

Hydraulic variables describe observations of the general accumulator, brake pressure, general accumulated pressure of the blades, and hydraulic group pressure. These parameters are generally used to control the pitch, yaw, and braking systems of the wind turbine. The pitch cylinder for each blade is actuated using a hydraulic accumulator for different operations, such as blade engagement and blade safety position.

Control variables are related to all control systems that guarantee safe operation, optimize power output, and ensure the long structural life of the wind turbine. The wind turbine is equipped with blade pitch control, which allows to maintain the optimum blade angle to achieve certain rotor speeds. The yaw controller is another important control system that is responsible for the rotation of the entire wind turbine. It ensures that the wind turbine is constantly facing the wind to fully capture the incoming wind power. Additionally, the rotor and generator speeds are two key parameters that must be controlled for power limitation and optimization. In addition to the SCADA data, we can access extra information that keeps track of the ordinary and extraordinary maintenance interventions required by each wind turbine over its lifetime. These details are typically stored in Excel files, where a description of the repair actions, together with a timestamp of the date on which it happened, are reported. Based on this aforementioned information, it is known that anomalies in the main bearing have been reported in the wind turbine $WT_1$ at the studied wind farm from January 1, 2014 to June 30, 2015. These anomaly details are used hereafter to test whether the proposed approach can correctly detect the appearance of the fault.
Table 1. Selected variables of the prediction models

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Range</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed (W)</td>
<td>[0, 25]</td>
<td>m/s</td>
</tr>
<tr>
<td>Ambiant temperature (A)</td>
<td>[-5, 40]</td>
<td>°C</td>
</tr>
<tr>
<td>Nacelle Temperature (N)</td>
<td>[0, 120]</td>
<td>°C</td>
</tr>
<tr>
<td>Main bearing temperature (M)</td>
<td>[0, 120]</td>
<td>°C</td>
</tr>
<tr>
<td>Median main bearing temperature (MM)</td>
<td>[0, 120]</td>
<td>°C</td>
</tr>
<tr>
<td>Delta main bearing temperature (ΔM)</td>
<td>[0, 120]</td>
<td>°C</td>
</tr>
<tr>
<td>Rotor Speed (R)</td>
<td>[0, 1800]</td>
<td>rpm</td>
</tr>
</tbody>
</table>

5. Anomaly detection and explanation methodology

In this section, we illustrate the details of the developed method to handle main bearing failure detection and explanation. The approach involves four key steps. First, the SCADA data is preprocessed and filtered. Second, the selected data is partitioned into training, validating, and testing datasets. Third, the normality models for each wind turbine in the wind farm are constructed based on two complementary models: autoencoder and Bayesian network. Finally, a novel anomaly detection and explanation method is proposed.

5.1. SCADA data preprocess

The SCADA dataset used in this study includes a large number of parameters with varying outliers, incomplete observations, and mismatches in time and date stamps. Therefore, preprocessing operations are crucial to obtain a clean dataset that is suitable for machine learning algorithms. The first step is to select the set of variables to be included in the model training phase. It is important to choose the most important features that provide valuable insights into the main bearing behaviors. According to domain experts, the mean values of environmental measurements, rotor speed, and the temperatures of the main bearing should be exploited. To justify the preference for exogenous variables, it is important to note that in wind turbine systems, component states are strongly correlated. As a result, selecting temperature features that are related to other components rather than just the one under investigation can reveal additional failures in components that are closely linked to the variables used. In such situations, the model may lose its ability to differentiate between the failures of interest and those occurring in other related components. We enhance the existing data by automatically generating new features related to the median of main bearing temperatures in the wind farm and the difference between the calculated median and the current temperature of the main bearing under study. Under the normal behavior of the main bearing, the difference between both temperatures is roughly equal to 0. Consequently, a large deviation between the two temperatures indicates a high likelihood of main bearing failure in the studied wind turbine. Tab.1 shows the list of selected variables. For each variable, we generate the lagged (t-1) and (t-2) variables to represent the temporal dimension during model learning. Overall, 21 variables are used to build our models. After the feature selection process, a data cleaning pre-processing step is executed to eliminate outliers and sensor measurement errors in the selected features. These abnormal observations do not contain valuable guidance in detecting anomalies. To address this issue, a variety of cleaning methods for wind turbine abnormal observations based on wind power have been proposed in previous research [12]. In our study, we initiate the cleaning process by removing out-of-range values for each selected variable, as shown in Table 1. To eliminate any remaining outliers, the second step of the cleaning process employs the quartile method. Specifically, the wind speed values are sorted and divided into several small and regularly spaced intervals. Next, we compute the lower and upper quartiles for each selected variable,
represented respectively by $Q_1$ and $Q_3$. The difference between these two quartiles is known as the interquartile range, which we denote as $IQR$. This is given by $IQR = Q_3 - Q_1$. To detect outliers in a given wind speed interval, we proceed as follows: if $x_i$ is less than $Q_1 - 1.5IQR$, then it can be considered too small; if it is greater than $Q_3 + 1.5IQR$, then it is considered too large. After identifying the outliers, they are treated as missing values and filled using a cubic Hermite interpolating polynomial (CHP) [13]. This method ensures that the interpolated values maintain the monotonic shape of the function. In situations where the dataset contains missing values at the boundaries, we suggest the use of the nearest available values before or after the missing values. Finally, we deal with the very different magnitudes of the selected features. For a fair training process, every variable $X$ is scaled using the min-max normalization process:

$$x'_i = \frac{x_i - \min(X)}{\max(X) - \min(X)}.$$ 

Carrying out these preprocessing procedures, we end up with an effective SCADA data quality that can be used by machine learning algorithms.

5.2. SCADA data splitting

Selecting the appropriate datasets for training, validation, and testing is a crucial step in developing an accurate main-bearing normality model. Therefore, it is essential to consider all operational and environmental conditions that the wind turbine may encounter, such as different wind velocities and seasonal conditions. To train and validate our one-class healthy data model, we only used SCADA data without main bearing failures. Specifically, we used data from 2011 and 2012 to train and validate the model, respectively, and we used the data from the entire year of 2014 to test the model’s accuracy. Notably, the maintenance interventions file showed that a main bearing failure has been detected on the WT1 machine on January 1, 2014. By testing the model’s performance against these different observations, we can ensure that it accurately distinguishes between normal and abnormal observations, regardless of the season and environmental conditions.

5.3. Auto-encoder-construction

Autoencoder (AE), also referred to as autoassociator, is a highly effective type of artificial neural network for diagnostic tasks that has been applied in various real-world applications [14]. Unlike supervised predictive models, autoencoders offer a prominent flexible model that can represent complex functions without requiring labeled data during the learning process. An AE is an unsupervised and symmetrical neural network that consists of two primary components: an encoder $f : \mathbb{R}^n \rightarrow \mathbb{R}^e$, which compresses the input data ($x_i$) into a lower latent representation ($h$), and a decoder $g : \mathbb{R}^e \rightarrow \mathbb{R}^n$, which maps the latent representation back to the original data ($x_i$), i.e., $\hat{x}_i \approx x_i$. Then, the desired output is the input itself, i.e., $h = f(x_i)$ and $\hat{x}_i = g(f(x_i)) = g(h)$. The number of neurons in the input has the same size as the output, which corresponds to the number of selected variables (see Tab.1). To perform the task of main bearing anomaly detection, we adopt the undercomplete architecture, which has shown advantages in monitoring the health of wind turbines as reported in [15]. This AE architecture is designed to encode the most important features of the input data using fewer dimensions while ensuring that we can still get back to the original input values. The model parameters ($f_\theta$ and $g_\theta$) are estimated by minimizing the reconstruction error (RE) between the original and reconstructed data, which we achieve by using the mean square error (MSE). Our model setup includes a five-layer architecture, which has been shown to be effective in detecting anomalies in wind turbines. The number of neurons in every hidden layer has been estimated through the use of Bayesian hyper-parameter optimization [16]. Optimal results were obtained with layers of 10, 6, 3, 6, and 10 neurons. We used the Keras implementation of the adam optimizer, as illustrated in [17]. The learning rate value is set to 0.001. We used the exponential linear unit (elu) activation function. The number of
epochs is set to 20. Finally, the mini-batch size during the gradient descent executed by the adam optimizer is set to 64 samples. After the training phase, the model is used to detect anomalies by comparing the input and the output data. The anomaly detection method will be described in detail in section 5.5.

Although the AE is often effective in detecting anomalies in SCADA data, it is nevertheless unable to reveal which features are the root causes of the anomaly. Roughly speaking, the deviation of only one of the considered input features is enough to cause the propagation of the error through the AE network, resulting in a significant reconstruction error in most other features as well. To address this limitation, we introduce a novel method based on the Bayesian network to help us figure out which features are responsible for the anomaly.

5.4. Bayesian network-construction

The issue highlighted previously immediately raises the question as to whether the deviation of one sensor other than those related to the main bearing temperature can trigger false positive alarms. To tackle this issue, we propose an anomaly explanation model based on the Bayesian network model [18] (BN). Unlike autoencoder, the BN is a type of probabilistic graphical model that uses a graph-based representation to compactly represent a high dimensional distribution over complex systems.

**Definition 1** (Bayesian network). A BN is a pair \((G, \Theta)\) where \(G = (V, A)\) is a directed acyclic graph (DAG), \(V\) represents a set of random variables, \(A\) is a set of arcs, and \(\Theta = \{\theta_{X_i|Pa(X_i)}\}_{X_i \in V}\) is the set of the conditional probability distributions (CPD) of the nodes / random variables \(X_i\) in \(G\) given their parents \(Pa(X_i)\), i.e. \(\theta_{X_i|Pa(X_i)} = P(X_i|Pa(X_i))\).

The BN encodes the joint probability over \(V\) as:

\[
P(V) = \prod_{X_i \in V} P(X_i|Pa(X_i)) \tag{5.1}
\]

By their graphical structure, BNs encode an independence model, i.e., a set of conditional independencies between variables, characterized by the \(d\)-separation property [18]. Several approaches for learning the BN graph have been proposed in the literature. These algorithms can be divided into 3 classes: i) the search-based approaches that focus on optimizing the scoring function of the structure [19]; ii) the constraint-based approaches that exploit statistical independence tests to find the best structure [20]; iii) the hybrid methods that exploit a combination of both [21]. Although these approaches are effective, they often fail to identify all causal directions in the graph. To cope with this problem, we decide to use an alternative approach which consists in exploiting experts' knowledge together with a score-based approach to optimize the causal discovery. In our situation, experts provide their knowledge about some causal relations between variables. This knowledge is about the existence or absence of arcs and is expressed as hard structural constraints, i.e., the BN learning algorithm is not allowed to modify these relations. Expert knowledge is also used after learning to modify, add or reverse mistaken causal relations. We now describe the proposed method to detect and explain the anomaly using AE and BN models.

5.5. Fault detection and explanation

The first stage involves the use of the AE to detect anomalies in the SCADA observations. To quantify the deviation between the input and output of the AE, we used the reconstruction error (RE), which is calculated as the absolute difference between the reconstructed and original data, i.e., \(|\tilde{x}_i - x_i|\). The threshold \(\epsilon\) is determined based on the distribution of the different \(RE_i\) that are computed using the validation dataset. In our case, observations are considered anomalous if the reconstruction error associated with an input set \(x\) is greater than three times the standard deviation above the mean.
vice-versa, i.e., Fig. 2. By using the chain rule for BNs, the joint diagnoses on query variables. As a concrete example, consider the simple BN illustrated in outlier or an anomaly in the evidence values is likely to lead to misleading fault anomaly

Let \( \xi \) be the probability query is to compute:

\[
E \rightarrow Z \\
E = e \text{ which is a subset of variables in the BN and their values, ii) the query variable } Q \text{ which is a variable in the network, where } Q \in V \setminus E.
\]

The goal of the conditional probability query is to compute:

\[
P(Q|E = e) = \frac{P(Q, E = e)}{P(E = e)} \tag{5.2}
\]

Note that the evidence variables represent information that is currently available about some part of the studied system (symptoms, measurement results, etc.). A second important type of probabilistic reasoning with BN is to find the most likely assignment \( q^{*} \) in the domain of \( Q (\Omega_Q) \) given the evidence \( E = e: MAP(Q|E = e) = \arg \max_{q} \sum_{Z} P(Q = q|E = e) \), where \( Z \subseteq V \setminus \{E, Q\} \). This type of query is called maximum a posteriori (MAP). Given conditional probability and MAP equations, it is useful to view the probabilistic reasoning query in our case as a flow in the graph. Thus, intuitively, whenever an active trail between two nodes \( X_i \) and \( X_j \) exists in \( G \), the influence of \( X_i \) can flow to \( X_j \) along the trail and vice-versa, i.e., \( X_1 \rightarrow \cdots \rightarrow X_k \rightarrow \cdots \rightarrow X_j \). This property is challenging in our task since an outlier or an anomaly in the evidence values is likely to lead to misleading fault anomaly diagnoses on query variables. As a concrete example, consider the simple BN illustrated in Fig.2. By using the chain rule for BNs, the joint \( P(W, A, R, M) \) (see Tab.1) decomposes as:

\[
P(V) = P(W)P(A)P(R|W, A)P(M|R) \tag{5.3}
\]

Let \( \xi_i = (w_2^{(i)}, a_2^{(i)}, r_2^{(i)}, m_2^{(i)}) \) be the \( i \)th assignments for variables \( W, A, R, \) and \( M \) in the data \( D \) respectively, \( E = \{W, A, R\} \), and \( e^{(i)} = (w_2^{(i)}, a_2^{(i)}, r_2^{(i)}) \). We assume that assignments do not contain anomalous measurements. By using the MAP query, the BN allows to show the most probable value \( m^{*} \) of \( M \) would have had given \( E = e^{(i)}: \)

\[
MAP(M|E = e^{(i)}) = \arg \max_{m \in \Omega_M} P(M = m|E = e^{(i)}) \tag{5.4}
\]

Under normal condition, the conditional probability associated with \( m_2^{(i)} \) (in \( \xi_i \) given \( e \) should be close to \( m^{*} \) returned by MAP (see Eq.5.4). Hence, the ratio between both probabilities, denoted by \( D(m_2^{(i)}|m^{*}) \), satisfies the following property:

\[
D(m_2^{(i)}|m^{*}) = \log \left( \frac{\Phi_E(m_2^{(i)})}{\Phi_E(m^{*})} \right) \approx 0 \tag{5.5}
\]

where \( \Phi_E(m_2^{(i)}) \) and \( \Phi_E(m^{*}) \) denote \( P(M = m_2^{(i)}|E = e^{(i)}) \) and \( P(M = m^{*}|E = e^{(i)}) \) respectively. Let’s consider a different scenario where there’s an anomaly on the rotor component \( (R) \), which is part of the evidence \( E \). In this case, the magnitude of rotation significantly deviates from the most probable value \( r^{*} \). It’s important to note that in the wind energy domain, lower wind speeds lead to lower rotor speed rates. Additionally, the
deceleration of rotor speed causes a decrease in the main bearing temperature. Let \( \xi_j = (w_2^{(j)}, a_2^{(j)}, r_0^{(j)}, m_0^{(j)}) \)\(^2\) an example of assignments for the considered variables, where \( e = (w_2^{(j)}, a_2^{(j)}, r_0^{(j)}) \). According to (5.3), the conditional probability \( P(M = m_0^{(j)}|E = e^{(j)}) \) is computed as follows:

\[
\Phi_E(m_0^{(j)}) = \frac{P(w_2^{(j)})P(r_0^{(j)}|w_2^{(j)}, a_2^{(j)})P(m_0^{(j)}|r_0^{(j)})}{\sum_M P(w_2^{(j)})P(a_2^{(j)}|w_2^{(j)}, r_0^{(j)})P(m_0^{(j)}|a_2^{(j)})P(M|a_2^{(j)})} \tag{5.6}
\]

The direct path between \( R \rightarrow M \) in the network allows the impact of an anomaly occurring on \( R \) to propagate to \( M \), as both variables are not d-separated by any subset of \( E \). The conditional probability of a low rotor speed \( (r^0) \) given a high wind speed \( (w^2) \) and a high ambient temperature \( (a^2) \) is extremely unlikely (0.0001) as can be seen in the CPD of \( R \) in Fig.2. Therefore, even in the absence of a main bearing anomaly, the conditional probability given in Eq. 5.6 is extremely small, resulting in \( \mathcal{D}(m_0^{(j)}||m^*) \rightarrow +\infty \).

To avoid the issues mentioned, we can make the assumption that the evidence includes only safe measurements. In this scenario, environmental variables seem to be a good choice for this purpose, as their observations are unaffected by anomalies in the system, and can be easily collected and verified. In addition, environment variables are the causes (or roots) of the wind turbine’s component variables. Having entered evidence values about ‘environment variables’, we typically use the BN inference engine to query gradually the state of \( \mathcal{M} \)’s component variables. Having entered evidence values about ‘environment variables’, we typically use the BN inference engine to query gradually the state of \( \mathcal{M} \)’s component variables.

**Definition 2** (Variables ordering). Let \( G \) be a Bayesian network and an ordering \( \prec_G \) over \( V \). Whenever we have that \( X_i \prec_G X_j \), we say that \( X_i \) precedes \( X_j \) in the graph, i.e., \( X_i \) can be either a direct parent (cause) or an ancestor of \( X_j \) in \( G \).

Let \( E \) and \( Q \) (where \( Q \subseteq X \setminus E \)) be a set evidence and query variables, where \( E \prec_G Q \). At a particular iteration \( t \), we analyze the set of new variables \( K \subseteq Q \) that is in the same causal hierarchy within the Bayesian network. In other words, the set of variables \( K \) satisfies the following condition: \( E \prec_G K \) and \( \forall K_i \in K, \exists K'_i \subseteq K \setminus \{K_i\} \) where \( K_i \prec_G K' \). The chronological order of diagnosing variables allows us to gain insights into the propagation path of anomalies within the system, thus enabling us to determine the optimal sequence of diagnostic steps.

Although the formula in equation (5.5) enables us to calculate the distance between the probability of expected and observed values, it is quite intricate to use in our scenario. In reality, a threshold \( \tau \) needs to be adjusted w.r.t. the form of the posterior distribution of each variable \( Q \). The difficulty of defining a generic threshold \( \tau \) that would allow us to classify any observation of a variable \( Q \) as anomalous is a key factor that motivates the need for more sophisticated techniques. To tackle this problem, we propose to use a probabilistic

\(^2\)The index 0 of an assignment of a variable \( X \) refers always to the smallest value in \( \Omega_X \).
framework to locate the conditional probability associated with \( q_i \) w.r.t. \( P(Q|E = q) \). For a given assignment \( q_i \) of \( Q \) and the computed posterior \( P(Q|E = e) \), we collect all posterior value's probabilities that are less or equal to \( \Phi_E(q_i) \): \( F(q_i) = \{ q_j \in \Omega_Q : \Phi_E(q_j) \leq \Phi_E(q_i) \} \). Given the set of elements in \( F(q_i) \) we calculate the probability \( G(q_i) \) which is correspond to the probability that \( P(Q|E = e) \) being less or equal to \( \Phi_E(q_i) \):

\[
G(q_i) = \sum_{q_j \in F(q_i)} \Phi_E(q_j)
\]

(5.7)

If \( G(q_i) \leq \tau \), where \( \tau \) is set to 0.3, then the observation \( q_i \) is classified as anomalous (or unusual). We consider a window \( w \) of one month of the SCADA data for our analysis. When the mean values of \( \{ G(q_i) \}_{i=1}^w \) of the sensor associated with variable \( Q \) is considered as anomalous. If a variable \( Q \) is diagnosed as safe, it can be added to the evidence set for the next step of variable analysis. However, it should not be included in the analysis of variables at the same hierarchy level as \( Q \) in the Bayesian network.

6. Experiments

In this section, we demonstrate the efficiency of our approach by testing it on normal and anomalous main bearing observations. We investigate the importance of the use of the explainable BN model to enhance the understanding of the anomaly and eliminate false positive alarms. To do so, we use the SCADA data from the considered wind farm. It is an onshore park composed of 5 wind turbines. The data from 2011 and 2012 were used to train and validate the normality model, while data from 2014 was utilized to evaluate the effectiveness of anomaly detection. Recall that an anomaly on the main bearing has been reported on the machine \( WT_1 \) during the whole test period (2014). During the training phase of the BN, all data was discretized using expert knowledge. To detect anomalies we compute the RE for every row in the dataset. These RE results are transformed into binary predictions, i.e. if the RE of the row \( i \) is greater than the fixed threshold \( \epsilon \), the anomaly prediction is equal to 1, otherwise, it is set to 0. This results in \( N \) tuple values that can be used to compute the accuracy score and then measure anomaly detection performance measure. Results in Tab.4(a) display the accuracy of the AE on the used data. The results show that the trained AE is highly effective in detecting main bearing anomalies with a score of 88% achieved for the testing data of the machine \( WT_1 \). High scores are obtained for the other machines under normal behaviors. This highlights the model’s efficiency in distinguishing between anomalous and normal observations. The distribution of compressed representation (bottleneck) of normal and anomalous testing observations shown in Fig.3 also validates the model’s ability to accurately differentiate between normal and abnormal main bearing data. The comparison with other classic methods (see Tab.4(b)) proves the reliability of using the AE model to detect anomalies on the main bearing. To emphasize the efficiency of utilizing a BN model in our context, we evaluated our approach in two distinct scenarios: (i) the presence of data containing anomalous main bearing (\( WT_1 \), January
<table>
<thead>
<tr>
<th>Dataset (WT)</th>
<th>Train</th>
<th>Validation</th>
<th>Test</th>
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<tbody>
<tr>
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<tr>
<td>WT_5</td>
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<td>0.86</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>Safe (MB)</th>
<th>Anomaly (MB)</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isolation Forest</td>
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<td>0.69</td>
<td>0.71</td>
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<tr>
<td>LocalOutlierFactor</td>
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<td>0.11</td>
<td>0.55</td>
</tr>
<tr>
<td>Gradient Boosting</td>
<td>0.82</td>
<td>0.91</td>
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</tr>
<tr>
<td>Auto-encoder</td>
<td>0.95</td>
<td>0.80</td>
<td>0.87</td>
</tr>
</tbody>
</table>

**Figure 4.** (a) Anomaly detection in the studied wind farm (b) Comparison of several approaches

**Figure 5.** Two scenarios of anomaly explanation: data with a true main bearing anomaly (a,c), data with a safe main bearing, and added noise to the rotor speed (b,d).

2014), and (ii) the presence of data from a healthy main bearing (WT_2, January 2014), but with added noise on the rotor speed observations. In both scenarios, we plot the probabilities associated with each sensor observation \( G(q_i) \) (see Fig5(a)(b)) and summarize them by calculating the mean Fig5(c)(d). As seen in Fig5(a)(c), the BN enables to detect correctly least probable sensors, which are those related to the temperature of the main bearing. In contrast, although the AE indicated that there is an anomaly on the main bearing in the second scenario, the BN clearly indicates that these anomalies are not related to the main bearing sensor, but instead to the rotor speed (see Fig. 5.(b),(d)). Then, the use of the BN helps to prevent false positive alarms in the second scenario, this demonstrating the effectiveness of our approach in detecting the true anomalies on the main bearing.

### 7. Conclusion

In this paper, we have proposed a new main bearing anomaly detection and explication based on two heterogeneous models (AE and BN). This approach relies on a very effective way to exploit BN properties to provide more details about the anomalies detected by the deep learning model. As shown in the experimentation, our method reaches a very high correctness score on the used SCADA data. For future works, we plan to develop a generic approach that handles several anomalies at the same time and also represents the inherent uncertainty in the SCADA data using a variational AE.
References