Feature Extraction in non-stationary conditions

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Abstract
Machine condition monitoring is a challenging task. This paper presents a technique on the domain of rotating machine fleet condition monitoring for non-stationary operating with emphasis on gears and bearings as the most critical mechanical components. The machines are working on non-stationary conditions, on factual applications. This condition is causing an effect on the vibration signal as the operating frequencies are varying. As a result, the signal cannot be used as a condition estimator on its raw form. Additionally, the signal could contain more than one mechanical part interference, as well as casing or other resonances. While we present the factor of non-stationary conditions and signal decomposing, current studies do not follow this path. Most researchers require a large historical data as they use artificial intelligence on their try to be less unproductive. More than that, on this study a comparison between the whole fleet and a single machine will be presented, compared to cluster methods or machine to machine comparison. The proposed solution contains the decomposition of the vibration signals, received from the main mechanical components of each individual, in order to separate the internal forces that contain information on kinematic parts and are therefore potentially symptomatic of faults in gears and bearings, to be used for Machine Health Monitoring. This decomposed signal of each individual defines a stochastic process in the fleet provide different realizations. The deviating machine is spotted within a monitoring framework by controlling if any new measurement can be accepted as a realization of this stochastic process. The originality of this method stands on the equalization scheme which is able to remove the effect of speed-varying transfer functions, so as to normalize the signal with respect to the structural fingerprint of each individual part of the fleet. All the above, were applied in parallel with the experimental procedure, on a set of machines, acting as a fleet. Vibration signals were taken from three points of each mechanism. On the paper, the experimental procedure is presented in depth as well as the evaluation of signals and the complete methodology of the condition monitoring.

1 Introduction

1.1 Context

It is extremely important to monitor the condition of rotating machines in real-world settings to ensure they are performing at their best, reduce unexpected downtime, and prevent disastrous failures. By utilizing advanced sensing technologies and data analytics, machine condition monitoring in actual conditions allows for proactive maintenance strategies, which ultimately lead to greater equipment reliability and cost savings. The majority of research endeavors within the domain of machine condition monitoring primarily emphasize the monitoring of individual machines, rather than adopting a comprehensive approach that encompasses the monitoring of an entire fleet of machines [1]. In other cases, the researchers are focused on a single part of the rotating machine to monitor [2]. However, in real world application, is even necessary sometime to provide real-time condition monitoring of similar quantities (fleet of machine, i.e airplanes [3], wind turbines etc.). The fault diagnosis of key components of a fleet is an idea that has been analyzed in [4]. The utilization of a fleet-based approach capitalizes on the analysis of multiple entities. Operating conditions significantly influence the effectiveness of machine condition monitoring, serving as a crucial parameter in the assessment and analysis of machine health. The dynamic nature of operating conditions, including factors such as load variations, temperature fluctuations, and speed changes, introduces variability and complexity in the measured signals. The transmission of structural vibrations in rotating machinery from the shaft and bearings to the surrounding structure, commonly referred to as the housing, is a prevalent occurrence. As the housing possesses a relatively expansive surface area, it frequently acts as the primary source of noise [5],[6],[7]. Due to their inherent non-stationarity and the presence of complex noise, vibration signals pose challenges for Fourier transform-based spectrum analysis methods. These techniques struggle to effectively filter and differentiate noise within the signals, leading to a masking effect where the frequency domain characteristics of the noise overshadow the relevant information within the signal. As a consequence, it becomes difficult to extract the desired features and accurately analyze the vibration signals using traditional Fourier transform-based approaches. To effectively address this challenge and accurately demodulate the signal in rotating machinery, additional steps are implemented. A speed spectral pre-whitening method has been developed and presented in [8]. The analysis of vibration in machines operating under non-stationary conditions requires special techniques such as order tracking algorithms and advanced signal processing methods [9]. The need for feature extraction in Fleet Machine Health Monitoring (FMHM) arises from the inherent complexity and high-dimensional nature of the data generated by multiple machines within a fleet. Fleet Machine Health Monitoring involves monitoring and assessing the health of numerous machines simultaneously, which results in a significant volume of sensor data. Dealing with this vast amount of data poses challenges in terms of computational efficiency and meaningful analysis. Feature extraction techniques play a crucial role in addressing these challenges by transforming the raw signal vibration data into a lower-dimensional feature space that retains relevant information for analysis and decision-making. By extracting informative features, such as statistical measures, spectral components, or time-frequency representations, FMHM can effectively capture and quantify machine health-related patterns and anomalies. The extracted features not only enable efficient real-time data processing but also enhance interpretability and understanding of the fleet's health status. These features serve as valuable inputs for developing diagnostic models, anomaly detection algorithms, and prognostic frameworks, facilitating timely maintenance actions and performance optimization A preprocessing technique is proposed for extracting relevant features from rotating machines, enabling their comparison as a cohesive fleet of mechanisms. The method aims to enhance the ability to analyze and evaluate the performance of the machines within the fleet.

1.2 Problem Statement

The challenge we encounter pertains to the extraction of high-quality and reliable data for conducting probabilistic tests. Our objective is to minimize noise and inconsistencies during the data extraction process, ensuring that the obtained data is as clean and accurate as possible. This is crucial for enabling robust probabilistic analyses and enhancing the validity of subsequent tests and evaluations. In [10] is analyzed that the operational speed of the exert a significant impact on the properties of the generated signal. This influence encompasses not only the signal's amplitude but also its spectral characteristics, thus influencing multiple aspects of the signal's behavior. As a flowchart of this paper, a visual inspection of the taken signal will take place with the use of Fourier Transform, to mitigate noise and extract relevant information, a filter is applied to a signal to selectively attenuate or enhance specific frequency components, thereby improving the signal quality and facilitating subsequent analysis or processing tasks. A comparative analysis will be conducted between the filtered signal and the raw signal to assess the effects of the filtration process. As next step, is the estimation of a speed varying filter. The purpose of the speed varying filter is to pre-whiten the signal to equalize the variance across different frequency components, allowing for more accurate and reliable analysis, particularly in the context of spectral estimation or statistical modeling. Then proceeding to order demodulation is a signal processing technique used to extract time-varying amplitude and phase information of specific harmonic components, known as orders, in the signal from rotating machinery [6].

2 Analysis of the Method

2.1 Fourier Transform

The Fourier transform of a vibration signal is a mathematical tool that decomposes the signal into its constituent frequency components, providing valuable insights into the frequency content and spectral characteristics of the signal. By performing the Fourier transform, engineers and researchers can analyze and interpret the vibration data, identify dominant frequencies, detect anomalies, and gain a deeper understanding of the underlying mechanisms and dynamics of the vibrating system. The Fourier transform of a continuous-time vibration signal x(t) is mathematically defined as:

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi f t}\, dt \tag{1}$$

where X(f) represents the complex amplitude spectrum of the signal at frequency f, t denotes time, and j is the imaginary unit. The Fourier transform maps the signal from the time domain to the frequency domain, providing a representation of the signal's frequency content. By computing the Fourier transform, various aspects of the vibration signal:

1. Frequency Analysis: The amplitude spectrum X(f) reveals the presence and strength of different frequencies present in the signal. Peaks in the amplitude spectrum correspond to dominant frequencies, aiding in the identification of vibration sources or harmonics associated with faults or operational conditions.

2. Power Spectral Density: The squared magnitude of the Fourier transform, $|X(f)|^2$, represents the power spectral density (PSD) of the signal. PSD can be written as:

$$P(\omega) = \left| \int_{-\infty}^{+\infty} x(t) e^{-j\omega t} dt \right|^2 = X(\omega) X^*(\omega) \tag{2}$$

   where $X(\omega) = \int_{-\infty}^{+\infty} x(t) e^{-j\omega t} dt$ is the Fourier transform of a signal, $X^*(\omega)$ is its complex conjugate, $\omega = 2\pi f$, and f is the frequency in Hz. The PSD provides information about the distribution of power across different frequency components, highlighting the frequency regions where the signal has the most energy.

3. Harmonic Detection: The Fourier transform can help identify and isolate harmonic components by analyzing the frequency peaks in the amplitude spectrum. This is crucial for understanding the vibration behavior and diagnosing issues related to rotating machinery, such as bearing faults or unbalance.

4. Frequency Filtering: Manipulating the Fourier transform allows engineers to selectively filter out or enhance specific frequency components of interest. This can be useful for noise removal, extracting desired features, or isolating specific vibration patterns.

2.2 Notch Filtering

Electromagnetic interference (EMI) is a common source of noise in vibration data that can be caused by nearby electrical equipment [11]. EMI can interfere with the accuracy of vibration measurements and make it difficult to detect faults or anomalies in the machinery. A notch filter is a type of band-stop filter that is specifically designed to remove a narrow band of frequencies, known as the notch frequency. Notch filters are commonly used in vibration analysis to remove EMI and other noise sources that are known to occur at specific frequencies. Improves signal-to-noise ratio EMI can reduce the signal-to-noise ratio of the vibration data, making it more difficult to detect small or subtle changes in the vibration signal. Notch filtering can improve the signal-to-noise ratio by removing the unwanted noise and improving the quality of the vibration data. Eliminates interference Notch filters can eliminate interference caused by EMI at specific frequencies. This can help to isolate the vibration signal and make it easier to identify faults or anomalies in the machinery.

2.3 Spectrum equalization

The fault signature is inherently associated with the rotational speed of the shaft through the periodic description of fault occurrences based on the shaft angle position. Additionally, there exists an explicit relationship between the fault signature and the speed, characterized by a speed-spectral modulation function. In the figure 1 below is depicted the calculation of the Power Spectrum of a faulty rotating mechanism, with 256 Hamming window, in 2 different steady speeds and in a speed fluctuated profile. It is clear that the content of the spectral changes as terms of energy and distribution.

This effect creates the need of a filter which equalizes the spectrum of the signal. Rotating machines often exhibit non-uniform frequency responses due to factors such as mechanical resonances, structural damping, and variations in sensor sensitivity. By applying spectrum equalization techniques, these frequency response

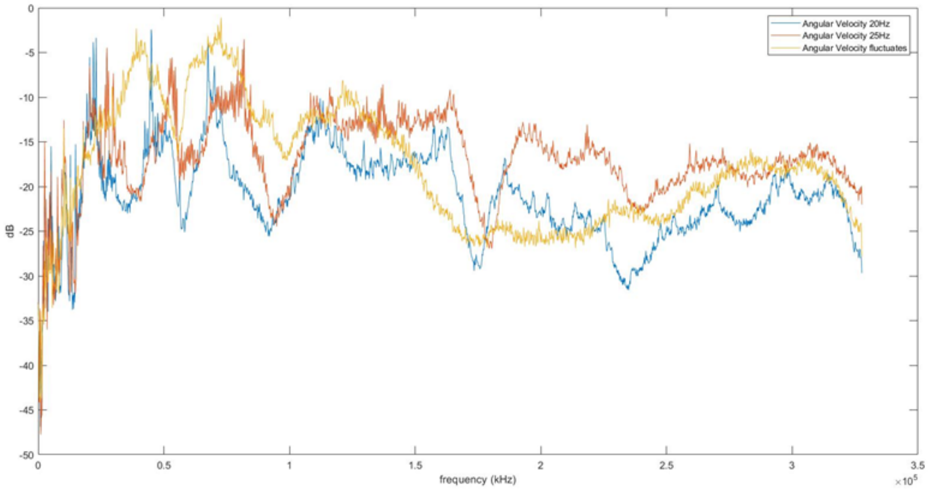

Figure 1: Power Spectrum of a faulty mechanism on three different operating conditions.

variations can be minimized or eliminated. The way that has been chosen to equalize the signal is by applying of Gabor transform on the signal. The Gabor transform and its inverse play a crucial role in signal equalization, providing a powerful framework for modifying the frequency content of a signal to achieve desired equalization characteristics. The Gabor transform, represented as:

$$G(t,f) = \int [x(t)g(t-\tau)e^{-2\pi ift}]dt \tag{3}$$

where x(u) is the input signal, g(t) is the window function (typically a Gaussian window), and f and t represent the frequency and time variables respectively, captures the time-varying frequency components of the signal. By convolving the input signal with the complex conjugate of the window function and performing a Fourier transform, the Gabor transform produces a time-frequency representation of the signal. To equalize the signal, the Gabor transform's time-frequency representation is analyzed to identify undesired frequency components that require modification. These components may include noise, interference, or specific frequency bands that need adjustment. The magnitude and phase of these components can be altered according to the desired equalization criteria. For example, if there are certain frequency bands that need amplification, their magnitudes can be increased, while attenuating specific frequency ranges can be achieved by reducing their magnitudes. The modified time-frequency representation is then subjected to the inverse Gabor transform, given by:

$$x'(t) = \int [G(t,f)g(t-\tau)e^{2\pi ift}]dfdt \tag{4}$$

where x'(t) represents the equalized signal. The inverse Gabor transform reconstructs the equalized signal by convolving the time-frequency representation with the window function in the time domain and performing an inverse Fourier transform. This process preserves the time-varying spectral properties of the signal while incorporating the modifications made during the equalization process.

To further address the non-uniform frequency responses and variations in sensor sensitivity in rotating machines, a whitening process is applied to the equalized signal obtained from the Gabor transform. The whitening algorithm aims to normalize the variances and decorrelate the components of the signal, resulting in a more uniform and enhanced representation.

The whitening process starts by calculating the covariance matrix, Σ, of the equalized signal, x'(t). The covariance matrix provides insights into the statistical relationships between the different components of the signal. Eigenvalue decomposition is then performed on Σ, yielding the eigenvectors, V, and eigenvalues, Λ.

From the eigenvalues, it is possible to determine the relative importance of each component in the signal. The eigenvectors represent the directions in which the components of the signal are maximally uncorrelated. Based on these eigenvectors and eigenvalues, the whitening matrix, W, is computed as:

$$W = V \cdot diag\left(\frac{1}{\sqrt{\text{diag}(\Lambda)}}\right) \cdot V' \tag{5}$$

The whitening matrix transforms the equalized signal, x'(t), by multiplying it with the whitening matrix:

$$white(t) = W \cdot x'(t) \tag{6}$$

This transformation normalizes the variances of the components and decorrelates them, effectively whitening the signal. The resulting whitened signal, often denoted as xeq(t), exhibits improved stationarity and a more balanced frequency spectrum. It enables the accurate detection and extraction of fault signatures, even in the presence of varying operating conditions.

The combined application of the Gabor transform for spectrum equalization and the subsequent whitening process offers a comprehensive approach to address the challenges posed by non-uniform frequency responses created by the fluctuations of the machines' angular speed. By leveraging the Gabor transform's ability to modify the frequency content of the signal and the whitening algorithm's capability to normalize and decorrelate the components, the resulting whitened signal provides an enhanced and more reliable representation for subsequent analysis, fault detection, and condition monitoring applications.

2.4 Order Demodulation

Order tracking is a technique used to analyze and interpret data from rotating machines. It involves transforming data from the time domain to the frequency domain, specifically the order domain, where the data is analyzed in terms of the speed and rotational characteristics of the machine. In the context of Angular domain, order tracking can help diagnose issues with vibration, balance, and alignment of rotating machinery. As contained in [6], modulation refers to the process of altering the amplitude or frequency of a sinusoidal carrier signal over time. Amplitude modulation refers to the variation of the carrier signal's amplitude, while frequency or phase modulation refers to the manipulation of its frequency.

2.5 Feature Extraction

In this section, we present a comprehensive feature extraction approach for rotating machineries operating in non-stationary conditions. The goal is to capture the structural response of the system and extract meaningful features that enable effective condition monitoring and fault diagnosis. The proposed feature set includes the power spectrum of the normalized whiten signal, the order amplitude, the order phase, as well as the mean and variance of the orders.

1. Power Spectrum of the Normalized Whiten Signal: The power spectrum of the normalized whiten signal is a crucial feature that provides valuable insights into the spectral characteristics of the machinery.

2. Order Amplitude and Phase: The order amplitude and order phase capture the magnitudes and phases of specific orders within the machinery.

3. Mean and Variance of the Orders: The mean and variance of the orders provide statistical insights into the system behavior.

4. Order Cross-Correlation: Additionally, the cross-correlation between different orders within the same machine is considered as a feature. The cross-correlation captures the relationships and dependencies between orders, providing valuable information about their synchronization and interactions.

By utilizing these equations, we aim to capture the spectral characteristics, order dynamics, statistical properties, and interdependencies within the machinery. Experimental validation and case studies are conducted to demonstrate the effectiveness and applicability of the proposed feature extraction approach.

3 Application

In the study conducted at LVA INSA Lyon, a small fleet of rotating machines, specifically hand drillers, was the focus of investigation. These machines were securely fixed to a measurement table to ensure stability during data collection. The primary objective was to analyze the vibration signals emitted by the machines at three distinct positions. Additionally, the angular speed of the rotating drills was measured to provide valuable insights into their operational characteristics. To capture the necessary data, a high sampling frequency of 25.6kHz was employed, allowing for precise and detailed measurements. In Figure 3, the temporal evolution of the machines speed is depicted, showcasing the variations in the rotational speed of the machines over time. This plot provides insights into the dynamic behavior and fluctuations of the machines' speed throughout the measurement period. On the other hand, Figure 4 presents the corresponding raw bearing accelerometers' signals, placed in position one. This signal represents the vibrations experienced by the machine's bearing during its operation.

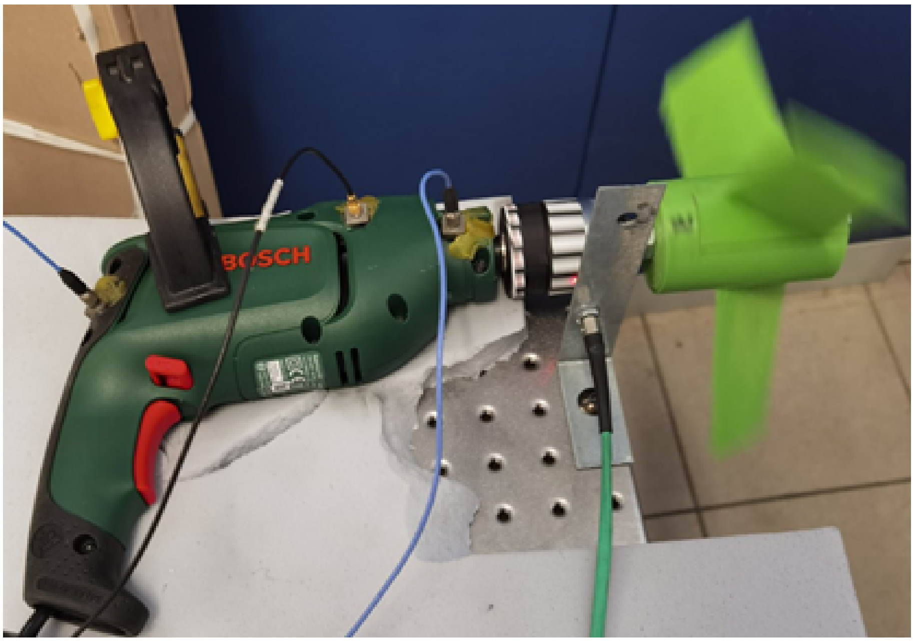

Figure 2: Experimental Mechanism.

Figure 5 illustrates the spectral content of the vibration signal obtained from the faulty mechanism. The plot demonstrates that the varying speed of the mechanism leads to fluctuations in the signal's frequency content over time, indicating a clear relationship between speed variations and spectral characteristics.

3.1 Results

The initial step in the method involves the removal of EMI from the signal, followed by the application of the Gabor transform for signal equalization. This process ensures the removal of unwanted noise and enhances the signal for further analysis.

Upon applying the whitening, it is evident that the signal has been effectively equalized across different frequencies, minimizing variations and inconsistencies. Additionally, the unwanted and background noise present in the original signal has been successfully attenuated. This equalization process results in a flattened spectrum (Figure 7), wherein the amplitude response becomes more uniform across the frequency range.

After estimating the structural responses on both machines, the median power spectrum is used as a reference to analyze the power distribution across frequencies for further analysis and comparison.

Utilizing the equalized signal, the next step involves order demodulation to monitor specific orders of interest. In this case, the focus is on monitoring the first order associated with the output shaft of the mechanism and the 43rd order associated with the gear mesh. This analysis enables targeted monitoring of these specific orders in both machines for further analysis and assessment. From the demodulation of the orders, we can

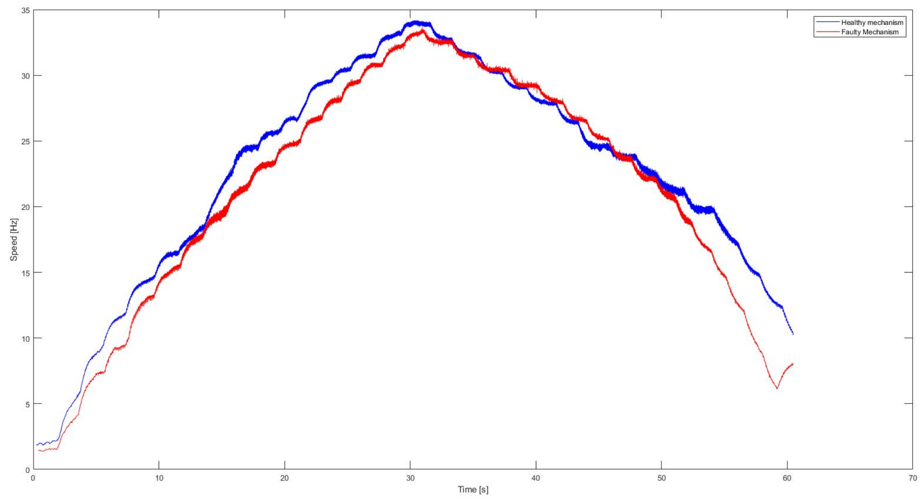

Figure 3: Temporal evolution of one faulty and one healthy machine.

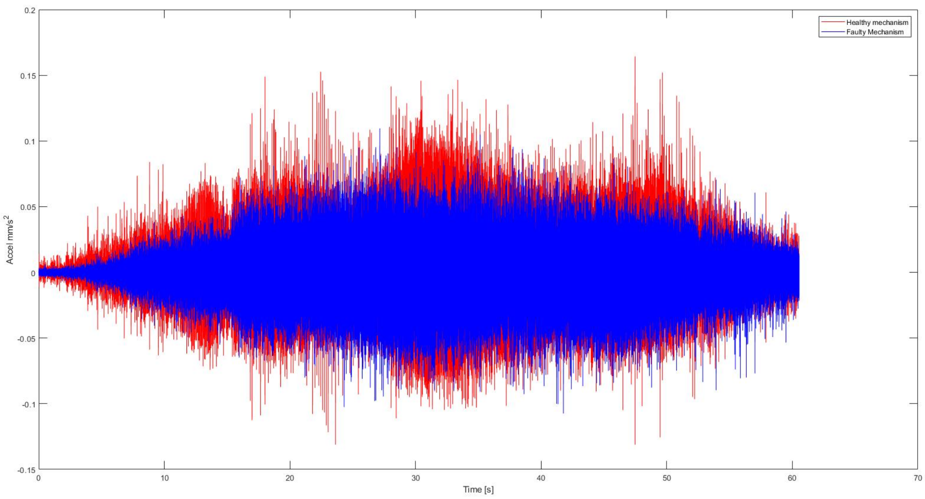

Figure 4: Accelerometer bearing signal from one faulty and one healthy machine.

extract some information and differences among the mechanisms. On the figure 9 the extracted orders are illustrated. With the circles are highlighted the differences among the healthy and non healthy mechanism.

4 Conclusion

This paper serves as the inaugural contribution in a series of papers centered around the theme of fleet condition monitoring from a probabilistic perspective. The objective of this research endeavor is to explore and develop novel methodologies for monitoring the condition of fleets, considering the inherent uncertainties and probabilistic nature of such systems. Through a comprehensive analysis of fleet data and the application of probabilistic models, this series aims to advance the understanding and implementation of effective condition monitoring strategies, ultimately enhancing the reliability, performance, and maintenance practices of fleets in various industries. In addition to the Gabor transform, this series will also introduce an alternative method for signal analysis and equalization. Furthermore, a machine categorization method will be proposed to effectively classify different machine types within a fleet. These contributions aim to enhance fleet condition monitoring

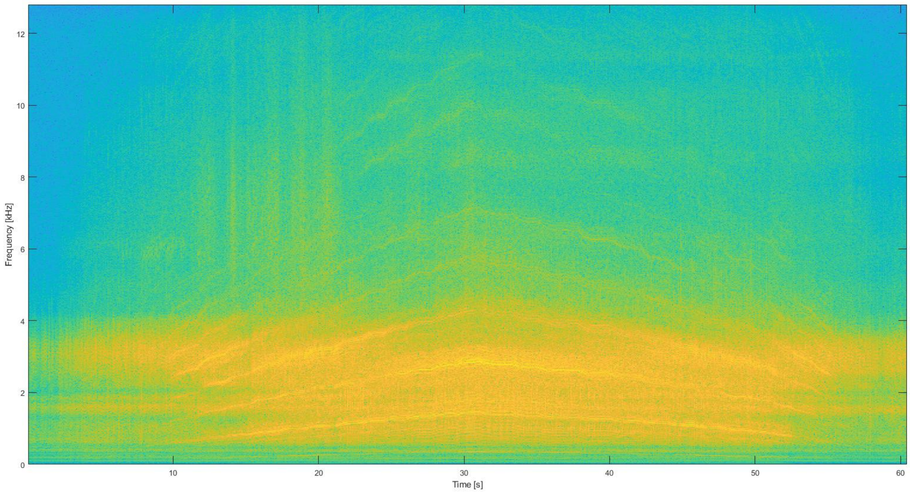

Figure 5: Spectrogram of faulty machine.

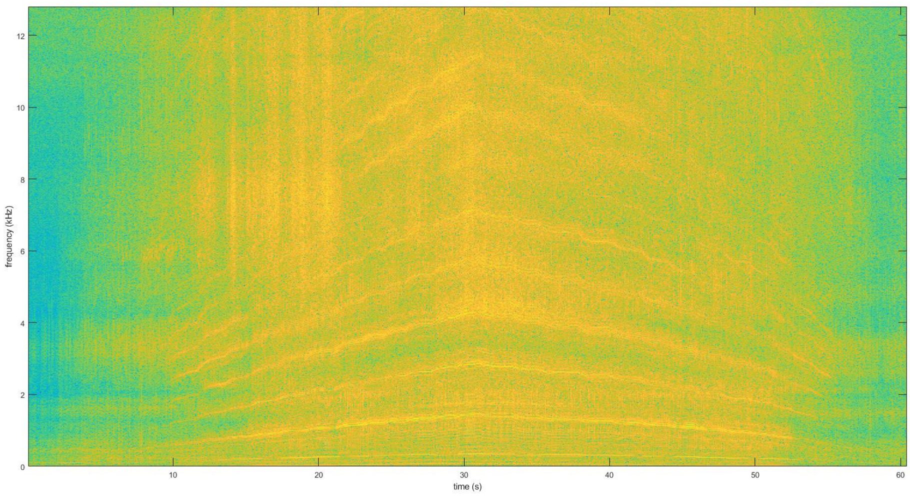

Figure 6: Equalized Spectrogram of faulty machine.

techniques, enabling more accurate diagnostics and maintenance decision-making.

5 Acknolegments

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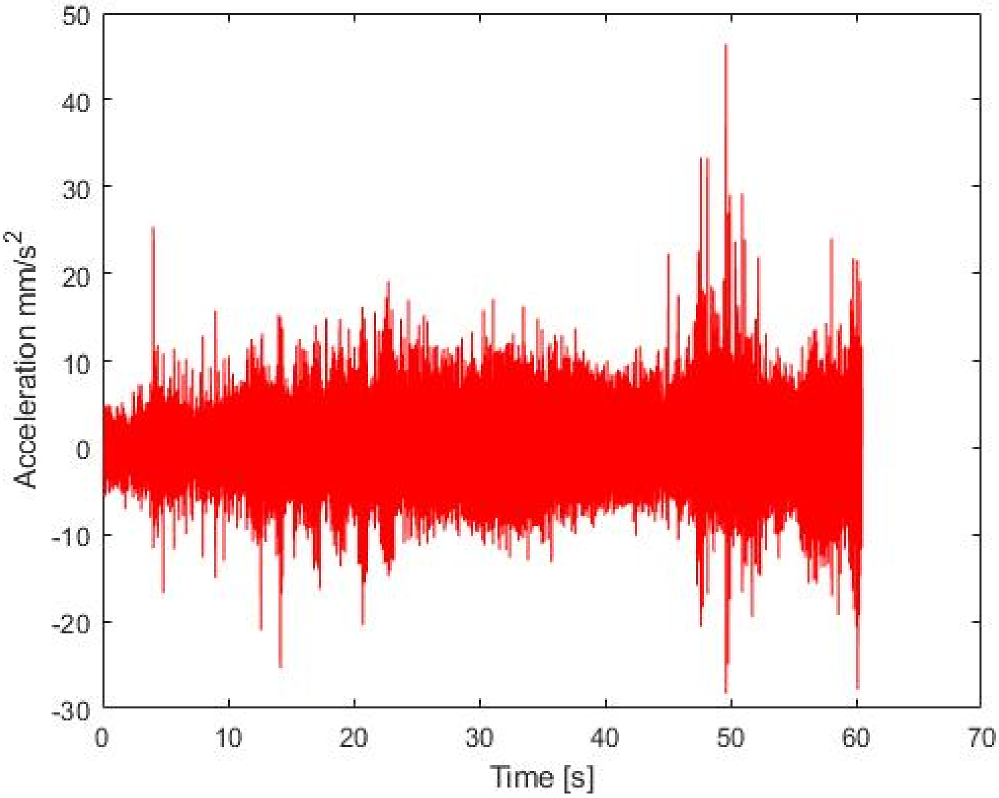

Figure 7: Whitened Signal of Faulty Machine.

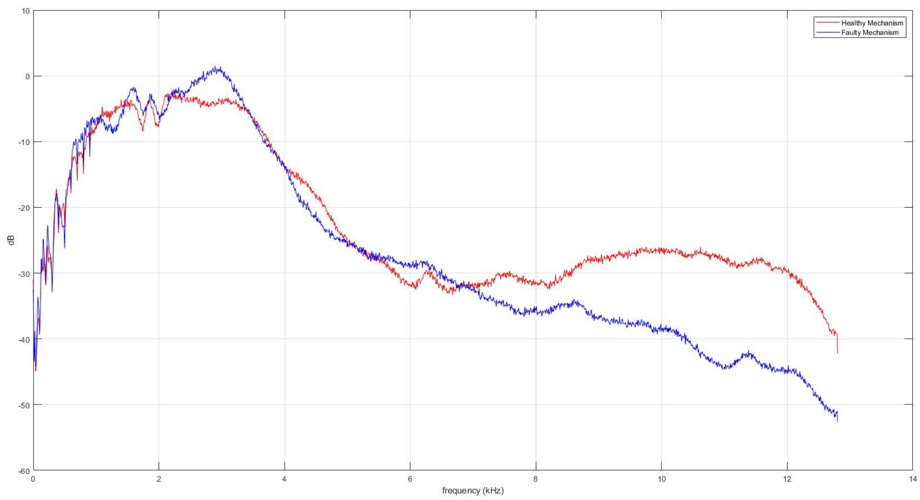

Figure 8: Estimated Structural response of mechanisms.

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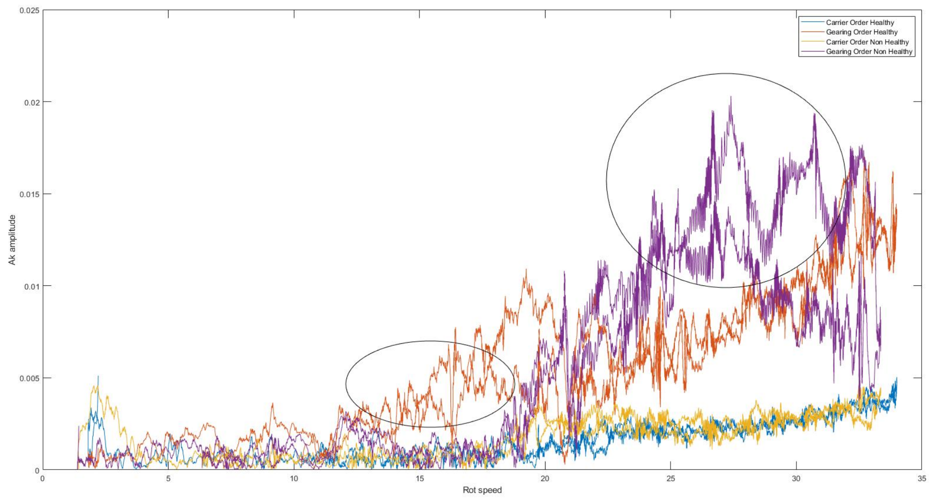

Figure 9: Magnitude of the orders corresponding to rotational speed.

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