

## Bearing Fault Detection in Single Phase Induction Motor using Sound Signal Analysis

Santosh\*, Dr. Andhe Pallavi<sup>#</sup>

\*PG Student in Industrial Electronics M.Tech

<sup>#</sup>Prof & Head, Dept of Instrumentation Technology

\*<sup>#</sup>RNS Institute of Technology, Bangalore

\*<sup>#</sup>Visvesvaraya Technological University

\*[santoshgp.2011@gmail.com](mailto:santoshgp.2011@gmail.com)

<sup>#</sup>[hodit\\_rnsit@yahoo.com](mailto:hodit_rnsit@yahoo.com)

### Abstract

Induction motors are one of the most commonly used electrical machines in industry because of various technical and economic reasons. The bearings are common elements of induction machine. The performance of bearing is influential on the performance of induction machine. The presence of bearing defects causes, a reduction in the efficiency of the machine or severe damage in induction machine. Therefore, this diagnosis is an intensively investigated field of research. Recently, many research activities were focused on the diagnosis of bearing faults using current signals and vibration signals. In this paper, the sound of electric motors is analyzed in order to obtain information for the detection of faults. Significant sound spectrum differences between healthy motor and motors with bearing faults are observed. The signal processing techniques that are being currently used for the analysis of sound signals of different induction motors are also investigated in this paper.

**Keywords**— Diagnosis, Induction Motor, Bearing Fault, Signal Processing.

### I. INTRODUCTION

Early diagnosis of faults in induction machines is an extensively investigated field for cost and maintenance savings. In fact, induction motors are still the most important rotating electric machines in industry mainly because of 1) their low price; 2) ruggedness; 3) efficiency; and 4) reliability.

Many papers can be found in the literature concerning the general condition monitoring of induction machines [1]–[4]

where the different fault types are analyzed. The distribution of failures within the machine

subassemblies is reported in many reliability survey papers [5]–[7]. A rough classification [1] identifies four classes: 1) bearings faults; 2) stator-related faults; 3) rotor-related faults; and 4) other faults (cooling, connection, terminal boxes). Depending on the type and size of the machine, bearing faults distribution vary from about 40% to about 90% from large to small machines [2].

This paper reviews the various bearing defects present in rolling element bearing and the reasons for the defects. This method based on sound analysis technique is contribute to limiting the problems and the cost induced by the failure of a motor in an industrial process. In this study, we take into consideration the electric and mechanical faults. These are revealed in some sidebands of the specific frequencies. It is a known fact that induction motor parameters will change because of the motors' faults. Hence these parameters have to be monitored to prevent/reduce breakdowns.

When a mechanical part of the motor either wears or breaks up, a frequency component of the spectrum will change. In fact, each fault in a rotating machine produces vibrations and noise with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis [9].

### A. Types of Defect

The bearing failure mechanisms are shown in table-1.

TABLE I  
BEARING FAILURE MECHANISMS

Failure Mechanisms	Reason for damage
Mechanical Damage	Permanent indentation created by rolling element overload
Crack damage	Manufacturing defect or operating stress due to overload

Faulty Installation	Excessive preloading, misalignment, loose fit, excessive force used in mounting the bearing
Incorrect Design	Poor choice of bearing type or size for required operation
Wear damage	Gradual deterioration or abrasive particle entrained
Corrosion	Humid ambient subjected to surface oxidation

The defect in the bearing may arise due to improper mounting, improper operation, and overloading. The defects may be classified into distributed and localized defects. Surface roughness, waviness, and misaligned races are included into the class of distributed defects. The localized defects include cracks, pits, and spall caused by fracture on the rolling surface. Some of the reasons for the cause of the defect are discussed above in table-1.

Sound is an important parameter for the condition monitoring of machines and their elements. In a machine under operation, sound is always present. The levels of sound usually increase with deterioration in the condition of the machine. Sound amplitude is normally measured. Sound can be extracted using microphone.

### B. Fault Detection Techniques

There are several techniques that can be employed to predict the condition of bearing, these include: Vibration monitoring, Current Signature Analysis, etc. [10].

Condition monitoring based on measuring and analyzing of machine vibration signals is one of the oldest monitoring techniques and widely used to detect motor faults especially mechanical faults. However, vibration of machines is defined as a result of dynamic forces in machines which have moving parts and in structures which are connected to the machine. The major disadvantage of vibration monitoring is cost. For example, a regular vibration sensor costs several hundred dollars [1].

The current signature analysis is used for detecting the bearing fault in electric machine. This method requires the operating motors input current and frequency for analysing/detecting the fault in the bearing [1].

### C. Monitoring Bearing Fault in Induction Motor using Sound Spectrum

The analysis of the bearing noise in electrical machines shows that the forces that occur in the rolling element bearings create the high frequency components of

vibrations. In normally working rolling element bearings, the main types of high frequency oscillating forces are friction forces. When a defect develops in the bearing, shock pulses can also be found due to the breaks in the lubrication layer between the friction surfaces [9].

This method of diagnosing rolling element bearings through analysis of high frequency noise has many advantages. It makes it possible to locate the defective bearing easier because the *noise signal does not contain any components from other units of the machine*.

When a defect of wear of rolling surfaces appears, the friction forces are not uniform. They depend on the rotation angle of the rotating surfaces in the bearing causing the friction forces to be modulated by a periodic process. Periodic shock pulses appear if cavities or cracks appear in the bearing. It is possible to detect the presence of the friction forces modulation and of the periodic shock pulses by the spectral analysis of the envelope of the random noise produced by these processes. When the friction forces are modulated by a periodic process the harmonic component of the frequency will be found in the measured envelope spectrum. The frequency is determined by the period of the modulating process [9].

The analysis of sound spectrum is used for the detection of bearing faults. The faults detection will be done by comparing two values: the amplitudes of the harmonic components obtained from monitoring the sound spectrum at different frequencies and the amplitudes of the harmonic components at the same frequencies obtained from the reference sound spectrum [9].

## II. ARCHITECTURE OF FAULT DETECTION SYSTEM

The architecture of fault detection system is shown in flow diagram of Fig. 1.

### A. Source of Motor Sound

Different parts of the motor like bearing, air gap distance between stator and rotor due to rotating action and design of the motor structure give rise to different sounds with variation in amplitude and/or frequency.

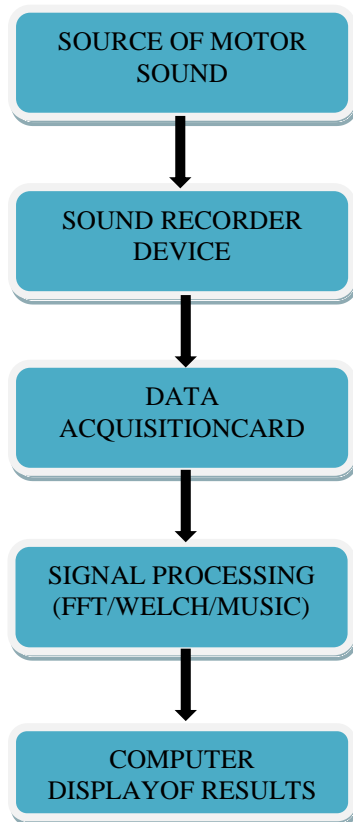


Fig. 1: Architecture of sound signal analysis

### B. Sound Recorder Device

For detecting the sound many devices are available, example microphone, sound meter and any electronic recording devices. In our research for sound recording we have used microphone in laptop (Lenovo G570). The recorded sound is in “wav” format.

### C. Data AcquisitionCard

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems (abbreviated with the acronym DAS or DAQ) typically convert analog waveforms into digital values for processing. The components of data acquisition systems include:

- Sensors that convert physical parameters to electrical signals.

- Signal conditioning circuitry to convert sensor signals into a form that can be converted to digital values.

- Analog-to-digital converters, which convert conditioned sensor signals to digital values.

The software in the Data Acquisition toolbox allows MATLAB to acquire data from sensors and to send out electrical signals that can be used to control or drive external devices. We will be using this toolbox with two different pieces of hardware. One is the sound card built into our laptop, the microphone and speaker will serve as the data acquisition (and output) devices.

### D. Signal Processing

In signal processing we are going to analyse the sound signal for different transformation methods using SP tool box of MATLAB. SP tool is a graphical user interface (GUI) that manages a suite of four other GUIs: Signal Browser, Filter Design and Analysis Tool, FVTool, and Spectrum Viewer. These GUIs provide access to many of the signal, filter, and spectral analysis functions in the toolbox.

#### 1. FFT

Fast Fourier Transformation is one of the most common mathematical functions, which is used for noise analysis of electrical machines. The use of complex exponentials has often been convenient rather than fundamental. The functions  $Y = \text{fft}(x)$  and  $y = \text{ifft}(X)$  implement the transform and inverse transform pair given for vectors of length  $N$  by

$$X(k) = \sum_{j=1}^n x(j)W_N^{(j-1)(k-1)}$$

$$x(j) = \left(\frac{1}{N}\right) \sum_{k=1}^n X(k)W_N^{-(j-1)(k-1)}$$

Where  $W_N = e^{(-2\pi i)/N}$  is an  $N^{\text{th}}$  root of unity.

## 2. WELCH:

Welch syntax is given by,  $[P_{xx},w] = pwelch(x)$

$[P_{xx},w] = pwelch(x)$  estimates the power spectral density  $P_{xx}$  of the input signal vector  $x$  using Welch's method. Welch's method splits the data into overlapping segments, computes modified period grams of the overlapping segments, and averages the resulting periodograms to produce the power spectral density estimate.

- The vector  $x$  is segmented into eight sections of equal length, each with 50% overlap.
- Any remaining (trailing) entries in  $x$  that cannot be included in the eight segments of equal length are discarded.

### ➤ HAMMING:

$w = \text{hamming}(L)$  returns an  $L$ -point symmetric Hamming window in the column vector  $w$ .  $L$  should be a positive integer. The coefficients of a Hamming window are computed from the following equation.

$$W(n) = 0.54 - 0.46 \cos\left(2\pi \frac{n}{N}\right), 0 \leq n \leq N$$

Window length  $L = N + 1$

$w = \text{hamming}(L, 'sflag')$  returns an  $L$ -point Hamming window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). The 'periodic' flag is useful for DFT/FFT purposes, such as in spectral analysis. The DFT/FFT contains an implicit periodic extension and the periodic flag enables a signal windowed with a periodic window to have perfect periodic extension. When 'periodic' is specified, hamming computes a length  $L + 1$  window and returns the first  $L$  points.

## 3. MUSIC:

The name MUSIC is an acronym for MULTiple SIGNAL Classification. The MUSIC algorithm estimates the pseudo spectrum from a signal or a correlation matrix using Schmidt's Eigen space analysis method. The algorithm performs Eigen space analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise. The eigenvalues and eigenvectors of the signal's correlation matrix are estimated if you don't supply the correlation matrix.

The MUSIC pseudo spectrum estimate is given by

$$P_{music}(f) = \frac{1}{e^H(f) \left( \sum_{k=p+1}^N V_k V_k^H \right) e(f)} = \frac{1}{\sum_{k=p+1}^N |V_k^H e(f)|^2}$$

where  $N$  is the dimension of the eigenvectors and  $V_k$  is the  $k$ -th eigenvector of the correlation matrix. The integer  $p$  is the dimension of the signal subspace, so the eigenvectors  $V_k$  used in the sum correspond to the smallest eigenvalues and also span the noise subspace. The vector  $e(f)$  consists of complex exponentials, so the inner product  $V_k^H e(f)$  amounts to a Fourier transform. This is used for computation of the pseudo spectrum estimate. The FFT is computed for each  $V_k$  and then the squared magnitudes are summed.

## E. Computer Display of Results

The results of sound signal of normal and faulty signal will be displayed in display window.

## III. SOUND SIGNATURE ANALYSIS OF SINGLE PHASE INDUCTION MOTOR

The recorded sound will be analyzed by using MATLAB code. The MATLAB code used is presented in section 5.

The results over time were processed using FFT, WELCH, MUSIC analysis using the MATLAB functions for digital signal processing—Signal Processing Toolbox.

The motor tested in this paper is a single phase induction motor, with the following parameters:

- Rated voltage –230 V,
- Rated power - 1.5 kW,
- Rated current - 6.7 A.

The experiment has target to single induction motor diagnosis, more precisely bearing fault using sound measurement. Initially the measurements were realized by using electric motor with “healthy” rotor. Then we made the measurement successive by the same motor with a bad bearing.

The Fig. 2 shows the FFT sound spectrum for motor operating in healthy condition.

The Fig. 3 shows the FFT sound spectrum for motor operating in bearing fault condition. The Fig. 2 and 3 shows the variation in sound (dB).

The Fig. 4 shows the FFT power spectrum for motor operating both healthy and bearing fault condition, in this figure top of the spectrum shows bearing defect and below spectrum shows the motor with healthy.

The Fig. 5 shows WELCH power spectrum for comparison between induction motor running with healthy and bearing fault condition.

The Fig. 6 shows MUSIC power spectrum for comparison between induction motor running with healthy and bearing fault condition

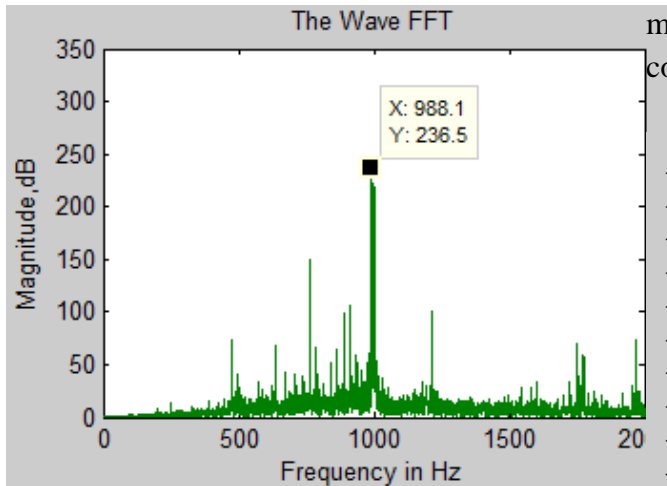


Fig. 2: The FFT sound spectrum for induction motor running with healthy condition

motor running with healthy and bearing fault condition

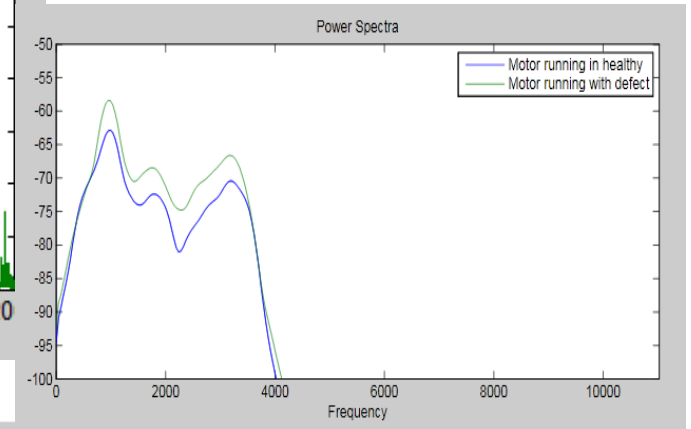


Fig. 5: Using SP Tool box WELCH power spectrum for comparison between induction motor running with healthy and bearing fault condition

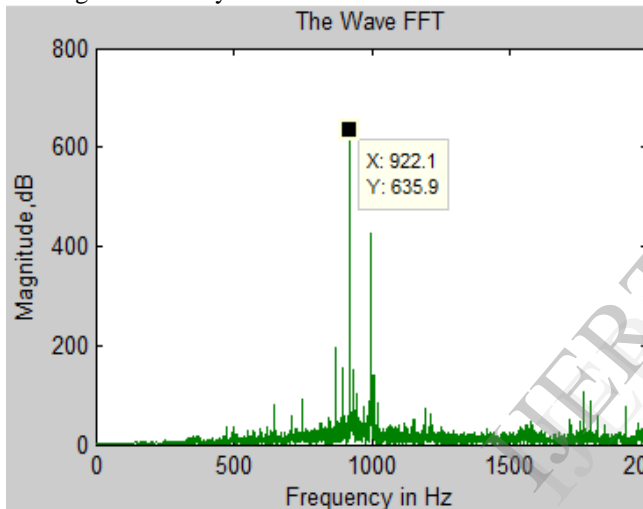


Fig. 3: The FFT sound spectrum for induction motor running with bearing fault

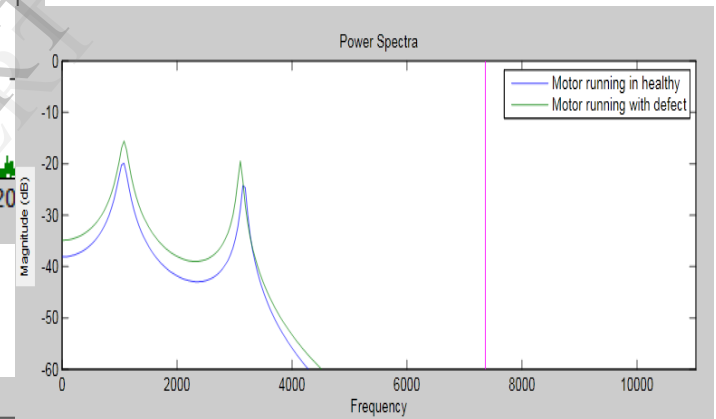


Fig. 6: Using SP Tool box MUSIC power spectrum for comparison between induction motor running with healthy and bearing fault condition

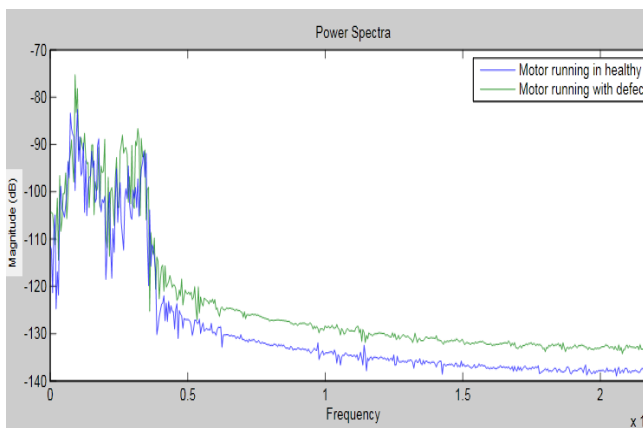


Fig. 4: Using SP Tool box FFT power spectrum for comparison between induction

#### IV. MATLAB CODE FOR SOUND SIGNATURE ANALYSIS

```
[wave,fs]=wavread('healthy.wav');
sound(wave,fs);
t=0:1/fs:(length(wave)-1)/fs;
figure(1);
plot(t,wave);
title('motorhealthy Wave File');
ylabel('Amplitude,dB');
xlabel('Length (in seconds)');
n=length(wave)-1;
```

```
f=0:fs/n:fs;
wavefft=abs(fft(wave));
figure(2);
plot(f,wavefft);
xlabel('Frequency in Hz');
ylabel('Magnitude,dB');
title('motor healthy Wave FFT');
figure(3);
specgram(wave(:,1),256,fs);
title('specgram of healthy condition');
xlabel('Time in sec');
ylabel('Frequency in Hz');
[wave1,fs]=wavread('faulty.wav');
sound(wave1,fs);
t=0:1/fs:(length(wave1)-1)/fs;
figure(4);
plot(t,wave1);
title('motor fault Wave File');
ylabel('Amplitude,dB');
xlabel('Length (in seconds)');
n=length(wave1)-1;
f=0:fs/n:fs;
wavefft=abs(fft(wave1));
figure(5);
plot(f,wavefft);
xlabel('Frequency in Hz');
ylabel('Magnitude,dB');
title('motor fault Wave FFT');
figure(6);
specgram(wave1(:,1),256,fs);
title('specgram of 1ph full-load');
xlabel('Time in sec');
ylabel('Frequency in Hz');
```

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## V. CONCLUSIONS

The technique of evaluating the motor condition by performing a FFT/WELCH/MUSIC of the induction motor sound has been verified by the experimental results. In this case electric motor sound motorizing is very useful to detect electric motor fault. It is demonstrated that the method of sound signature is efficient to make electrical motor diagnosis. In this way, the plant maintenance can successfully detect mechanical and electrical fault that lead to unexpected downtime.

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