Noise Signal Analysis for Fault Detection

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Abstract:

The fault detection of electric machinery is important necessity for stability of system. The noise signal of rotating machinery is utilized for early fault diagnostic. A measured noise signal is divided down by short time duration parts. Fault carrying frequencies are extracted from digitalized signal. Envelope detector and demodulation were utilized for identifying fault frequencies with their harmonics and sidebands. Automated noise analysis is dedicated to detect and report a machinery abnormal condition. Implementation was conducted with noise signals which were obtained from electric motors, turbine generators and bearing fault motors.

Keywords:

Noise Signal, Fault Detection, Mechanical Fault Detection, Signal Processing

1. Introduction

In power plant, rotating machinery is essential to achieving high availability and are involved to regress operation regime. Therefore, its breakdown from inaccuracies possibility and failure conditions are quite significant. The on-machine monitoring goal is to prevent unscheduled downtimes and reduce maintenance cost. Currently, in industry the on-line condition based maintenance is mainly used in parallel with planned maintenance schemes. However, it is still the operators need to make final decision on whether to cut a motor from service or keep it run. The dynamic predictive maintenance of electrical machinery is important to keep up of safety and is a must in ensuring trouble-free operation. Power energy system is one of the main user of rotating machinery for its operation. The condition based monitoring has controlled the change of operating parameters which are current, vibration, and temperature so on. Keeping up the continuous process, which depends on a regular operation of electrical machinery, to detect incipient failures in advance is a vital requirement. To monitor the diagnosis of incipient failures for a preventive maintenance in power energy, there are several measurements under comparable working condition need to acquire to ensure unerring diagnosis about a level of flaws and condition of operation to be monitored [1]. The most popular techniques for electrical motor's fault detection are using a vibration and motor current signature analysis (MCSA) analysis. The MCSA based technique covers an analysis of a stator current which is supplied from AC network [2]. This technique provides good results in fault diagnosis; however, current data not sensitive enough under inverter fed motors derived from low signal noise ratio. Also, the disadvantages which known are involved to the spectral leakage, its low frequency resolution and current signals can be carried out during a steady state regime of induction motors [3]. Thomson, William T et al., surveyed about MCSA analysis for induction motors with industrial case histories. According the this survey "A crucial point about MCSA is that it is sensing an electrical signal that contains current components that are a direct by-product of unique rotating flux components caused by faults such as broken rotor bars, airgap eccentricity, and shorted turns in low voltage stator windings, etc.," [4]. The MCSA techniques may not be possible to detach the load from the motor and without load condition [5]. The other fault diagnosis using a vibration signal has been developed mainly to identify a bearing fault [6, 7, 8]. And has good results that are independent of the type of power supply. However, this technique requires accelerometers as the basic sensors that need to be mounted on the motors which is difficult to achieve [3, 9]. The noise signal based analysis for fault detection of induction motors are investigated very less than the vibration and current based signal analysis. Acoustic emission signal based monitoring technique involves to analysis of sound pressure and the sound intensity methods for detecting the bearing were surveyed [7-10]. The prevalent faults of electrical machines are bearing, the stator or the armature faults, the broken rotor bar, and eccentricity related faults [11]. The conventional diagnostic methods which are MCSA, vibration, and acoustic emission are detecting a certain faults. For instance, MCSA method is more sensitive for rotor and stator faults; however, do not state the bearing fault spectra. A vibration method is mainly used for bearing and mechanical related faults. The Acoustic emission is for detect a faults which are related for materials such as contamination, and cracks etc. The acoustic sound analysis and acoustic emission signals for fault detect have been used less. Using the sound signal for fault detection has been increasing attraction among researchers. The extent summarize of analysis of acoustic sound signal for fault detection, Y.Ono et all [12] presented a method using F value for anomaly sound of motor for condition monitoring and bearing fault detection. Regarding to state of the art for sound signal analysis for fault detection, the sound signal used to detect mainly for bearing fault spectral resolution and less from them contributed for detect rotor fault, and unbalance using sound signal that is recorded via the microphone [13-17]. This is not the case with noise signal as has been introduced by previous study for sound signal spectral analysis for certain fault detection. This work contributes a spectral resolution of the noise signal for different types bearing faults, and examination on noise signal analysis in power industrial cases. The resolution of fault spectrum is studied on different methodologies which are proposed to reduce interferences. The goal of this work is to evaluate the fault severity level using noise signal recorded by a smart phone.

2. Research Objective

The electrical machines which are running in power stations are normally work with steady regime. Their timely preventive maintenance done by vibration based measurement parallel with other system's control. The vibration based maintenance has following disadvantage regarding to Mongolian current condition of power plants:

- The main disadvantage is vibration measurement's result can not evaluate state condition, and which consumes a experience of manpower and cost derived from specific measurement devices.

- It cannot monitor the operation condition of electrical motors in real time, which causes a time lag.
- electrical motors which are used in power pump station are mainly affected by bearing fault, those are mainly affected the effective failure due to start up regime.

According to solve this problem, find new approach to monitor the electrical motors and fault detection. Therefore, an automated noise analysis research would be new approach to monitor the electrical motors and detect the faults. Therefore, the aim of the research work:

- investigate faults caused by vibration and study on faults related noise propagation from electric machines
- to emphasis on spectral analysis of noise signal in faults and to determine how estimate the machine health condition with its noise signal.

3. Mechanical Faults and Fault Signature

3.1. Materials and Methods

Every mechanical component when they are failed to produce a fault signature with harmonics. Therefore, fault detection purpose is identifying faulty frequencies. Before analyzing the noise signal, need to study on mechanical failures of electric machinery. The mechanical failures are represented in table 2 regarding frequency ranges of malfunctions. There are the faults which are commonly occurred and influenced system efficiency, heating, and to increase vibration. These are bearing their defects, gearbox, rotor unbalance, journal ovality, bent shaft, and sliding contacts etc. All fault having characteristic frequencies. For instance, bearing and their defect are showed in table 3. Gearbox faults also produce same different fault signatures such as

$f_c = \frac{N_{rpm}}{60}$, $f_{gear} = \frac{N_1 T_1}{T_2}$, $f_{gearmesh} = N_1 T_1 = N_2 T_2$. All mechanical faults can divide frequency ranges regarding types of failures. Also, the mechanical malfunctions are related noises which generated from rotation of motors.

Table 1. *Frequency ranges for mechanical system.*

Frequency range	Fault type	Frequency selection calculation
Low frequency range	Low frequency domain defined as the frequency from below rotational speed up to low harmonics. It contain information about unbalance, misalignment, bent shaft, instability in journal bearings and mechanical looseness	2nd harmonic: 2X rotational speed component for bent shaft, misalignment (40-49%) x rotational speed derived from shaft with loaded high speed self-excited. (0.5, 1.5, 2.5) x rotational speed indicate inter harmonics and sub-harmonics components for mechanical looseness.
Medium frequency range	Medium frequency domain: information about fault in gearboxes. The degree of gear wear can be seen at the tooth meshing frequency and its	(n*rev/60)f: Its harmonics can indicate an incipient fault. Tooth meshing frequency signal is weak signal high spectral energy.

	harmonics	
High frequency range	High frequency range called blade spectral components which are usually low in amplitude. Typically, it is into the frequency range from few hundred hertz to 10-20 kilohertz [18].	9.6-11.3KHz heap spectrum indicates the possibility of rolling element bearing faults and steam flow thrust forces.

Table 2. *Frequency ranges for mechanical system [19].*

Shaft rotational frequency	$f = \frac{N\ (rpm)}{60}$
Ball pass frequency inner race	$BPFI = \frac{N}{2} f(1 + \frac{Ball_d}{Pitch_d} cos\beta)$
Ball pass frequency outer race	$BPFI = \frac{N}{2} f(1 - \frac{Ball_d}{Pitch_d} cos\beta)$
Fundamental train frequency	$FTF = \frac{1}{2} f(1 - \frac{P_d}{B_d})$

4. Proposed Noise Processing Techniques

The condenser microphone and the data acquisition card were used for all sample creation. Sampling and quantization were made automatically by software based algorithm.

4.1. Noise Signal Preprocessing

Noise signal recognition system is splitting a noise signal track in to smaller pieces which helps to identifying precise features. Software based data splitting with has a new .wav header is represented in Figure 1 and Figure 2.

wav header	DATA 00:00:10-00:00:15

Figure 1. *Sampled data track.*

wav header	DATA 00:00:11	DATA 00:00:12	DATA 00:00:13	DATA 00:00:14	DATA 00:00:15

Figure 2. *Sample after spitting.*

Afterward the new wav data was added to each chunk of data. The noise signal recognition system consists of pattern recognition. The fast Fourier transform (FFT) transformation is utilized for digitalized signal in frequency domain. This helps to extract fault frequency features. Then normalize signal in both amplitude and frequency separately for each spectrum analysis. Fault features extracted selected from a frequencies which has peak amplitudes were detected. We create database from feature vectors for different cases because in power plant failures are impossible to predict and collecting structural and condition information is a time consuming.

5. Frequency Selection

The dominant noise frequency is related to malfunctions and their defects. A frequency selection is estimated by frequency spectrum. The state of electrical machinery is dependent on power and load variation. Also, it is depending on a construction of the electric motors.

5.1. Frequency Analysis of Some Mechanical Faults

The noise analysis is focused to address signal smearing and frequency beating during noise recording. In order to identify the fault carrying frequency, their harmonics and sidebands, this paper is proposing the demodulation techniques and signal envelope detector techniques for fault detection system which is used the noise signal. Generally, fault carrying frequency is derived from rotational speed and can indicate a characteristic frequency of early fault state. The structural scheme of noise analyzing is showed in a Figure 3.

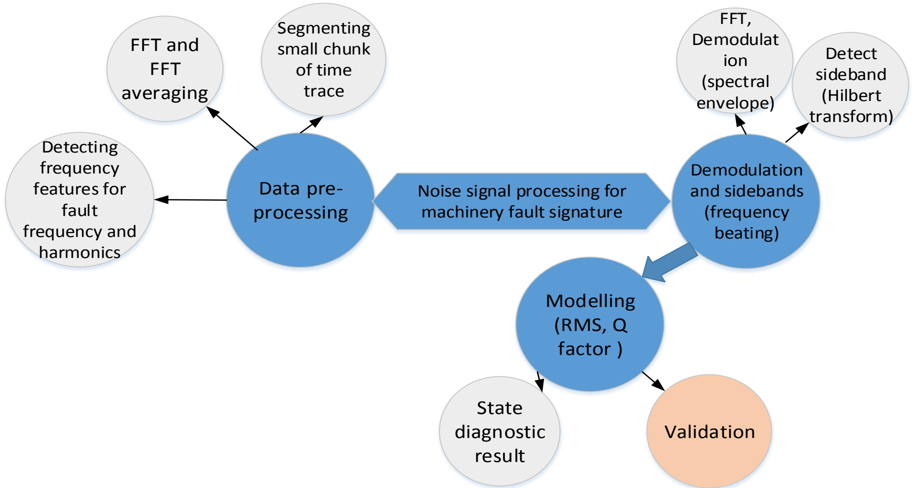

Figure 3. *Automated noise signal processing scheme.*

5.2. Hilbert Transform

Hilbert transform can helps to create analytic signal from original real valued signals.

$$z(t) = x(t) + j\hat{x}(t) \tag{1}$$

$\hat{x}(t)$ is the Hilbert transform. Hilbert transform of original signal $x(t)$ is defined as following equation [20].

$$H_x(t) = \hat{x}(t) = \rho v \frac{1}{\pi} \int_{-\infty}^{\infty} x(\tau) \frac{1}{t-\tau} dt = \frac{1}{\pi} x(t) \frac{1}{t} \tag{2}$$

The Cauchy principle value is denoted $x(t)$ [21]. Hilbert transform $x(t)$ distribution of signal $x(t)$ enables an analytic signal in following way:

$$z(t) = x(t) + jH_x(t) = |Z(t)|e^{j\varphi(t)} \tag{3}$$

where $x(t)$ is mono-component signal, $x(t)$ is an amplitude of analytic signal identifies an instantaneous amplitude or enveloping signal of phase $x(t)$ in instantaneous phase. The instantaneous frequency is referred as carrier frequency. Hilbert transform applies as demodulation techniques also.

5.3. Short Term Fourier Transform

Noise signals can contain lots of main information. Also, can detect faults in time and frequency domain or time-frequency domain. For instance, a misalignment fault can detecting by noise signal in time domain. The bearing faults are detecting in both time and frequency domain comprehensively. Common Fourier analysis decomposes signal into its frequency components and determines relative strengths. The Fourier transform formulated as:

$$\begin{cases} F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega\tau}dt \\ f(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)e^{j\omega\tau}d\omega \end{cases} \tag{4}$$

The difference between existing transformation is the term of computational complexity, simplicity, and unambiguity of the interpretation of signal output [21]. In this, a spectral analysis of noise signal is performed by STFT. A signal is dived into small sequential or overlapping data frames Figure 4. The STFT is used windowed function $x(t)$ at $x(t)$ on the time axis. Then the FFT implemented into a windowed signal is expressed by following equation.

$$F(\omega,\tau) = \int_{-\infty}^{\infty} f(t)\varphi(t-\tau)e^{-j\omega\tau}dt \tag{5}$$

This transform is generated by modulation and transformation function $\varphi(t)$. Where τandω are location of time axis and window function respectively [18].

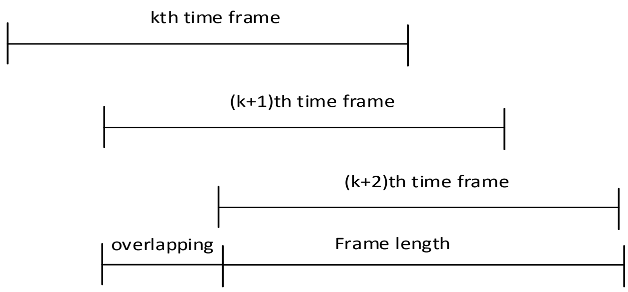

Figure 4. *Data frame.*

Given signal $x(t)$ is described by STFT at the frequency band k and time n given by:

$$X_n\left(e^{j\omega k}\right) = \sum_{m=-\infty}^{\infty} x(m)\omega(n-m)e^{-j\omega_k m} \tag{6}$$

$\omega_k = 2\pi k/N$ Frequency in radians, n number of frequency band. $\omega(m)$ symmetric window size L; $L \leq N$. Reconstructing using AM modulation into above that is equivalent to:

$$X_n\left(e^{-j\omega_k}\right) = e^{-j\omega_k n}\bar{X}_n(\omega_k) \tag{7}$$

where

$$\bar{X}_n(\omega_k)\sum x(n-m)\omega(m)e^{j\omega_k m} = x(n)h_k(n) \tag{8}$$

is result of kth band pass filter, with impulse response $h_k(n)$, center frequency $h_k(n)$.

$$\begin{cases} h_k(t) = \omega(n)e^{j\omega_k n} \\ \qquad f_k = \frac{f_s k}{N} \end{cases} for\ k = 0,1,\ldots,N-1 \tag{9}$$

Considering $\omega_k = 2\pi k/N$ as above, pluging into AM modulation formula gives expression as follow:

$$X(n,k) = X_n\left(e^{j\omega_k}\right) = \sum_{m=-\infty}^{\infty} x(m)\omega(n-m)e^{-j2\pi km/N} \tag{10}$$

$X(n,k)$ is short term spectral amplitude of $x(n)$ signal.

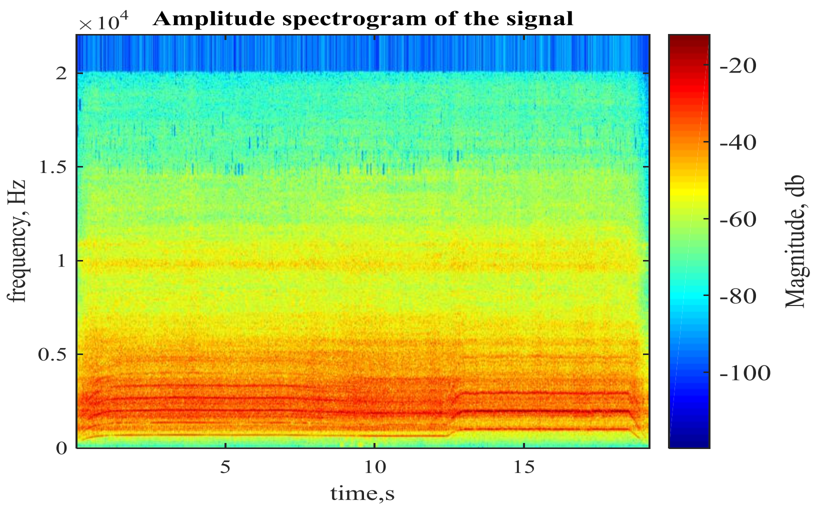

Figure 5. *Spectrogram of healthy motor.*

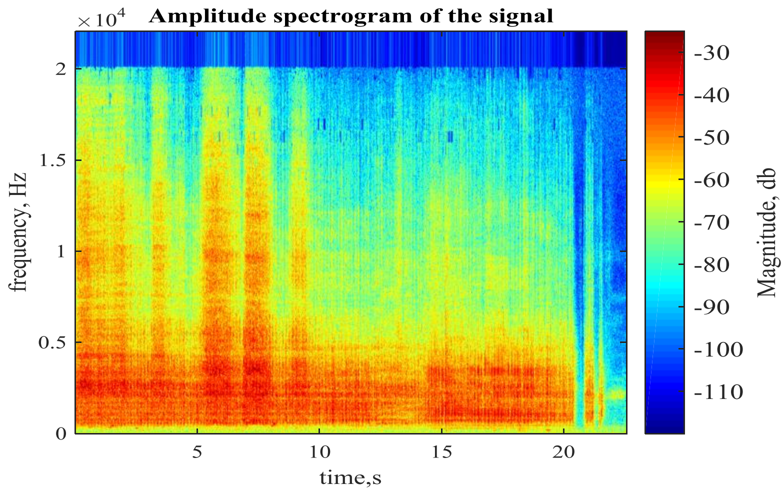

Figure 6. *Spectrogram of motor with gear tooth defects.*

The STFT distribution was calculated with window that in time domain resulting in wide frequency band. The STFT distribution simulation results are illustrated in Figure 5 and 6. In our case, the STFT is used a window functions such as Gaussian, β-splin, Hannning etc. These functions determine the size of the time frequency window. The window width at time scale is equal to the root mean square duration in window function multiplied by two. The height is estimated by the root mean square bandwidth of the window function is multiplied by two. The window functions of Gaussion function:

$$g_a(n) = \frac{1}{2\sqrt{\pi\alpha}} e^{-\frac{n^2}{4\alpha}} \quad \alpha > 0 \tag{11}$$

The Gaussian function is provided to optimize window function as possible as fixed time frequency window size that controlled by variable α.

6. Feature Extraction for Decision Making Stage

Every mechanical component which is detected failure produce significant fault characteristic signature in frequency ranges. For example the bearing faults and their defect have fault carrying frequencies which are showed in table 3 in mechanical vibration noise range. These will selected for bandpass filters for further diagnostic. The system's diagnostic section is introduced in Figure 7.

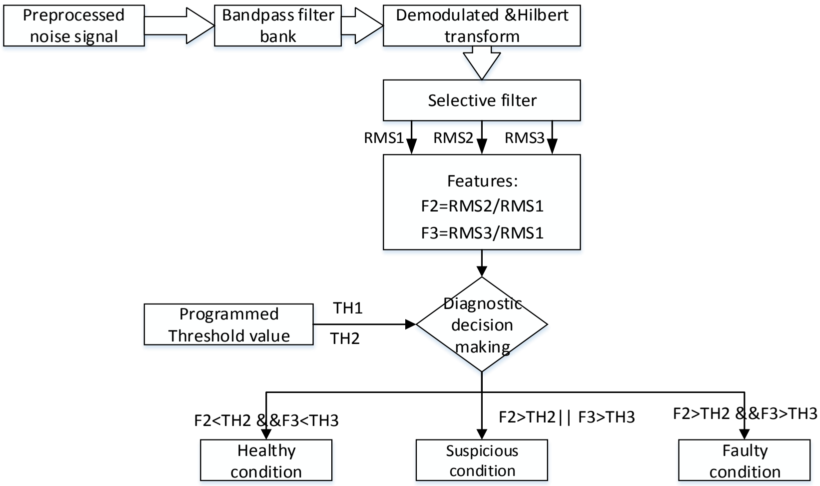

Figure 7. *Flowchart of decision making for fault detection.*

The fault detection algorithm is consists of three sections that were illustrated in Figure 3.

Signal Pre-processing: In order to increase the efficiency of signal processing, the recorded noise signal was digitalized and pre-processed before the features can be extracted in a computer based system.

Modulation and Envelope detector methods were associated with STFT transform.

Fault detection algorithm is simulated for detecting and recording abnormal state of motors.

In study case as mentioned before, study on noise signal for bearing fault detection. Simulation is extract features for every single types of bearing failure utilizing the proposed noise signal processing algorithm. Before we having difference on noise signal context between normal and faulty, we will applied simulation result both two condition respectively. The pre-processing such as remove background noise is evaluated. The simulation results of segmenting in small chunk in time domain are in following Figures 8. The recorded noise signals in time domain are filtered by averaging FFT. After increasing SNR for measured noise signal, the FFT was calculated for frequency feature selection.

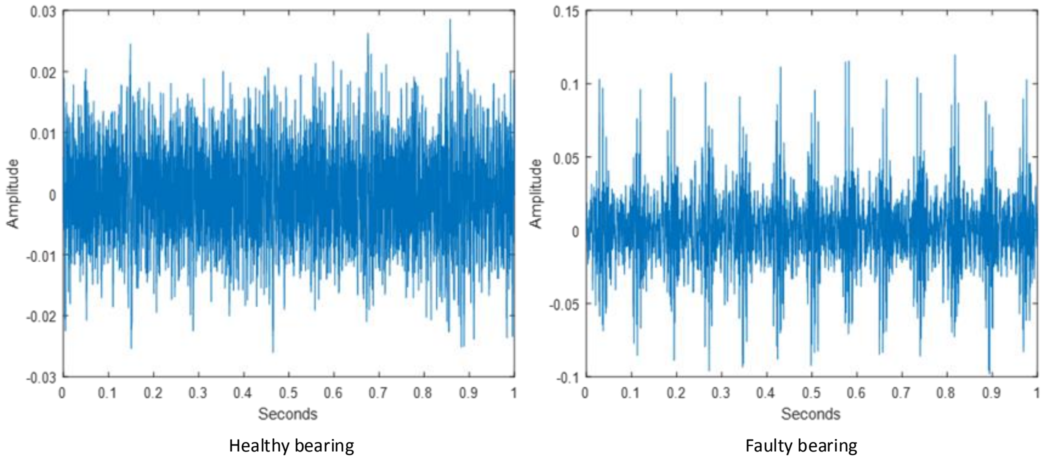

Figure 8. *Pre-processed noise signal in time domain.*

Carrying frequency feature selection was simulated after filtering. The implementation giving result for many investigating amplitudes of frequencies might cause numerical errors in calculation step. Thus extraction using threshold amplitude for common characteristic frequencies for all states of motor Figure 9.

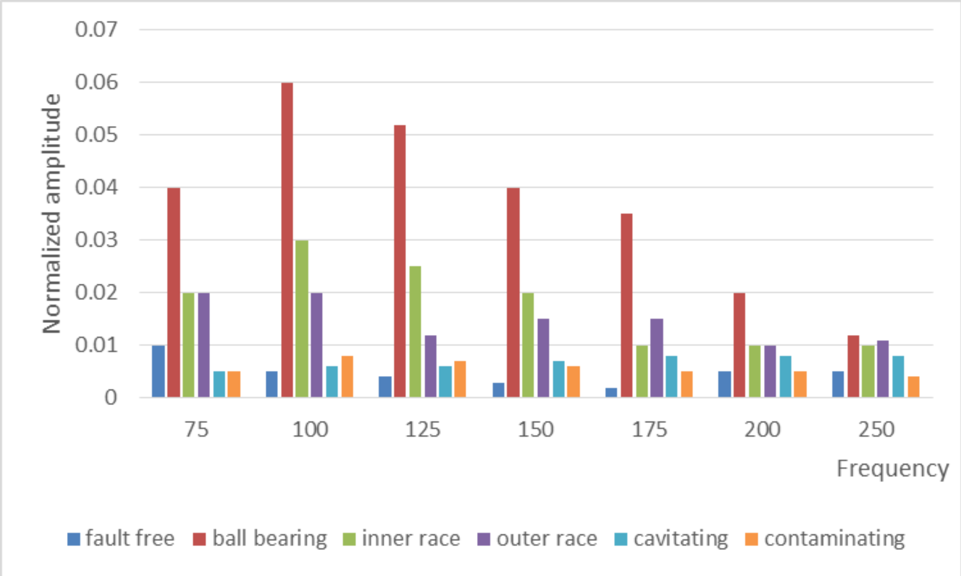

Figure 9. *Frequency spectrum of motors at frequency selection.*

The selection of a frequency with its amplitude potentially indicates the failure features in frequency domain. Due to utilizing noise signature ratio method for ambient noise may affect eliminate important information noise signal. More efficient way in this case was averaging FFT method. The low pass filtering was one attempt to reduce ambient noise content; however some mechanical faulty signature exists in low frequency range. In Figure 10 is showing the FFT analysis in noise signal. The results of analysis, in the frequency plots are been having noise.

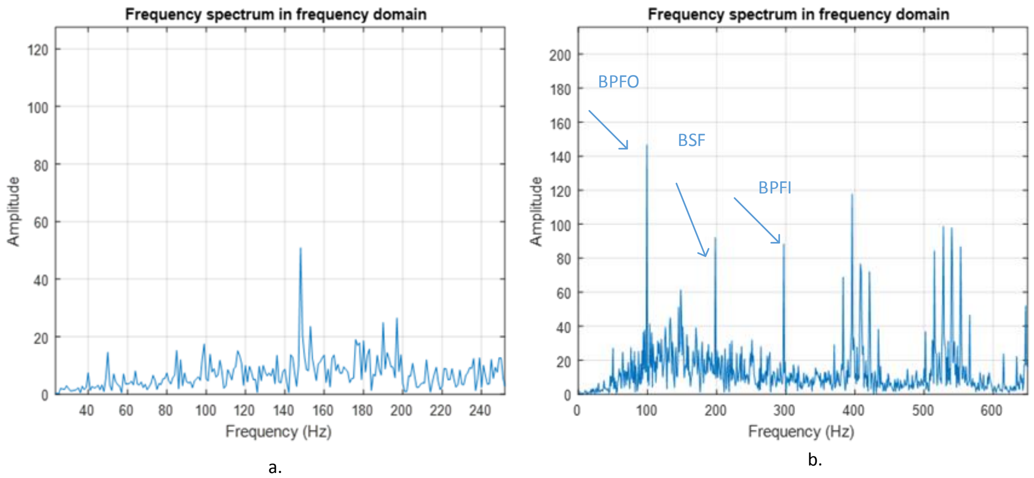

Figure 10. *Demodulation with STFT result after preprocessing for a. healthy, b. ball bearing fault.*

In mechanical signal processing, the machine's rotating speed undergoes a change because of a power supply variation and load variation. These speed variation $rpm \pm \Delta rpm$ is been influencing to signal smearing in noise signal. These clearly showed in band pass filtering after FFT transform.

7. Diagnostic of State Condition and Experimental Data Result

Automated noise analysis (ANAS) for fault detection system used a statistical feature calculation method and signal processing techniques (Figure 7). In this algorithm, the noise signal is analyzed in selective band pass filter bank. The short term Fourier transform (STFT) is utilized to identify certain frequency bands for different failures. The RMS identifies the average of maximum and minimum amplitude. In digital noise signal, the maximum RMS allowed 0dB. In algorithm, the programmed threshold RMS is estimated equal as 0.6dB. This value indicates that a peaks were detected. In addition crest factor was utilized for increase algorithm result for fault detection.

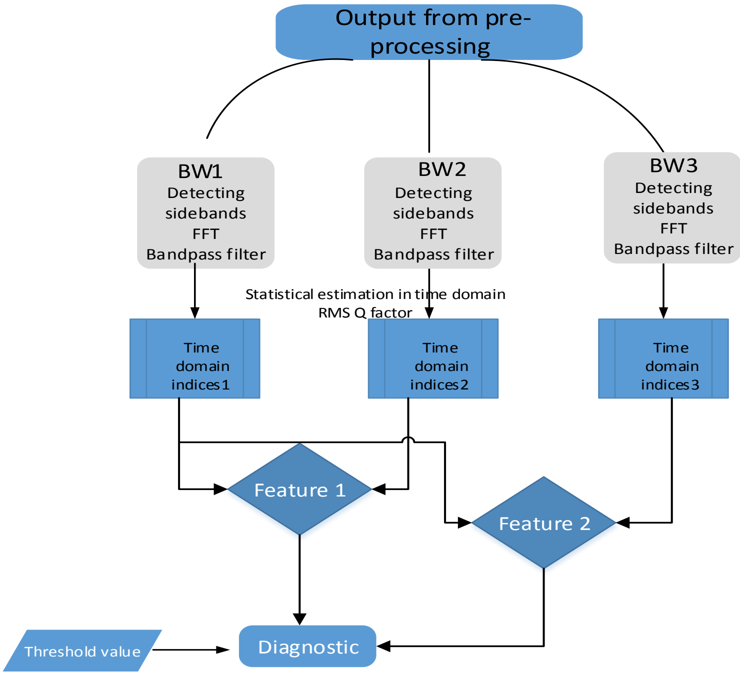

Figure 11. *Automated fault detection algorithm.*

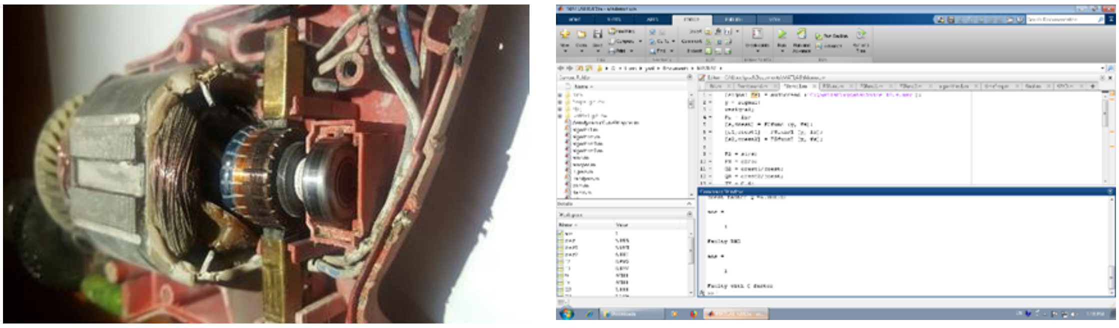

Figure 12. *Test rig and data analysis.*

The RMS is calculated in each frequency band. Low frequency band RMS is used as reference value. Others mid and high frequency band RMS are used for feature calculation. In order to reducing complexity of analysis processing identifying spectrum content in time domain using STFT. In this algorithm determining signal processing in concrete frequency band that set of three bandpass FIR filter. Band pass filtering designed as Matlab filter design tool. The filter design template utilizing bandpass FIR filter. The noise signal processing and fault detection algorithm which is illustrated in Figure 11 are simulated in Matlab. Case study measurement and result are introduced in Figure 12. We conducted different type of bearing noise signals, noise measurement on three turbine generators, twenty motors which are running for pump and cooling system in thermal power stations. Samples which were collected from industrial cases analyzed for state condition with its noise signal using automated noise signal analysis which is stated in Figure11. Some results of experimental data represented in Figure 13.

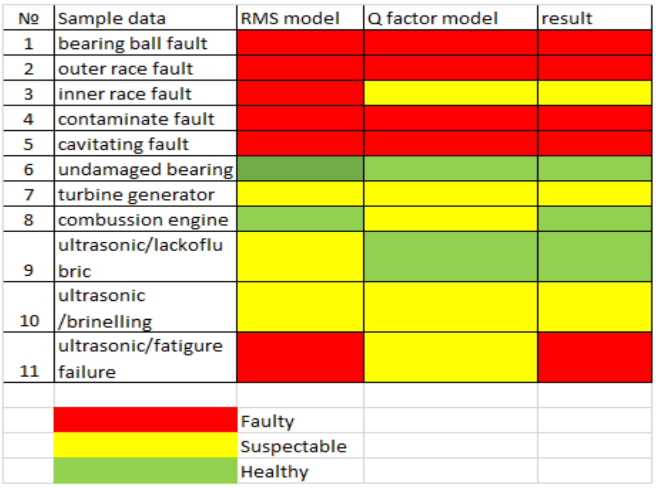

Figure 13. *Experimental data results.*

8. Conclusions

Mechanical system complexity for fault detection is potentially diagnosed by a noise which is emitted from its mechanical vibration. The main goal of automated noise analysis system is to alarm against future failures whether no action is taken. All tests were done in order to clarify the possibilities to construct an automatic on-line condition monitoring for the rotating machinery. This system can use in practical scenarios. Also this system has an advantage for implementation without complexity for a power and size increases of motor. The automated noise analysis system is implemented with high effective result for fault detection. However, experiment could not carry on speed and load dependence measurement.

The work conducted to implement automated noise analysis for fault detection. During this work, the noise signal which is acquired through microphone can indicate condition for any rotating machines even in noisy environment. Implementation was succeeded in high level of ambient noise measurement. The mechanical malfunctions like gearbox, bearing have been required a specific techniques according to its complexity. For instance, detecting the bearing failures its certain fault frequencies side band detection used by STFT band pass envelope cepstrum analysis that generates the exact features. The bearing faults can produce several fault signatures in table 2. Other failures such as unbalance, misalignment and rotor's brush commutator create faulty frequency and 1X, 2X,.., harmonics. Concluding all mechanical failures from estimation of statistical features which are the RMS, mean, kurtosis and or crest factors can result to alarm level of the diagnostic. General automated noise analysis system is implemented with high effective result for state condition with its noise signal from motors. Currently, experiment could not carried on speed and load dependence measurement and localize faults.

Note: Noise signal analysis can indicate motor's condition, and can detect mechanical faults. Noise signal would indicate rotor bar fault spectra during signal processing step (Figure 3).

Future works are focused on follows:

To doing the more detailed experiments for different failures which are not conducted in theses in laboratory and in the industry condition.

To creating the fault feature database.

To make a fault detection in variety of power range regarding dynamic changes which are load variation and power supply variation etc.

To extend the fault detection algorithm with fault localization.

Conflicts of Interest

I will declare there is no conflict interest regarding the publications based on this research are sent, and in all public presentations of this research.

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