Anomaly detection in vibration signals for structural health monitoring of an offshore wind turbine

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Abstract. The current approach for detecting anomalies in acceleration signals relies extensively on feature engineering. Indeed, detecting rotor imbalances in wind turbines starts by first isolating and then assessing the energy of the 1P harmonic, leading to a feature that is efficient but not failure mode agnostic. While different engineered features can be used concurrently, some anomalies in the acceleration signal might remain undetected by the algorithm, even though they are visually noticeable to a human in the signal’s spectrogram. Thus, this project aims to build an AI algorithm capable of detecting anomalies in spectrograms, agnostic of their origin, providing an early warning for potential structural issues. The proposed algorithm infers spectrograms of acceleration signals through a deep autoencoder. Anomalies are identified based on a custom reconstruction error. A sensitivity analysis is performed for two types of anomaly, in which waveforms with different energy levels are artificially added to an acceleration signal measured from an offshore wind turbine (OWT). For a 1P harmonic anomaly representing 20% of the total signal energy, the proposed approach yielded an efficiency (AUC) equal to 96% thanks to a novel reconstruction error, which significantly increased the performances.

Keywords: Acceleration measurements · Offshore wind energy · novelty detection · Machine learning · Autoencoder.

1 Introduction

In recent years, the use of sensors has increased significantly. At the same time, the demand for processing and extracting valuable information is becoming more and more relevant [1]. A typical application of measurement interpretation is Structural Health Monitoring (SHM).
An essential part of SHM is anomaly detection. In the broadest sense, an anomaly can be defined as a deviation in the system behavior that harms its current or future performance [2]. In this paper we will develop a method to detect anomalies directly in timeseries data coming from accelerometers. Such an idea is not novel as Tukey [3] presented a statistical method for detecting anomalies in time-series data in 1979. Also more recent examples in which timeseries are used to detect anomalies are easily found. In [4], defects in WT blades are detected using a grid of accelerometers and an actuator to excite the structure. A Mahalanobis distance is used as an anomaly index; this distance calls for training with non-anomalous data.

Another relevant example is DCASE Task2: Unsupervised Anomalous Sound Detection for Machine Condition Monitoring [5], the participants use the most up-to-date strategy to detect anomalies based on microphones readings. Reviewing the participants’ technical reports, one can notice the diverse panel of strategies used to approach the problem. For example, in [6] the authors present a neural network model, namely the Auto-Encoder (nonlinear dimensionality reduction) (AE), which can reconstruct the normal signal with low error. However, the reconstruction error surpasses a threshold if an anomalous signal is provided. This approach is also used for SHM, for instance, in [7], in which the authors first transform the time series into a set of features before inferring it into an AutoEncoder. There are many variations to this approach, as in [8], in which the author replaces the MSE loss function by a correntropy function. In [9] the authors uses an AE with feature enhancement, which is based on a competition and enhancement policy that favors neurons with greater activation values.

The problem issued in this contribution differs from the latter mentioned research in SHM by the target to build an agnostic failure mode detection. Therefore, it is essential not to rely on extensive feature engineering. Plus, while the DCASE challenge targeted the use of sound (sampled up to 44.1 kHz) this contribution targets the use of acceleration signals, sampled at far lower frequencies. To formalize the matter in more detail: The goal is to build an algorithm to identify whether a 10-minute acceleration signal is normal or anomalous. This task is in the scope of unsupervised learning because anomalies are infrequent and very diverse. The envisioned algorithm is then limited to flag signals that deviate from the training dataset as anomalous. Hence it is agnostic of the actual deviation. [5].

This paper is organized as follows. Section 2 proposes the details on the overall case and present the artificial anomaly that is used. Section 3 presents the proposed algorithm to tackle the issued theme of anomaly detection in timeseries along with a baseline method for reference. Subsequently, Section 4 includes the conclusion of this contribution, and suggestions for future work are given.
2 Case Presentation and Data Exploration

In this section, the data used are investigated, and the restrictions on the operational condition are discussed. Then, the simulated anomalies are given. The data used in this contribution originates from two accelerometers installed on an offshore wind turbine (OWT); the measurement reference is then rotated to the reference of the nacelle (fore-aft and side-side) using the yaw angle measurement. As such, the used data is the acceleration in both side-side (SS) and Fore-Aft (FA) directions. The signals are given in 10-minute chunks, with a sampling frequency of 12.5Hz. Therefore, the highest frequency of a waveform that can be reconstructed from these readings is 6.25Hz. Figure 2.1 displays an example of SS acceleration measurements.

The dataset used in this contribution consists of 1000 signals; each has two channels representing FA and SS direction. The operational condition is restricted and covers a wind speed range between 11m/s and 12m/s, with a rotor speed of approximately 13.7rpm. Restricting the operational condition allows a more controlled environment and eases up the task for its first iteration. Nevertheless, it does not bring many shortcomings, since this algorithm could be run whenever the turbine operational conditions are met with the one presented above, meaning that the major downside is increasing the reaction time and limiting the method to persistent issues (e.g. such as a permanent damage). In a further study, the operational condition will not be restricted, which should decrease reaction time and potentially use the method for intermittent issues.

The power spectral density (PSD) plot is standard for apprehending stationary signals. Figure 2.2 shows how the PSDs of the used dataset is distributed, the x-axis is limited to 2Hz for figure neatness. All 1000 PSDs of the considered signals follow the same pattern. Noteworthy, is that despite that all data is collected during a restricted operational condition, some variation in amplitudes does occur. Of course when data from different operational rotor speeds is considered, then more variation in the spectrum will occur. The testing set must contain samples with anomalies to quantify the model performances in detecting an anomaly. However, anomalies occur rarely and are highly diverse. Consequently, obtaining an anomalous labeled signal in measured signals is quite improbable. Furthermore, exhaustive anomalous signals are inconceivable to collect in the case large civil structure since one has to damage the civil structure. Therefore, the author resorts to simulated anomalies to mitigate this limitation.

During this project, the anomaly is simulated by adding a waveform to the measured signal. The anomalies are only introduced to the side-side channel. The dataset comprises 1000 measured data points constituted by both SS and FA readings. Of
these, 800 are chosen and considered as non-anomalous. They are used to train a model responsible for detecting deviation from the regular pattern. The remaining 200 signals are used to build the testing dataset. These 200 signals are duplicated, and an anomaly is added to the double. Leading to a testing dataset composed of 200 normal and 200 anomalous signal.

Two types of anomalies are considered; the first type (type 1) Eq. (1a) is a simulation of rotor unbalance in which a 1P harmonic, at 13.7RPM, is added to the signal. It is persistent in the signal and present in the entire 10-minute window. Much like a rotor unbalance would be present persistently. The type 2 anomaly in Eq. (1b) is an addition of a wavelet-like waveform. The purpose of this second type is to simulate an anomaly with varying frequency and appears only in a small time window and to demonstrate the methodology is agnostic of the actual anomaly. The frequency and amplitude of the sinusoidal changes in time. The parameter $p$ governs this frequency change in time and is set such that the waveform covers a range of the spectrum. $\tau$ and $\sigma$ govern the amplitude change. They are parameters of a Gaussian bell and are set such that the bell curve is centered and relatively thin.

$$y_a(t) = A \sin(2\pi \frac{13.7}{60} t)$$  \hspace{1cm} (1a)

$$y_a(t) = A \exp\left(\frac{-(t - \tau)^2}{2\sigma^2}\right) \sin(\omega(t) \cdot t) \quad ; \quad \text{with} \quad \omega(t) = \sin(p \cdot t)^2 \hspace{1cm} (1b)$$

In both equations, the parameter $A$ represents the amplitude of the anomaly; varying this latter will influence the severity of the introduced anomaly.
Figures 2.3 and 2.4 show the impact of introducing anomaly type 1 and type 2 to the signal. One can see the effect of increasing the amplitude (A in the equations 1a and 1b) on the spectrum. It seems a prior that anomaly type 2 brings a more subtle deviation from the normal behavior than anomaly type 1.

Finally, instead of using the amplitude level as a severity measure, another metric is introduced, which will be called relative Root Mean Square (rRMS) in the following. It is defined as the ratio between the RMS of the introduced anomaly and the average RMS of the whole data set:

\[
rRMS(\text{anomaly} | \text{dataset}) = \frac{\text{RMS}(y_a(t))}{\frac{1}{n} \sum_{i=0}^{n} \text{RMS}(y_i(t))}
\]

where \( n \) is the number of original signals \( y_i(t) \) in the dataset, \( \text{RMS}(y_a(t)) \) is the RMS value of the anomaly and \( \text{RMS}(y_i(t)) \) is the RMS of the i-th signal of the dataset.

3 Methodologies & Results

As mentioned before, the aim of this paper is to build a data-driven algorithm capable of detecting anomalies in vibration signals. The signals used are measured from an offshore wind turbine, with simulated anomalies added to them. This section is divided into three subsections. Firstly, the evaluation metric is discussed. Secondly, a baseline method based on statistics is established. Thirdly, the proposed approach is described, and the steps to improve it are discussed. Finally, the performances of the different models are compared along with a small discussion.
3.1 Evaluation Metric

The models considered in this contribution take as inputs a 10-minutes signal and are responsible for outputting an anomaly score. To decide whether the given signal is anomalous, one might apply a high or low threshold to the classifier output and decide that the anomalies are present if and only if the threshold exceeds the threshold value. There is a trade-off between True-Positive-Rate (TPR) and False-Positive-Rate (FPR). The ROC curve and its Area Under the Curve (AUC) are used to validate and compare the approaches. It is built by varying the decision threshold and quantifying the TPR and FPR. Therefore, the latter is independent of the threshold and allows detailed model evaluation. The AUC describes the discriminative power of the model. The AUC is the area under the ROC curve. It can be interpreted as the probability that, the value of the abnormality score is higher for the abnormal than for the normal, among two randomly selected signals. Therefore, an AUC of 50% indicates that the marker is uninformative. An increase in the AUC indicates improved discrimination abilities, with a maximum of 100%.

3.2 Baselines Models

Before tackling the project with a deep learning approach, the author proposes a models founded on logic to serve as a reference. After all there is only added value to the inclusion of the deep learning approach when the anomaly is not obvious from simple statistics. The baseline model is based on Mahalanobis Distance (MD).

The MD differs from the Euclidean distance in that it considers the variance of the training dataset and correlation. Therefore, unlike Euclidean distance, where all the components of the PSD are treated independently and in the same way, the MD gives less weight to the most dispersed components. The resort to the Mahalanobis is quite natural when examining how the PSD is distributed at Figure 2.2. In fact, in the latter figure, the low frequency has a narrow distribution compared to the high frequency since the red area represents the training data range. Therefore, a deviation in the high frequencies is more expected than in the low frequencies.

The Mahalanobis distance \( D \) of the PSD \( Y = \{Y(f_1), Y(f_2), \ldots, Y(f_n)\} \) to the training dataset is calculated as follows. Consider the mean of the PSDs in the training dataset \( \mu = \{\mu_{f_1}, \mu_{f_2}, \ldots, \mu_{f_n}\} \) and a covariance matrix \( \Sigma \), where \( \Sigma \) which is a positive-defined matrix, the \( D \) of \( Y \) then is defined as defined in Equation 3  [11]:

\[
D(Y) = \sqrt{(Y - \mu)^T \Sigma^{-1} (Y - \mu)^T} \tag{3}
\]

The author is aware of the problem of distance concentration in high-dimensional space, and that the Mahalanobis distance is not exempted from the curse of dimensionality [15].
3.3 Proposed approach

Preprocessing: Data preprocessing is critical for deep learning algorithms, and appropriate data preprocessing is mandatory to achieve better performance. It involves data cleaning, normalization, transformation, feature extraction, and selection [13]. In the proposed approach, the feature considered is a min-max normalized spectrogram, which is a graphical illustration of the frequency spectrum of the signal as it varies over time, which allows for a higher granularity compared to the PSD. Figure 3.1 shows an example of a signal spectrogram (side-side component limited to 2Hz) with the two anomalies added simultaneously; the type 1 anomaly causes a horizontal line to appear in the signal spectrogram (at frequency = 0.23Hz). Contrarily, the type 2 anomaly is not limited to a single frequency, nor is it persistent in the spectrogram, and it causes the appearance of a diagonal region. Finally, a min-max normalization is applied before feeding the spectrogram to the neural network.

![Fig. 3.1. An example of a spectrogram of a signal (only the side-side component) with the two anomalies added simultaneously.](image)

Model: The proposed model in this contribution is the AutoEncoder (AE). It is a neural network used to learn representations in an unsupervised manner [14]. The encoder is responsible for compressing the input spectrogram into a low-dimensional representation often named latent vector, while the decoder attempts to reconstruct the input spectrogram from the latent dimension. To fit the parameter of the AE, back-propagation is used, and its purpose is to reduce the loss function by updating the weight of the neurons. A commonly defined loss function is the mean-squared error. During inference, to assess whether the input spectrogram is anomalous or not, a reconstruction error is used.
Figure 3.2 presents an overview of the data flow in both training and inference, the steps specific to the training are in yellow, and the ones specific to the inference are in purple. The blue boxes show the model itself and the preprocessing step. In this figure, the AE is composed of both encoder and decoder, as described earlier. The latent dimension is tuned to reduce the loss function during the training. In this contribution, the focus is not on the model hyper-parameters, and they will not be described later, except the fact that the established latent dimension size is 8, meaning that the most important details of the spectrogram can be summarized using a vector of 8 dimensions.

Evaluation and improvement: This paragraph evaluates the autoencoder approach using different Reconstruction Errors (RE) and Loss functions (L). First, the standard configuration is considered, corresponding to the Mean Square Error (MSE) for both functions. The reconstruction error map $r_{xx'}(t, f) \in \mathbb{R}^{n_t \times n_f}$ for a spectrogram $x(t, f) \in \mathbb{R}^{n_t \times n_f}$ of signal $y(t)$ against the reconstructed spectrogram $x'(t, f)$ is defined in Equation 4a, producing a per pixel squared error map. The error at frequency $f$ and time $t$ is denoted $r_{t,f}(x)$. Based on this reconstruction error map, the MSE can be defined as in equation 4b.

$$r_{xx'}(t, f) = \left(x(t, f) - D_{\theta} \left(E_{\phi} \left(x(t, f)\right)\right)\right)^2$$ (4a)

$$RE(x, x') = L(\phi, \theta; x) = \frac{1}{n_t n_f} \sum_{f=1}^{n_f} \sum_{t=1}^{n_t} r_{xx'}(t, f)$$ (4b)
Where $E_\phi$ and $D_\theta$ are respectively encoder and decoder function with parameter vectors $\phi$ and $\theta$. Finally, $n_f$ and $n_t$ are respectively the height and width of the spectrogram. This reconstruction did not show good result. After, analysing the model behavior a novel reconstruction error is proposed, this latter is shown in Equation 5.

$$RE(x, x') = p_{95} \left( \frac{r_{xx'}(f) - m(f)}{s(f)} \right) \text{ with } r_{xx'}(f) = \frac{1}{n_t} \sum_{t=0}^{n_t} r_{xx'}(t, f)$$

In Equation 5, the mean value over time of the reconstruction error map $r_{xx'}(t, f)$ is first calculated, leading to an error over frequency $r_{xx'}(f)$. Then, the mean $m$ and standard deviation $s$ of $r_{xx'}(f)$ over the training data set is computed. Finally, the 95th percentile of the normalized $r_{xx'}(f)$ is computed over the axis of frequency. The idea underlying this RE is that the actual noise in the model and data cancel out over time. This RE also focuses on the frequency error: by taking the 95th percentile, if there is a change of 5% of the frequency band, the RE value will be high. The need to normalize $r_{xx'}(f)$ comes from the fact that the error distributions for some frequencies are different.

**Results** : Table 1 shows the performance of the above-described approaches with varying levels of severities and for the two types of anomalies. The severity level is quantified using the rRMS defined in Eq. (2). The Auto-Encoder (AE) with the Reconstruction Error (RE) defined in Eq. (5) (custom reconstruction error) outperforms the baseline method and the classical AE. For anomaly type 1, the AE with a custom RE is able to detect the anomaly when it has an rRMS 16% with an AUC of 0.78 and detects the anomaly perfectly when their rRMS 26%. While the MD-based starts to detect the anomaly only when the rRMS is about 21% and has an AUC of 0.74, the MD-based model perfectly separates the anomaly from the normal signal when the rRMS is about 106% (this value is not depicted in the table). However, the anomaly type 2 is more subtle, covers a more significant part of the spectrum compared to anomaly type 1, and requires a higher level of energy to be detected with all the studied approaches. The baseline model shows lousy performance for all anomaly levels, while the proposed approach starts to separate the normal from the abnormal when the rRMS is approximately 21% and has an AUC of 0.76 and has a good performance when the rRMS is about 26% with an AUC of 0.85. The reason for the Mahalanobis distance not working well as an anomaly score is the high dimensionality of the problem. If a single frequency or a small subpart of the spectrum deviates from its standard range (sigma band), it has to deviate broadly to take importance in the distance [15].

Figure 3.3 shows a control chart of the proposed approach. It can be seen that there is a clear shift in the anomaly index when anomalies are introduced. From this, one can think of many strategies to detect anomalies, for example, by examining the
Table 1. Experimental results over testing dataset with varying level of severities. The performance metrics considered in this table is the AUC, the level of severity is measured using the rRMS

<table>
<thead>
<tr>
<th>Level of severities (rRMS)</th>
<th>Anomaly type 1</th>
<th>Anomaly type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>11% 16% 21% 26%</td>
<td>11% 18% 25% 32% 36%</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td>0.54 0.63 0.74 0.83</td>
<td>0.5 0.5 0.51 0.58 0.68</td>
</tr>
<tr>
<td>Auto-Encoder (MSE)</td>
<td>0.54 0.58 0.63 0.69</td>
<td>0.5 0.5 0.5 0.55 0.6</td>
</tr>
<tr>
<td>Auto-Encoder (Custom RE)</td>
<td><strong>0.64 0.89 0.96 0.99</strong></td>
<td>0.53 <strong>0.68 0.84 0.92 0.94</strong></td>
</tr>
</tbody>
</table>

average value over a moving window instead of inspecting the anomaly index sample by sample, this leads to a more robust and sensitive (detect anomalies with lower energy) method at the cost of a slower detection time.

![Fig. 3.3. Control chart for the proposed approach with the two anomalies type](image)

4 Conclusion

This study presents the challenge of anomaly detection in wind turbine structures from acceleration measurements. This problem is addressed using a data-driven model. Since there is no readily available labeled data set containing anomalies in the context of large civil structures, it is necessary to use a simulated anomaly to
evaluate the model. Two anomaly types are introduced; the first one mimics 1P rotor imbalance, and the second is a subtle drift in the PSD pattern.

This paper proposes a strategy based on a neural network model, namely the auto-encoder, which can be trained in an unsupervised manner leading to an anomaly agnostic model. This agnosticism is validated using the two aforementioned types of anomaly. This contribution shows that using a customized RE increases the performance considerably. The performance of the detection model is evaluated using the AUC, which is a well-established metric. For the rotor imbalance anomaly with a relative energy of 21%, the proposed model shows an AUC of 96%, which outperforms the baseline model based on the Mahalanobis distance that has an AUC of 63%.

In the future, a more diverse signal dataset with varying operational conditions should be used. The latent model vector could be included in the reconstruction error. A feasibility study on unsupervised clustering could be conducted to classify the signal depending on the type of anomaly.

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References


