Journal of Information Systems Engineering and Management
2025, 10(25s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Acoustic Based Fault Analysis of Induction Motor Using FFT and Wavelets- A Comparative Study

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 18 Feb 2025

Accepted: 01 Mar 2025

ABSTRACT

Detection of fault in induction motors is indispensable for avoiding unforeseen failures. This work intends to diagnose bearing faultin an induction motor. Fault diagnosis is performed on the basis of audio signals emitted by the rotor during rotation of an induction motor. The audio signals which are obtained via a microphone is analysed in Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) methods. It is seen that even though FFT technique was able to differentiate between the frequency spectrum of the faulty motor and the healthy motor, discrete wavelet transform showed a better level of differentiation with respect to the faulty condition and the healthy condition, which were evaluated based on certain statistical parameters.

Keywords: induction, differentiation, statistical

1. INRODUCTION:

Induction motors are commonly used motors which play an important role in industrial applications. They have so many advantages compared to that of other motors like low cost, reliability, robustness etc… which makes them more prominent in industrial and domestic application. Fault in certain critical machines can lead to unscheduled downtime of the faulty machines. The main reason for the fault is due to the continuous exposure to a variety of harsh environment, inappropriate operations, manufacturing defects etc…The major faults that could be anticipated are the bearing faults, stator turn fault,rotor faults etc., Out of these categories, bearing faults have the highest probability of occurrence in a machine. The early detection of these kinds of faults will minimize the damage of induction machine and also reduces the energy consumption.[1-2].

The intended objective of this work is to bring about comparative study on how efficiently fault detection can be performed by using Fast Fourier Transform (FFT) technique and the wavelets transformation as well. Certain statistical indices are chosen and evaluated with the available data and features to the frequency spectra of a healthy and a faulty motor have been arrived at. The data has been obtained by the audio signals emitted by the rotor of a 3Φ, 50Hz, 415V, 3HP Induction motor available in the laboratory.

1.1 Motivation:

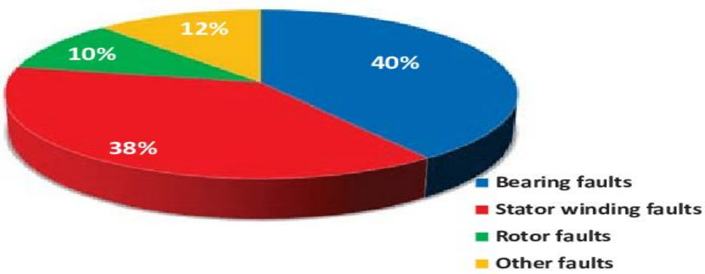

Fig 1: Pie chart demonstrating different faults in induction motor

From the induction motor faults statistics in fig1 most of the faults are dominated by bearing failure. The bearing fault is seen as 40% comparatively higher than other faults. So the motivation of this work is to find out bearing faults for various load conditions of a 3Φ, 50Hz, 415V, 3HP Induction motor available in the laboratory and accounting it with the help of statistical indices.

1.2 Significance:

A comparison between FFT and waveletsis done which leads to a conclusion that wavelets can give better results than FFT. Wavelets givesaccurate results,accurate prediction is required because there are similar frequency components present in both healthy and faulty conditions and there must be exact values obtained out of the spectrum in order to arrive at accurate predictions.

1.3 Organization:

The literature survey of induction motor faults, fast Fourier transform and Wavelet transform is explained in chapter 2. In chapter 3 the methodology of the proposed work is considered in which the system over view is explained in detail. In chapter 4 the simulation results with various statistical indices are exhibited for both FFT and Wavelets and a conclusion from the obtained result is shown in chapter 5.

2. LITERATURE SURVEY

The literature survey gives information about various induction motor faults, reason for the occurrence of the faults and also discusses about various bearing fault monitoring techniques. It also discusses about the importance of signal processing techniques such as FFT and wavelets in identifying the faults and a comparison between these two techniques is carried out.

2.1 Introduction motor faults

The induction motor is an asynchronous machine consists of a magnetic circuit which interlinks two electrical circuits rotating with respect to each other. In induction motor the power is transferred by electromagnetic induction from one circuit to other [3]. In induction motor energy converts from electrical to mechanical energy hence it is an electromechanical energy conversion device [4]. The major fault of induction motor can be classified as

- Broken rotor bar faults – Mainly occurs due to problem with die casting technique, non uniform metallurgical stress, thermal stress, due to heavy end rings. This will lead to unbalancing rotor currents and damage the rotor bars.
- Stator winding fault- mainly occurs due to insulation failure of stator winding. If a large circulating current flows heat will be developed .If the heat which is proportional to the square of the circulating current exceeds the limiting value the complete motor failure may occur. All most 37% of induction motor faults are stator winding faults.
- Air gap eccentricity fault – The rotor is center aligned with the stator bore for healthy motor. When the rotor is not center aligned unbalanced force will act and cause stator rotor rubs and damages the stator and rotor.
- Bearing fault- All most 41% of induction motor faults are bearing fault. Continuous stress on bearing will pave the way for fatigue failures, shaft voltages and current, high bearing temperature, corrosion, improper lubrication and installation all will lead to bearing fault.
- Load fault- Mainly seen in air craft application. It is mainly associated with gear problems [5].

Techniques for Monitoring Bearing Faults

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. 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 periodicshock 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. The other method is the Monitoring Bearing Faults in Induction Motor Using Noise Spectrum**.** The faults detection will be done by comparing two values: the amplitudes of the harmonic components obtained from monitoring the noise spectrum at different frequencies and the amplitudes of the harmonic components at the same frequencies obtained from the reference spectrum [6-7].

2.2 Signal processing methods

2.2.1. Fast Fourier Transform

A Fast Fourier transform(FFT) is an algorithm that samples a signal over a period of time and divides it into its frequency components. These components are single sinusoidal oscillations at distinct frequencies each with their own amplitude and phase. An FFT algorithm computes the discrete Fourier transform(DFT) of a sequence, or its inverse(IFFT). Fourier analysis converts a signal from its original domain to a representation in the frequency domain and vice versa. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse factors [8].

2.2.2 Discrete Wavelet Transform:

The wavelet transform is a signal processing algorithm which used in the detection of abnormal operating conditions based on decomposition of the power signals into different ranges of frequencies by the help of a series of low-pass and high-pass filters. This usually provides a time-frequency multi-resolution analysis that greatly useful for identifying any short of abrupt variations in the electrical parameters such as voltage, phase, current, frequency etc. Usually, the signal is divided into two a set of approximate and a set of detail co-efficient representing the low-frequency and high frequency bands respectively. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar and earthquake prediction [9].

The MCSA FFT based method cannot diagnose the fault during startup. The FFT processor is applicable only for steady signals and cannot use for transient analysis of motor where both amplitude and frequency varies. Only a precise detection of fault is possible in induction motor with varying loads.The FFT-based MCSA method which uses side-band components around fundamental harmonic to detect the fault, suffers from this difficulty.A simple approach is to move a short time window along the signal obtain the Fourier spectrum as a function of time shift. This is called the short time Fourier transform (STFT). The problem here is that the transform divides a non-stationary signal into small windows of equal time. The Fourier transform is then applied to the time segment being examined and the accurate analysis of frequency for the entire small window will be not performed and the ability to identifying transients for all the small time change will be lost. The Wavelet transform is a signal processing tool which is more powerful than the other techniques .The main difference is that for STFT it uses a fixed windowing width function that is both frequency and time is fixed but WT have a adjustable widths with frequency that is higher frequency have narrow width and lower frequency have broader width. The ability of the WT to focus on short time intervals for high frequency components and longintervalsforlow-frequency components improves the analysis of signal [10-11].

Conclusion

Various types of induction motor faults is analyzed and from the statistical studies it is proved that 41% of induction motor faults are bearing faults and the most accurate method of fault detection is using wavelet transform method.

3. METHODOLOGY ADOPTED FOR THE SIGNAL ANALYSIS

3.1 Introduction

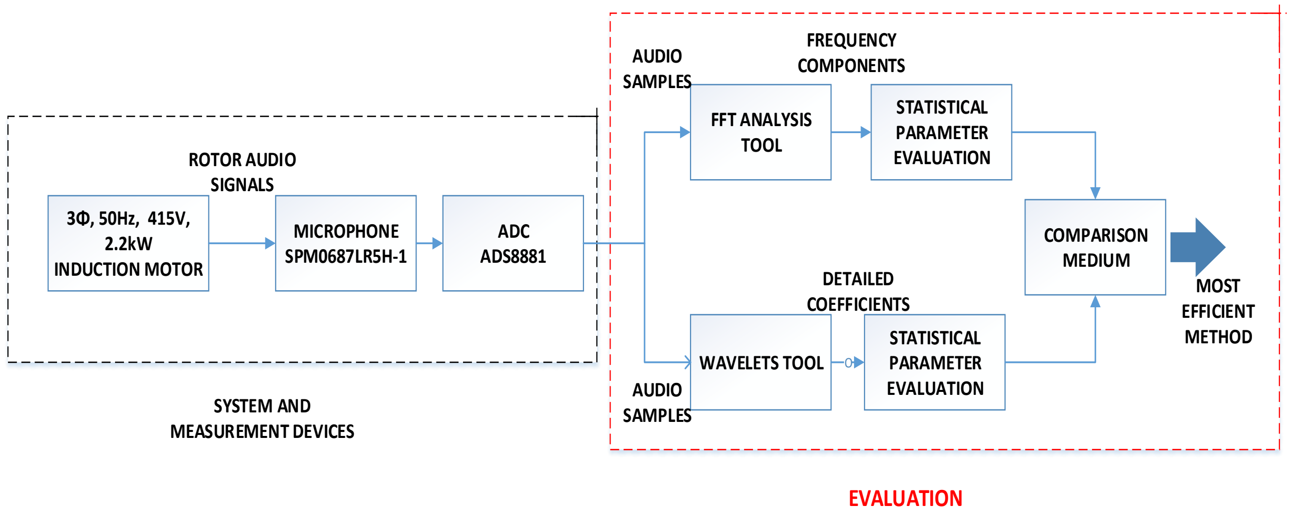

Fig.2. Overall block diagram of the Acoustic Signal Analysis

Fig.2. shows the overall block diagram of the signal analysis system. A3Φ, 50Hz, 415V, 3HP Induction motor available in the laboratory has been considered for the analysis. There are mainly three different loads under which the motor has been operated- no load, half load, 3/4th of full load. The audio signal of three phase induction motor at different load conditions are obtained using a microphone The data which is obtained from the microphone is processed by an ADC to obtain discrete samples in the form of Comma Separated Values. With these values FFT and wavelet transformation has been performed and with the help of some statistical indices analysis and comparison is carried out to give the most efficient technique.

3.2 Specification of the Induction Motor Considered

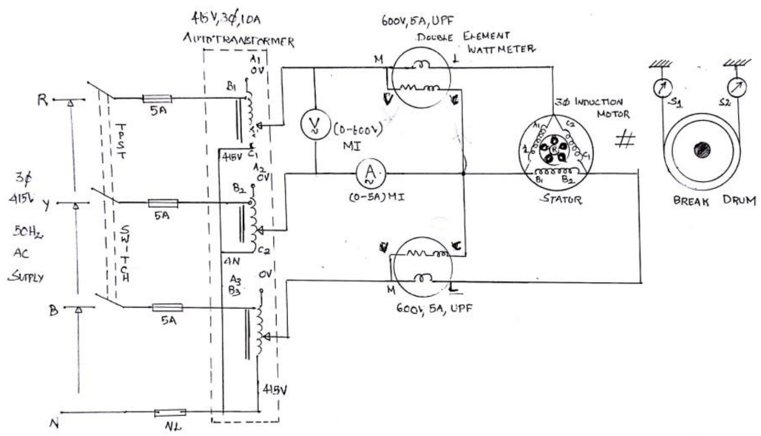

Fig.3. Loading of an induction motor

The audio signals emitted on rotation of the rotor of a 3Φ, 50Hz, 415V, 4.7A Induction motor available in the laboratory as shown in fig.3. An induction motor can be realized as a transformer which works with a rotating magnetic field at the input side. The induction motor is run for a specified time under three conditions

a.)No Load Condition

b.) Half Load condition

c.) 3/4th of the full load condition

The loading of the motor is controlled by inspecting the current that passes through the stator. It has to be made sure that the current does not exceed twice the rated current. That is the maximum value of current that can be passed into the stator. The audio signals emitted by the rotor under the aforementioned conditions have been recorded by a microphone - SPM0687LR5H-1

3.3 Specifications of the microphone employed

KEY PARAMETERS	SPECIFICATIONS
Signal-to-noise ratio (SNR)	70 dB (A)
Acoustic Overload Point (10% AOP)	130 dB SPL
Low Frequency Roll Off (LFRO)	< 13 Hz
Bandwidth (±3dB)	13 kHz
Current consumption	285uA @ 2.7V
Sensitivity and Tolerance (dBv/Pa)	-40 +/- 1 dB (Single Ended) -35 +/- 1 dB (Differential)
Supply voltage (V)	2.3 to 3.6V
Interface	Analog (SE/Diff)
Port location	Bottom Port
Package dimensions	4.72 x 3.76 x 1.25 mm

Fig.4 Datasheet Specifications of the microphone

SPM0687LR5H-1 is an analog microphone for far-field and IoT application manufactured by *Mouser Electronics*. It has a 70db Signal to Noise ratio (SNR) and a 130db Acoustic Overload Point (AOP).

3.4 Analog to Digital Converter

The signals recorded by the microphone are further sent to an Analog to Digital Converter which is capable of providing a sampling rate of 100kHz. It is an 18 bit ADC and the device operates with a reference of 2.5 V to 5V which is given as an external input. It is a successive approximation type register based ADC. The ADC gives out values as samples which is nothing but the count. The count is saved in the form of a Comma Separated Values (CSV) which is used for further analysis.

3.5 Fast Fourier Transform (FFT)

The fast Fourier transform is proposed by Cooley and Tukey in 1965. The fast Fourier transform is a highly efficient method to compute discrete Fourier transform (DFT) of a finite series. It requires less number of computations than DFT. FFT computation technique is used in digital spectral analysis, simulation of filter, recognition of pattern etc...Functionally, the FFT decomposes the set of data to be transformed into a series of smaller data sets . Then decomposes those smaller sets into even smaller sets. For example, an FFT of size 32 is broken into 2 FFTs of size 6, which are broken into 4 FFTs of size 8,which are broken into 8 ffts of size 4,which are broken into 16 FFTS of size 2.Calculating a DFT of size 2 is trivial or it is possible to take the DFT of the first n/2 points and combine them in a special way with the DFT of the second n/2 points to produce a single n-point DFT. Each of these n/2-point DFTs can be calculated using smaller DFTs in the same way. one (radix-2) FFT begins, therefore, by calculating n/2 2-point DFTs. These are combined to form n/4, 4 point DFTs. The next stage produces n/8, 8-point DFTs, and so on, until a single n-point DFT is produced.

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{j2\pi nk}{N}} \qquad (1)$$

The evaluation of DFT using (1)requires N^2 complex multiplication and N (N-1) complex additions so for large values of N, DFT require so many computations. Using FFT number of computation can be reduced for an N point DFT number of complex multiplications required using FFT is $N/2\log_2(N)$.

3.5.1 FFT Terminologies

3.5.1.1 FFT radix:

The radix is the size of an FFT decomposition. For example in the case of radix-2 FFT the number of output N is expressed as a power of 2. That is $N=2^M$, where M is an integer. The number of addition and multiplication required for radix-2 FFT is $N\log_2(N)$ & $N/2\log_2(N)$.

3.5.1.2 Twiddle factors:

Twiddle factors are the coefficients used to combine results from a previous stage to form inputs to the next stage.

3.5.1.3 Bit reversal:

Bit reversal is just what it sounds like: Reversing the bits in a binary word from left to right. Therefore the MSBs become LSBs and LSBs become MSBs. But what does that have to do with FFTs is that the data ordering required by radix-2 FFTs turns out to be in bit reversed order, so bit reversed indexes are used to combine FFT stages.

3.6 Wavelet Transform

Wavelets are certain specific type of functions which exhibit an oscillatory behavior. Such functions exists for a very short period of time. Fourier series divides the signal into components of Sine and Cosine. Where as in wavelets, the computation is carried out by using the same wavelet and its dilations and translates. By doing this, a set of orthonormal basis functions are generated to represent the original signal. Currently for this work, Daubechies 3 wavelet has been utilized for analysis. Unlike Fast Fourier Transform, wavelet analysis is performed in a specified localized area of a larger signal

3.6.1 Wavelet Terminologies

Analyzing the signal with wavelet transform means that the signal is getting associated with two specific functions – Scaling function and wavelet functions

3.6.1.1 Translation and Scaling

Say the wavelet is represented as φ(t). The scaled version of the functions would be nothing but φ(t-1), φ(t-2) etc. This means that , the central position of the wavelet has been shifted along the time axis. Such functions, which are the scaled version of the mother wavelet are called translates of each other.

3.6.1.2 Orthogonality of Translates

Orthogonality of the translates of a wavelet is defined by (2)

$$\int_{-\infty}^{\infty} \varphi(t)\varphi(t-1) = 0 \quad (2)$$

It means that , a point wise multiplication of a wavelet and its translates must be equal to zero.

4. SIMULATION RESULTS OBTAINED FOR ACOUSTIC DATA ANALYSIS

4.1 Introduction

The data which is obtained from the microphone is processed to obtain discrete samples in the form of Comma Separated Values. The samples of the data are analyzed for their frequency components and their detailed coefficients obtained using wavelet transform individually. Certain chosen statistical indices are evaluated and inferences are obtained with the two techniques.

4.2 Analysis of the Audio signals

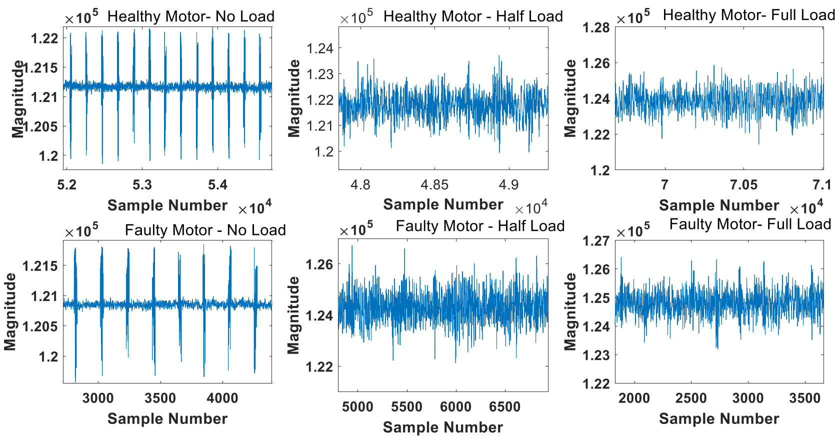

Fig.5 Plot of the data obtained after recording

Fig.5. shows the plot of the data which is obtained post the audio signals were converted to CSV format. The data processed were extracted to MATLAB editor window using the *csvread* command in MATLAB. There is a low level of magnitude difference seen between the audio signals of the healthy and faulty condition. It is seen that there are high levels of external noise in the audio samples which needs to be filtered out for evaluating the motor since the chosen parameter is audio signals of the rotor.

Hence the raw signals were passed into a moving average filter which would filter out the unnecessary noise in the system. A moving average filter is nothing but a low pass FIR filter. Such a filter has been chosen under the assumption that the external noise would be a high frequency noise and a low pass filter must be capable of attenuating the high frequency signals in the available audio samples. *Filter()* command was used in MATLAB to implement the moving average filter.

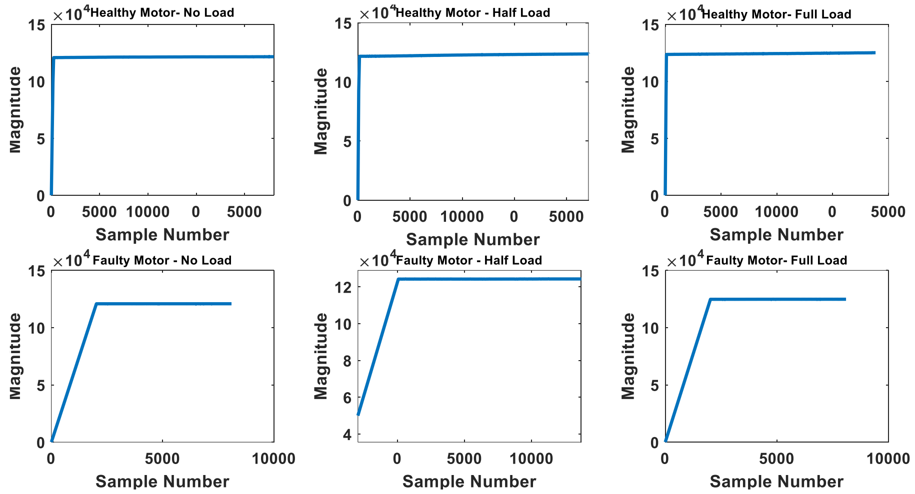

Fig.6. Signals obtained post filtering

Fig.6 shows the signals obtained post filtering. A moving average filter was employed with a window size of 2024. The size of the filter is chosen based on the maximum number of samples available. Here, the number of samples of available data is 8096 and hence the chosen window size. It is observed from the plot that unnecessary external noise has been eliminated from the waveform when compared to the raw signal.

4.3 Results obtained for Fast Fourier Transform

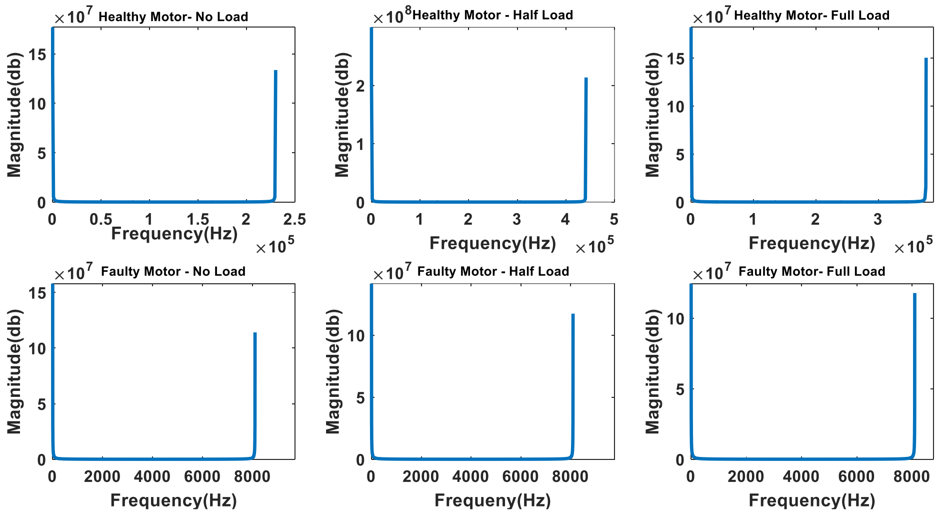

Fig.7 Frequency components of the filtered data

Fig.7. shows the plot of the frequency components of the available data and their corresponding magnitude. Apart from the fundamental frequency, the subsequent dominant frequency is found to be different for all the six

considered conditions. So , it is understood that this could serve as a medium of evaluation of the health of the motor.

Table.1. Observed frequency components of the audio signal

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	230kHz	441kHz	376kHz
Faulty	8096Hz	8097Hz	8098Hz

Table.1. shows the dominant frequency components of the data available other than the fundamental frequency. Even though the frequency at which the dominant contribution occurs at more or less the same value in case of a faulty motor, the magnitude of the frequency component remains different in the three faulty cases. The magnitude is found to increase when the motor is gradually loaded to its maximum. There are other lower frequency components also whose frequency and the respective magnitude haven't been mentioned.

4.4 Evaluation of statistical indices of frequency components of FFT

Since there are other frequency components also present along with the dominant frequency components which have been mentioned in table.1, certain statistical indices are chosen in order to differentiate between a faulty and a healthy motor. The chosen indices are:

a. **Mean**

Mean is nothing but the average of the values present in a given set of values. It is determined by using the *mean()* command in MATLAB

b. **Variance**

Variance is the expectation of squared deviation of a random variable from its mean. It is determined by using the command *var()* in MATLAB.

c. **Standard Deviation**

Standard deviation is the measure of the dispersion of the dataset with respect to its mean. It is also represented as the square root of the variance. It is determined using the command *std()* in MATLAB.

d. **Skewness**

Skewness is the measure of the distortion or the asymmetry in a symmetrical bell curve. It is determined by using the command *skewness()* in MATLAB.

e. **Kurtosis**

Kurtosis is the measure of the taildness of the probability distribution of a real valued variable. It is determined using the command *kurtosis()* in MATLAB

4.4.1 Mean of the frequency components

Table.2. Mean of the frequency components

Condition	No-Load$\times 10^5$	Half-Load$\times 10^5$	$3/4^{th}$ Load$\times 10^5$
Healthy	4.844	4.9261	4.9827
Faulty	4.5264	4.6554	4.6740

Table.2. shows the mean of the frequency components that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A mean which is below 4.5 could be stated as a faulty motor and a mean which is above 4.5 could be a healthy motor.

4.4.2 Variance of the frequency components

Table.3. Variance of the frequency components

Condition	No-Load$\times 10^{15}$	Half-Load$\times 10^{15}$	$3/4^{th}$ Load$\times 10^{15}$
Healthy	3.3685	6.6304	5.8007
Faulty	0.098360	0.10400	0.10488

Table.3 shows the variance of the frequency components that are determined for the three considered cases. It is seen very clearly that there could be a line of separation between the faulty variance and the healthy variance. A variance below 0.1 could be a faulty motor and a that which is above 0.1 could be a healthy motor.

4.4.3 Standard Deviation of the frequency components

Table.4. Standard Deviation of the frequency components

Condition	No-Load$\times 10^{7}$	Half-Load$\times 10^{7}$	$3/4^{th}$ Load$\times 10^{7}$
Healthy	5.8039	8.1428	7.6163
Faulty	0.99177	1.0198	1.0241

Table.4 shows the standard deviation of the frequency components that are determined for the three considered cases. It is seen very clearly that there could be a line of separation between the faulty standard deviation and the healthy standard deviation. A standard deviation below 1 could be a faulty motor and a that which is above 1 could be a healthy motor.

4.4.4 Skewness of the frequency components

Table.5. Skewness of the frequency components

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	477.7058	662.9905	612.1146
Faulty	80.0343	80.0316	80.0327

Table.5 shows the skewness of the frequency components that are determined for the three considered cases. It is seen very clearly that there could be a line of separation between the faulty skewness and the healthy skewness. A skewness below 81 could be a faulty motor and a that which is above 81 could be a healthy motor.

4.4.5 Kurtosis of the frequency components

Table.6. Kurtosis of the frequency components

Condition	No-Load$\times 10^{5}$	Half-Load$\times 10^{5}$	$3/4^{th}$ Load$\times 10^{5}$
Healthy	2.2836	4.4024	3.535
Faulty	0.068553	0.068550	0.068551

Table.6 shows the kurtosis of the frequency components that are determined for the three considered cases. It is seen very clearly that there could be a line of separation between the faulty kurtosis and the healthy kurtosis. A kurtosis below 0.07 could be a faulty motor and a that which is above 0.07 could be a healthy motor.

4.5 Results obtained for Discrete Wavelet Transform

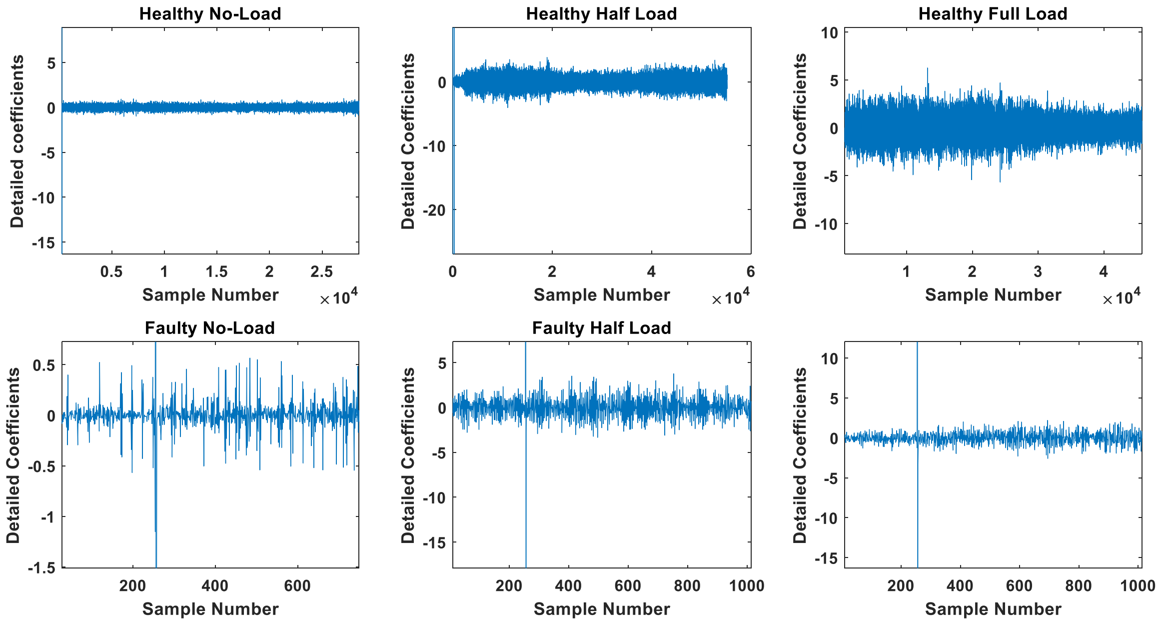

Fig.8. Plot of the Detailed coefficients

Fig.8. shows the plot obtained on decomposing the signals into detailed and approximate coefficients. Db3 level was the highest considered level. There is a huge level of difference observed in the plot of the detailed coefficients.

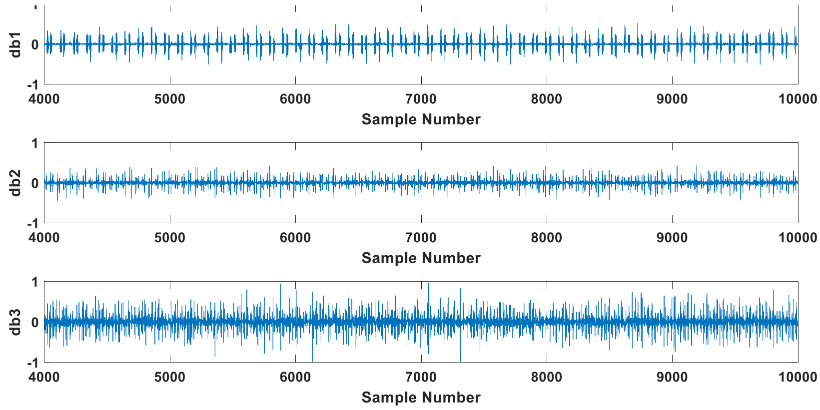

Fig.9. Plot of the detailed coefficients of healthy Half Load conditions

Fig.9 shows the plot of all the three level of detailed coefficients which were obtained for a healthy motor under no load conditions. Certain observations were made with respect to the number of coefficients. The length of the coefficients in each sub band is exactly equal to half the number of coefficients in the preceding stage. In this case considered, the length of db1 level coefficients is 220802. Db2 level coefficients were exactly half the number obtained for level db1 which is 110401 and db3 level had a total number of coefficients that were half the number observed in db2 which is 55201.

4.6 Evaluation of Statistical indices for Wavelet Transform coefficients

4.6.1 Mean of the detailed coefficients

Table.7. Mean of the detailed coefficients

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	-0.0025	-0.0016	-0.0019
Faulty	-0.0752	-0.0801	-0.0746

Table.7. shows the mean of the detailed coefficients that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A mean which is below 10m could be stated as a faulty motor and a mean which is above 10m could be a healthy motor. There is no overlap between the detailed coefficients.

4.6.2 Variance of the detailed coefficients

Table.8. Variance of the detailed coefficients

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	2.0761	1.6325	2.3944
Faulty	58.0940	62.1203	62.5297

Table.8. shows the variance of the detailed coefficients that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A variance which is below 3 could be stated as a healthy motor and a variance which is above 3 could be a faulty motor. There is no overlap between the detailed coefficients.

4.6.3 Standard Deviation of the detailed coefficients

Table.9. Standard Deviation of the detailed coefficients

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	1.4409	1.2777	1.5474
Faulty	7.6219	7.8816	7.9076

Table.9. shows the standard deviation of the detailed coefficients that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A standard deviation which is below 2 could be stated as a healthy motor and a standard deviation which is above 2 could be a faulty motor. There is no overlap between the detailed coefficients.

4.6.4 Skewness of the detailed coefficients

Table.10 Skewness of the detailed coefficients

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	-23.8634	-18.0668	-12.5212
Faulty	-4.5570	-4.4774	-4.3766

Table.10. shows the skewness of the detailed coefficients that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A skewness which is below -5 could be stated as a faulty motor and a skewness which is above -5 could be a healthy motor. There is no overlap between the detailed coefficients.

4.6.5 Kurtosis of the detailed coefficients

Table.11 Kurtosis of the detailed coefficients

Condition	No-Load	Half-Load	$3/4^{th}$ Load
Healthy	8.2857	7.1526	4.24
Faulty	300.9724 e+03	287.4858e+03	295.2597e+03

Table.11. shows the kurtosis of the detailed coefficients that are determined for the three cases chosen. It is seen that there is a separation possible between the healthy and the faulty motor. A kurtosis which is below 9 could be

stated as a healthy motor and a kurtosis which is above 9 could be a faulty motor. There is no overlap between the detailed coefficients.

4.7 Comparative analysis of FFT method and Wavelet Method

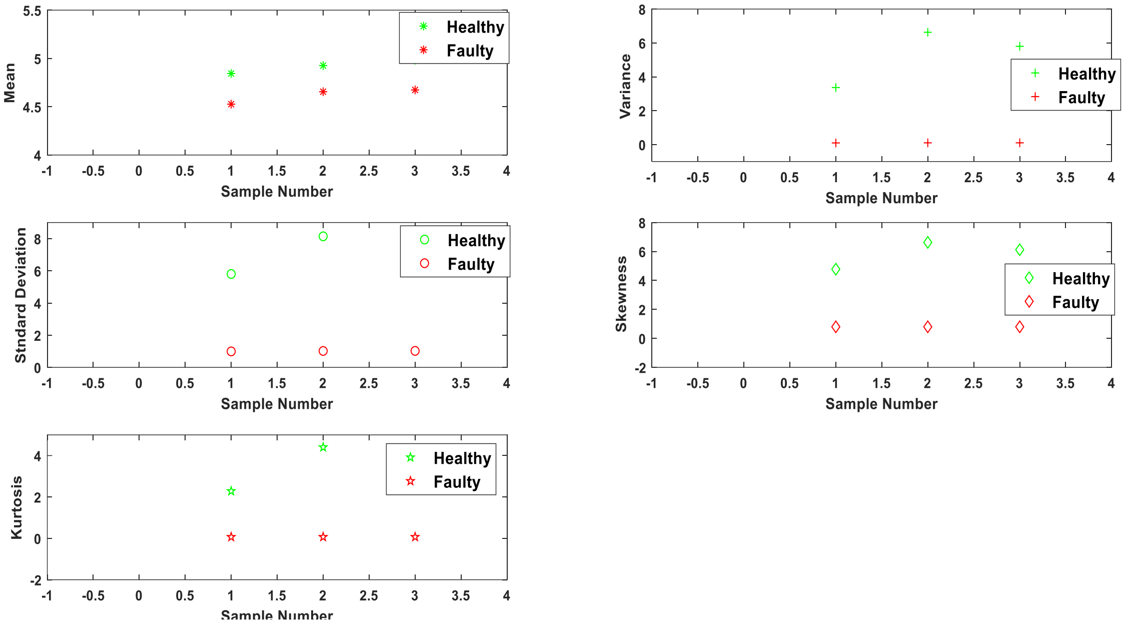

Fig.10. Plot of the statistical parameters obtained by FFT method

Fig.10. shows the plot of the statistical indices evaluated using the Fast Fourier Transform technique. The green data points show the various indices of the healthy motor. It can be seen that there is a very narrow difference between the indices of a healthy motor and a motor with a bearing fault.

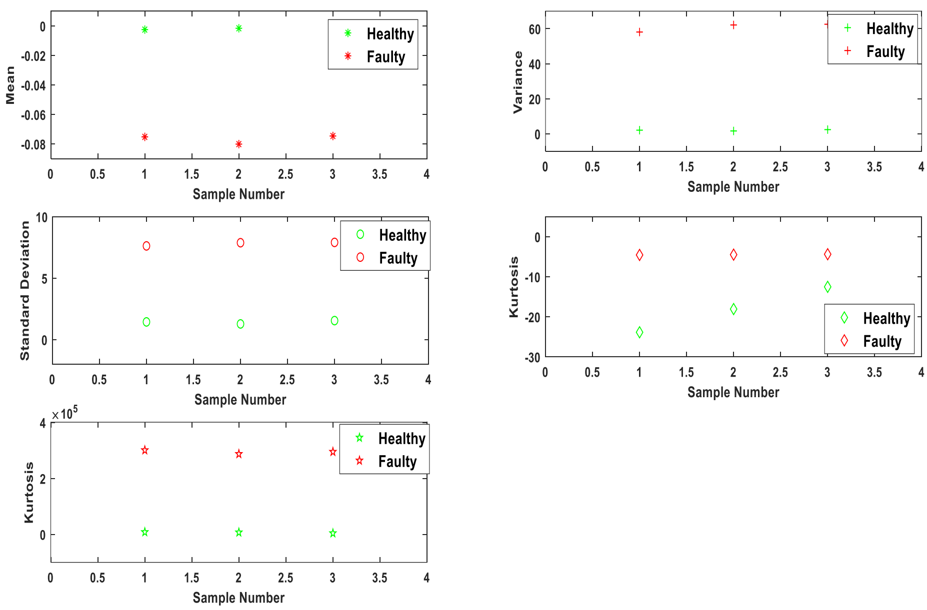

Fig.11 Plot of the statistical parameters obtained by wavelet transformation method

Fig.11. shows the plot of the statistical indices evaluated using the Discrete Wavelet Transform technique. The green data points show the various indices of the healthy motor. It can be seen that there is a very wide difference between the indices of a healthy motor and a motor with a bearing fault. This can ensure that the faults are detected at a very accurate level.

4.8 Comparison on the difference in evaluation parameters obtained using FFT and Wavelets technique

Table.12. Comparison on difference between No Load Data Indices

Statistical Parameter	FFT Technique	Wavelets Technique
Mean	0.32	0.0727
Variance	3.26164	53
Standard Deviation	4.812	6
Skewness	3.97	19
Kurtosis	2.2151	300×10^3

Table.12. shows the absolute difference between the healthy and faulty motor parameters which are evaluated under no load conditions. There is a comparative difference which is shown in the table. It can be very clearly seen that there is a very thin line of separation that could be drawn for the parameters that are obtained using the FFT technique. Whereas, the absolute difference in the parameters evaluated using the Wavelet Transform technique showed a clearer band of separation between the healthy motor parameters and the faulty motor parameters.

4.9 Conclusion

The simulation results show that Wavelet Transform technique is capable of bringing out better fault detection that the Fast Fourier Transform Technique.

5. CONCLUSION

5.1 Conclusion

This work emphasizes on differentiating the audio signals emitted by a healthy induction motor as well as a faulty induction motor which has a bearing fault. Analysis was performed on its frequency components using Fast Fourier Transform Technique and by using Discrete Wavelet transform technique. It was found that even though the FFT Technique was able to determine the health of the motor with certain chosen statistical indices, Discrete Wavelet transform showed a clear demarcation between the order to the detailed coefficients that are obtained for both the cases considered. Effect of input filter has a great level of hold on the evaluation parameters. It is indispensable that the input audio signals are always filtered to remove the additional high frequency noise which appear as transients on observing the overall plot of the system.

5.2 Future Scope

This work can be further extended by developing a machine learning model where the chosen features could be the statistical indices which are evaluated in this work. Also, in the current work, there has been a moving average filter that has been incorporated to filter out the noise in the audio samples. There can be a comparative study on the various kinds of filters and their corresponding response and results with the chosen samples.

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