GAS TURBINE CONDITION MONITORING USING ACOUSTIC EMISSIONS

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Condition monitoring of a cyclostationary process, such as a gas turbine acoustic emissions (AE), is shown to be feasible through capturing the average behavior of the AE signals. In this paper, it is shown that the condition of a gas turbine can be uniquely represented through a so-called feature vector, if the AE signals that are taken from the process is of sufficiently long duration. The feature vectors are then used for determining the health state of the gas turbine engine and for detecting an anomaly as well as its severity in the process, through comparison with a baseline feature vector corresponding to the process in the healthy state.

Keywords: Condition monitoring, cyclostationary process, acoustic emissions, gas turbine engine, feature vector

1. Introduction

Industrial condition monitoring (CM) techniques for gas turbine engines are invariably based on vibration and thermal analysis of certain parts in conjunction with simultaneous measurements of the system performance. Vibration sensors are supplied on and equipped in the bearings and/or casing, and on the gearbox in the form of proximity sensors, velocity meters and accelerometers, depending on the required range of spectrum of the vibration frequencies. The fluid temperature is periodically measured through thermocouples at certain locations, such as the compressor inlet/outlet as well as turbine wheel spaces and at the exhaust portion. In addition, pressure transducers process fluid pressure and, collective processing of the parameters yield decisions that are made on the overall health of the machine. However, condition monitoring is considered as a disruptive process by machine manufacturers, due to the added complexity, and the inherent intrusion of additional sensors within the machine components. It would therefore be quite advantageous if one could perform condition monitoring of the system through external means and in non-intrusive manners and outside of the main process. AE signals are ideal candidates especially if the signals could be monitored through microphones or sensors that are located outside the engine compartment.

As far as the feature extraction techniques that are developed for health monitoring using AE are concerned, the authors in [1] have published a collection of available methodologies for low speed rotary components, and broadly categorized the techniques into two classes, namely, (1) AE hit parameters, and (2) AE signal processing feature extraction and pattern recognition methods. The above techniques unfortunately have not been successfully utilized in AE condition monitoring of a gas turbine engine (in contrast to numerous component-based CM approaches). This is firstly due to lack of a universal feature extraction technique, and secondly due to specifying the criterion of a condition change.
2. Definition of a Condition and the Machine Condition Monitoring

Condition monitoring is the process of monitoring the physical parameters of a rotary machine, in order to identify significant changes beyond the normal operating circumstances, that are indicative of a developing fault, or shortening the lifespan of the system. The condition monitoring technique that is discussed in this paper deals with quantifying the health condition of a cyclostationary process by statistical processing of the AE signals, recorded through a set of microphones that are located exterior, but in close proximity of the equipment that is emitting acoustic signals. The microphones need not be installed in a specific point and do not need to be directed toward a specific direction, therefore can also be constructed through mobile devices. The involved signal processing techniques are extremely simple, and can be carried out online via conventional commercial (non-industrial) microprocessors.

Although acoustic signals emitted from rotary machines are generally of a random nature, in the meantime exhibit average behavior of the machine, as in the body temperature can indicate the onset of an infection or a virus in the body. Through this analogy, one can realize that the body temperature, changing randomly and instantaneously in effect of numerous biological interactions, still project symptoms of an illness when measured in an average manner, whereas instantaneous measurements (separately and individually) entail very little (and often unreliable) information, if any. In this paper, we will introduce a general notion for machine condition. However, the scope of our derivations and results encompass only mechanical equipment of a cyclic nature (cyclostationary processes).

Definition 1: The average behavior of an acoustic signal \( x(t) \) emitted from a cyclic mechanical equipment, under a fairly constant set of inputs, is hereinafter regarded and defined as a "machine condition", or simply a "condition", that is denoted by \( C_{x(t)} \).

In case the set of inputs (e.g., fuel flow, ambient temp., load, etc.) to the mechanical system under investigation changes, the average behavior of the system would also naturally change consequently. Therefore, for our analysis here we require a fairly constant set of inputs in order to correctly detect the possible system anomalies. We will see that this definition allows us to identify unique characteristics (hereinafter referred to as features, as formally defined in Definition 2) of a given cyclic system, and also to distinguish anomalies in that system with respect to a benchmark, being the average behavior of the same system under "healthy" or "normal" state and circumstance.

3. Problem Statement and Contributions

Machine condition monitoring consists of three key steps: data acquisition, feature extraction, and condition identification. It is therefore a procedure of mapping the information obtained in the measurement space (AE signals) to the features in the feature space, and finally to machine conditions in the condition space (to be precisely defined subsequently). Hence, it is essentially a problem of pattern recognition and classification (often referred to as clustering analysis).

Cluster analysis, as a multivariate statistical analysis method, is a statistical classification approach that groups signals into different (condition) categories on the basis of the similarity of the characteristics (or features) they possess. It seeks to minimize within-group variance and maximize between-group variance. The result of the cluster analysis is a number of heterogeneous groups (i.e., groups of samples with non-similar features), with homogeneous contents (i.e., contents with similar features).

AE signals from rotating and reciprocating machinery can be non-stationary, implying that the
shorter the time waveform used to calculate the statistical parameters, the greater the likelihood that the parameter does not accurately describe the underlying signal. Even an average of the parameters calculated from a large ensemble of waveforms may not be particularly useful, as it does not describe the spread of a parameters’ values. Hence, the calculated average will also depend on the number of waveforms in the ensemble and the duration of each. Consequently, the random nature of the AE signals entails reliability concerns to the decisions rendered through AE CM techniques.

As a solution to the non-stationarity of the AE signals, researchers have devised to quantify the non-stationarity associated with an AE signal and calculate confidence limits in addition to an ensemble average. Changes in the underlying machine conditions are therefore observed as changes not only in the mean parameter, but also its confidence interval. However, the problem lies in the fact that in order to deduce safe decisions pertaining to a machine condition, large number of samples would be required to compute an ensemble average, which is obviously not always practical. Additionally, interpretation of the confidence limits depend on the associated parameter. Consequently, multiple parameters may need to be considered collectively to make an accurate decision. Therefore, another challenge is that one has to assign appropriate weights to individual parameters in order to attain reliable features corresponding to a signal.

To summarize, the main contributions of this paper can be listed as follows:

• There are numerous successful feature extraction techniques that are used for AE condition monitoring in certain applications. However, variations in the available techniques in the literature implies that no generic solution exists that could ensure successful results for a wide range of applications, even under a specified set of conditions. Although the feature extraction technique that is introduced in this paper (refer to Definition 2) may have been successfully applied in some particular cases in the past, this work tries to stipulate conditions (refer to Assumption 1) under which our proposed methodology can guarantee to produce optimum results, regardless of the application (refer to the Main Result in the next page).

• This work underlines conditions (set forth in Assumption 1) under which a gas turbine AE signal of sufficient length can be used to deduce properties of a large family of AE samples possessing similar statistical parameters. Therefore, the features obtained based on the proposed procedure derived in this work (as per Definition 2) could be free of all random effects associated with an AE signal. This could be considered as a general solution for a certain class of non-stationary signals, applicable to any application that meets these conditions.

• Contrasting with the feature extraction techniques that are available in the literature, not much research has been done in clustering analysis. In conclusion, available CM methods are still challenged by rendering a seamless method to evoke and classify features with a desirable level of confidence at the same time. Although, our work requires certain conditions to be met, we have proposed a classification system with a definable level of certainty, (virtually) capable of classifying machine conditions with no error.

4. The Feature Vector and the Condition Space

A WSC process, in general, is a cyclic process that is obscured by noise. The cyclic behavior of a random signal can be accessed by the autocorrelation function of the signal. Let us show this through an example. Fig. 1 illustrates the autocorrelation function of AE samples corresponding to three equivalent gas turbines operating scenarios under different machine conditions.

All the three plots in Fig. 1 represent noisy sinusoidal waveforms of constant frequency (that is exactly equal to the rotor speed, since all gas turbines (actually real-life machines) were connected to the same power grid through synchronous generators, therefore locked to the speed of the network).
Additionally, if \( x(t) \) and \( [x(t)]_{T_x} \) are random signals satisfying the conditions in Assumption 1, then \( [x(t)]_{T_x} \) can be decomposed into orthogonal mono-components (i.e., sinusoidal waveforms) \( [x_k(t)]_{T_x} \), so that \( [x(t)]_{T_x} = \sum_k [x_k(t)]_{T_x} \), and \( 1/T_x \int_{t_s}^{t_s+T_x} [x(t)]^2_{T_x} \, dt = 1/T_x \sum_k \int_{t_s}^{t_s+T_x} [x_k(t)]^2_{T_x} \, dt \), where,

\[
\frac{1}{T_x} \int_{t_s}^{t_s+T_x} [x_k(t)]^2_{T_x} \, dt = |X_k|^2 \quad \text{and} \quad X_k = \frac{1}{T_x} \int_{t_s}^{t_s+T_x} [x(t)]_{T_x} e^{-j2\pi k T/T} \]

Additionally, if \( [x(t)]_{T_x} \) is sufficiently long, i.e., \( T_x \gg T \), then (for all \( k \)) \( |X_k|^2 \) converges to a deterministic quantity (denoted by \( E[|X_k|^2] \)) that can optimally represent \( C_{x(t)} \), where,

\[
E[|X_k|^2] = \lim_{T_p \to \infty} \frac{1}{T_p} \int_0^{T_p} [x_k(t)]^2_{T_p} \, dt
\]

The formal technical proof of the above result is not provided here due to space limitations.

Now let us investigate the significance of our above result. Assumption 1 presumes that the machine condition \( C_{x(t)} \) can be fully accessed through the autocorrelation function \( R_x(\tau) \). Our main
result then implies that $C_{x(t)}$ can be optimally represented by a vector of $[x_k(t)]_{T_x}$ energies (i.e., $1/T_x \int_{t_s}^{t_s+T_x} [x_k(t)]_{T_x}^2 dt$), in a sense that no other set of features could estimate $C_{x(t)}$ better. This is due to the fact that the energy of $[x_k(t)]_{T_x}$ approaches to $E[[X_k]^2]$ as $T_x \to \infty$, while it can be shown that (proof omitted due to space limitations),

$$R_x(\tau) = \sum_{k=-\infty}^{+\infty} E[[X_k]^2] e^{i2\pi k \tau / T}$$

(1)

and

$$E[[X_k]^2] = \frac{1}{T} \int_0^T R_x(\tau) e^{-i2\pi k \tau / T} d\tau$$

(2)

**Definition 2:** If $x(t)$ and $[x(t)]_{T_x}$ are random signals, and if the conditions in Assumption 1 hold, $X_k$ is defined as a feature of $x(t)$, where,

$$X_k = E[[X_k]^2] / \sum_{i=-\infty}^{\infty} E[[X_i]^2] \quad (i \text{ is an integer})$$

(3)

and a vector composed of the features $X_k$ will be referred to as the feature vector of $x(t)$ and is denoted by $X$. Additionally, an estimate of the feature vector $X_k$ under the condition $C_{x(t)}$, that is approximated by $N$ features, is denoted by $\hat{X}_k | C_{x(t)} = [\hat{X}_1, \hat{X}_2, ..., \hat{X}_N]^T$, and referred to as the feature vector estimates, where

$$\hat{X}_k = \int_{t_s}^{t_s+T_x} [x_k(t)]_{T_x}^2 dt / \int_{t_s}^{t_s+T_x} [x(t)]_{T_x}^2 dt$$

(4)

and is referred to as the feature estimate, where $x_k(t)$ is the $k^{th}$ subband of $x(t)$.

It can be further shown (proof omitted due to space limitations) that the feature estimates are independent random variables, i.e.,

$$E[\hat{X}_i \hat{X}_j] = E[\hat{X}_i] E[\hat{X}_j] \quad \text{for all} \quad (i \neq j) \in \{1, 2, ..., N\}$$

(5)

One may note that our main result implies that $\hat{X}_k$ can be (theoretically) made as close as desired to $X_k$ by increasing $T_x$. Once $X_k$ is obtained one could identify $C_{x(t)}$ accurately from $[x(t)]_{T_x}$. However, this is practically not always possible since the machine condition $C_{x(t)}$ cannot be held constant for too long, and this invalidates the Assumption 1.

**Definition 3:** Since the features $X_k$ are real numbers and $X_k \in [0, 1]$, therefore the feature vector lies in an $N$ dimensional space denoted by $\mathbb{R}_N^{[0,1]}$, and referred to as the feature space.

We will now show how a machine condition such as $C_{x(t)}$ can be uniquely associated with a subset in $\mathbb{R}_N^{[0,1]}$. This is an important step toward machine condition monitoring, due to the fact that once a unique subspace in $\mathbb{R}_N^{[0,1]}$ is associated to a unique condition, each time the feature vector of an AE signal falls within that subspace, one can conclude that the machine is in condition $C_{x(t)}$.

In order to facilitate simple derivations, let us assume that $T_x >> T$ and $T_x = mT$ where $m$ is a positive integer. Let us further assume that $1/T_x \int_0^{T_x} [x(t)]_{T_x}^2 dt = 1$. Then according to Equation (4)

$$\hat{X}_k = 1/T_x \int_{t_s}^{t_s+T_x} [x_k(t)]_{T_x}^2 dt,$$

or $\hat{X}_k = 1/m \sum_{i=0}^{m-1} \int_{t_s+iT}^{t_s+(i+1)T} ( [x_k(t)]_{T_x}^{(i)})^2 dt$, where $( [x_k(t)]_{T_x}^{(i)}) = [x_k(t)]_{T_x}$ for $t \in [t_s+iT, t_s+(i+1)T]$ and $i \in \{0, 1, 2, ..., m-1\}$. Therefore, $\hat{X}_k = 1/m \sum_{i=1}^{m} \hat{X}_k^{(i)}$. 

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where $\hat{X}^{(i)}_k$ is the energy of $[x_k(t)]^{(i)}$. However, Equation (5) implies that $\hat{X}^{(i)}_k$ is an i.i.d random variable. Therefore, $\hat{X}^{(i)}_k$ will have a Gaussian distribution as per the Central Limit Theorem, i.e.,

$$\hat{X}^{(i)}_k \sim N(\mathbb{E}_{\hat{X}^{(i)}_k}, \sigma^2_{\hat{X}^{(i)}_k})$$  \hspace{1cm} (6)

where $\mathbb{E}_{\hat{X}^{(i)}_k} = E[\hat{X}^{(i)}_k] \approx 1/m \sum_{i=1}^{m} (\hat{X}^{(i)}_k)^{(i)}$, and $\sigma^2_{\hat{X}^{(i)}_k} = \text{VAR}[1/T_x \int_{t_s}^{t_s+T_x} x_k^2(t) dt]/m$, when $x(t)$ represents $\mathcal{C}^{(i)}_x$, as long as Assumption 1 holds. Consequently,

$$p_{\hat{X}^{(i)}_k}(\hat{X}_1^{(i)}, \hat{X}_2^{(i)}, ..., \hat{X}_N^{(i)}) = \prod_{i=1}^{N} p_{\hat{X}^{(i)}_k}(\hat{X}_i^{(i)})$$  \hspace{1cm} (7)

where

$$p_{\hat{X}^{(i)}_k}(\hat{X}_i^{(i)}) = \frac{1}{\sqrt{2\pi \sigma_{\hat{X}^{(i)}_k}}} e^{-\left[\frac{1}{2} \left(\frac{\hat{X}_i - \mathbb{E}_{\hat{X}^{(i)}_k}}{\sigma_{\hat{X}^{(i)}_k}}\right)^2\right]}$$  \hspace{1cm} (8)

The objective is to define a criterion to differentiate $\mathcal{C}^{(i)}_x$ from any other condition. The criterion could be based on a desirable false-alarm rate. Let us assume that the objective is to design a condition monitoring system with a 99% reliability. Hence, one can only tolerate $P_{FA} = 1\%$ false-alarm. Therefore, the objective would be to find the smallest space $\mathcal{R}^{(i)}_x \subset \mathbb{R}^N_{[0,1]}$, such that $\int_{\mathcal{R}^{(i)}_x} p_{\hat{X}^{(i)}_k}(\hat{X}) d\hat{X} = 1 - P_{FA}$. The space $\mathcal{R}^{(i)}_x$ is defined as the Condition Space for $\mathcal{C}^{(i)}_x$, and denoted by $\mathcal{R}^{(i)}_x : \{\hat{X} \in \mathbb{R}^N_{[0,1]} | \mu^-|\mathcal{C}^{(i)}_x| \leq \hat{X} \leq \mu^+|\mathcal{C}^{(i)}_x| \}$, where $\mu^+|\mathcal{C}^{(i)}_x| = \mathbb{E}_{\hat{X}^{(i)}_k}|\mathcal{C}^{(i)}_x| + \Phi^{-1}(1(P_{FA}/2)^{1/N})/\sqrt{m}$, and $\Phi^{-1}(\cdot)$ denotes the cumulative distribution function (CDF) for the Gaussian distribution, and $\sigma_{X|\mathcal{C}^{(i)}_x}$ is an $N \times N$ diagonal matrix whose diagonal elements are $\text{VAR}[1/T_x \int_{t_s}^{t_s+T_x} x_k^2(t) dt]^{1/2}$, and $I$ is an $N \times 1$ vector whose elements are all 1.

For identification of every condition $\mathcal{C}^{(i)}_x$, it is necessary to first obtain $m$ independent samples $\hat{X}^{(i)}_k$ with $i = 1, 2, ..., m$ (with $m >> 1$), given that the condition is fairly constant. Then the mean, and standard deviation of the samples ($\mathbb{E}_{\hat{X}^{(i)}_k}$ and $\sigma_{X|\mathcal{C}^{(i)}_x}$, respectively) are computed, to marginate the condition space $\mathcal{R}^{(i)}_x$, as explained above. Once the limits of $\mathcal{R}^{(i)}_x$ are specified, for every other future sample $\hat{X}^{(i)}_k$, if $\hat{X}^{(i)}_k \in \mathcal{R}^{(i)}_x$ then it can be inferred with a probability of $1 - P_{FA}$ that the machine is in condition $\mathcal{C}^{(i)}_x$.

The interesting fact about the clustering method that is discussed above is that one can shrink the condition space $\mathcal{R}^{(i)}_x$ to any desirable boundary, by increasing $m$. Hence, it would be possible to separate the conditions $\mathcal{C}^{(i)}_x, \mathcal{C}^{(j)}_x, \mathcal{C}^{(k)}_x, ...$ so that no overlapping occurs among the conditions. Consequently, it would be possible to accurately infer about the machine condition regardless of how close the condition spaces might be. Moreover, one can desirably choose any required rate for false alarms, without undesirably expanding $\mathcal{R}^{(i)}_x$, by increasing $N$. As one may note increasing $m$ is effectively the same as increasing the sub-signal length $T_x$.

5. Practical Condition Monitoring Simulation Scenarios

5.1 Detecting a Problem in a Gas Turbine Gearbox

Data collection carried out for the purpose of this research work, involved AE recordings from several gas turbines of same make, type and size. The samples were taken through a mobile phone sound recorder at $f_s = 44, 100$ samples/sec, for several seconds each, and several samples for every operating gas turbine under different conditions. Among the samples, there were 4 sets of newly commissioned gas turbines all equally loaded and running under fairly equivalent conditions. The feature
vectors of one of the machines were significantly different from the others, that were later found, was due to a problem in its gearbox. The problem was so insignificant that neither the vibration detectors, nor the drain oil thermocouples could detect. Now let us look at the condition space for the normal gas turbines (denoted as $C_{\text{Normal}}$) versus the problematic one (denoted as $C_{\text{Gearbox}}$). In this scenario the false-alarm rate is set to $P_{\text{FA}} = 1\%$. It was identified that for a gas turbine stationary application, $N = 4$ would provide sufficient spacing among the conditions to be demarcated clearly, and $T_s \geq 3.4$ seconds would allow the vectors to strongly converge. The following condition spaces were obtained:

$$R_{\text{Normal}} = \{X \in \mathbb{R}_4^T \mid \begin{bmatrix} 0, 4.2 \times 10^{-4}, 0.057, 0.88 \end{bmatrix}^T < X < \begin{bmatrix} 3.7 \times 10^{-5}, 14.42 \times 10^{-4}, 0.115, 0.943 \end{bmatrix}^T \}$$

(9)

$$R_{\text{Gearbox}} = \{X \in \mathbb{R}_4^T \mid \begin{bmatrix} 0, 50.4 \times 10^{-4}, 0.305, 0.49 \end{bmatrix}^T < X < \begin{bmatrix} 4.05 \times 10^{-5}, 83.1 \times 10^{-4}, 0.502, 0.69 \end{bmatrix}^T \}$$

(10)

It can be observed that $R_{\text{Normal}} \cap R_{\text{Gearbox}} = \emptyset$, therefore it is expected that one is able to precisely demarcate the gearbox problem from the normal machine state. Next, we considered 1000 random recordings of 4.5 sec. duration each, of machines in normal states (i.e., $[x(t)]_{4.5\text{Sec.}} \in C_{\text{Normal}}$), and 1000 samples of the machine with the gearbox problem ($[x(t)]_{4.5\text{Sec.}} \in C_{\text{Gearbox}}$), and the feature vectors of all the samples $\hat{X}^{(1)}, \ldots, \hat{X}^{(1000)}$ were classified as per the criterion $\hat{X}^{(i)} \in R_{\text{Normal}}$, or $\hat{X}^{(i)} \in R_{\text{Gearbox}}$. The results obtained were excellent, without even having one case of error. Specifically,

$$P_X[X \in R_{\text{Normal}} \mid C_{\text{Normal}}] = 100\%, \text{ and } P_X[X \in R_{\text{Gearbox}} \mid C_{\text{Gearbox}}] = 100\%$$

The process that lead to identification of the gearbox problem was straightforward. The microphone was moved around, and inside different compartments of the gas turbine, such as the Gas Valve compartment, the Turbine compartment, around the coupling, the Gearbox compartment, the Generator, etc. The feature vectors $X$, obtained in the Gearbox compartment showed a relatively higher energy in the second component of the vector, i.e., $X_2$, whereas other components were comparatively weaker, demonstrating that high energy $X_2$ was emitted from the gearbox. When the lubricating oil was changed and the oil pipelines were flushed, it then followed that the problem was rectified.

In conclusion, the above is a manifestation of a problem that could only be detected through gas turbine AE analysis, while the sensors installed on the engine were not able to detect any anomaly and deviation or problem.

### 5.2 Gas Turbine Misalignment

This scenario demonstrates the presence of very mild rotor bowing or misalignment problem that causes radial forces on the shaft. These cases together with rotor unbalances represent as one of the most common malfunctions in turbomachinery. Radial forces cause the rotor to be displaced from its original position to high eccentricity ranges triggering nonlinear effects, causing the response of the rotor to contain synchronous component along with the $2^{nd}$ and $3^{rd}$ (and higher order) harmonics. A gas turbine startup and warm-up cycle often produces similar behavior temporarily. As the engine approaches its thermal stability, radial forces diminish and harmonic components fade away. Hence, in this work we have used the AE signal of a healthy gas turbine when the engine was brought into service, from a fully cooled-down state, to emulate the condition space of a rotor misalignment
problem, that is denoted as $C_{\text{alignment}}$. As described in the Scenario 5.1, the condition space was computed by using $m = 100$ feature samples. A misalignment space was formed as follows:

$$\mathcal{R}_{\text{Misalignment}} = \{ \mathbf{x} \in \mathbb{R}^4_{[0,1]} \mid 
\{ \mathbf{x} \in \mathbb{R}^4_{[0,1]} \bigg| \begin{bmatrix} 6 \times 10^{-5}, 17.8 \times 10^{-4}, 0.061, 0.762 \end{bmatrix} ^T < \mathbf{x} < \begin{bmatrix} 732 \times 10^{-5}, 128 \times 10^{-4}, 0.22, 0.93 \end{bmatrix} ^T \} \}$$

(11)

It is evident again that $\mathcal{R}_{\text{Misalignment}} \cap (\mathcal{R}_{\text{Normal}} \cup \mathcal{R}_{\text{Gearbox}}) = \emptyset$, since $\mathbf{x}_1 | \mathcal{R}_{\text{Misalignment}} \in [6 \times 10^{-5}, +\infty)$, whereas $\mathbf{x}_1 | (\mathcal{R}_{\text{Normal}} \cup \mathcal{R}_{\text{Gearbox}}) \in [0, 4.05 \times 10^{-5}]$.

In order to verify the boundaries of $\mathcal{R}_{\text{Misalignment}}$, 1000 feature estimates were collected again (i.e., $\hat{\mathbf{x}}^{(1)}, ..., \hat{\mathbf{x}}^{(1000)}$), while the engine had not yet been thermally stabilized. It was confirmed that $\hat{\mathbf{x}}^{(i)} \in \mathcal{R}_{\text{Misalignment}}$ for $i = 1, 2, ..., 1000$, which implies that $P_{\mathbf{x}}[\mathbf{x} \in \mathcal{R}_{\text{Misalignment}} | \mathcal{R}_{\text{Misalignment}}] = 100\%$, and obviously, $P_{\mathbf{x}}[\mathbf{x} \in (\mathcal{R}_{\text{Normal}} \cup \mathcal{R}_{\text{Gearbox}}) | \mathcal{R}_{\text{Misalignment}}] = 0\%$, since the samples $\mathbf{x} \sim \mathcal{R}_{\text{Normal}}$ and $\mathbf{x} \sim \mathcal{R}_{\text{Gearbox}}$ in Section 5.1 cannot also belong to $\mathcal{R}_{\text{Misalignment}}$, due to the fact that $\mathcal{R}_{\text{Misalignment}} \cap (\mathcal{R}_{\text{Normal}} \cup \mathcal{R}_{\text{Gearbox}}) = \emptyset$. Additionally, since $\mathcal{R}_{\text{Normal}} \cap \mathcal{R}_{\text{Gearbox}} \cap \mathcal{R}_{\text{Misalignment}} = \emptyset$, one can generally confirm that if the gas turbine is running in one of the conditions $\mathcal{C}_i$, $i \neq j \in \{\text{Normal, Gearbox, Misalignment}\}$, then by taking the AE subsamples $[x(t)]_{4.5\text{sec}}$, one will be able to detect the condition without false alarms, i.e., $P[\mathcal{C}_i | \mathcal{C}_i] \approx 1$ and $P[\mathcal{C}_i | \mathcal{C}_j] \approx 0$.

Generalizing the notion described above, one can note that for any given condition $\mathcal{C}_c$ it is possible to construct a condition space $\mathcal{R}_c$, so that $\mathcal{R}_c \cap \mathcal{R}_{c} = \emptyset$ ($\sim c$ denotes any condition other than $c$), with (virtually) any desirable false-alarm rate, as long as it is possible to take an AE recording of the machine (under the non-varying condition $\mathcal{C}_c$) for a sufficiently long duration of time. Thereafter, it would be possible to detect the condition $\mathcal{C}_c$ with a desirable certainty.

6. Future Work

The concern associated with our proposed methodology presented in this paper is the fact that a “normal” operating condition does not correspond to a constant condition space for too long. In fact every condition is a function of time, i.e., $\mathcal{C}_c(t)$, that consequently renders a time-varying condition space $\mathcal{R}_c(t)$. For instance a gas turbine operating normally is subject to build-up of adhering debris on its compressor blades, due to the dust that is present in the air. This reduces the effective air path and causes performance degradation until a compressor water washing is applied. Therefore, it is necessary to marginate an adaptive condition space that responds to natural changes in the conditions. This is a topic of our future research that we are pursuing by invoking machine learning solutions.

REFERENCES