VIBRATION ANALYSIS FOR BEARING FAULTS OF THREE PHASE INDUCTION MOTOR USING TIME-FREQUENCY DOMAIN

Alka Thakur[1], Dr. S. Wadhwani[2], Dr. A.K. Wadhwani[3]
[1]Research Scholar, [2]Associate Professor, [3]Professor
Department of Electrical Engineering, Madhav Institute of Technology & Science, Gwalior, M.P.,India

Abstract: Induction motors plays a major role in almost all the industrial drive systems because of their simple, efficient and robust nature offering high degree of reliability. Detection and diagnosis of faults while the system is running can help to reduce all kind of losses because it causes decrease in production, loss in valuable time and above all repairing cost. Rolling element bearings are interpretative components in induction motors and monitoring their condition is important to avoid failures. In this paper fault detection in induction motor is done using vibration analysis.Any fault present in the rolling bearing element will generate a mechanical impulse of higher amplitude as compared with the healthy bearing element. If the amplitude of the vibrations reaches to a certain level the fault can be detected and identified. In this paper, the signals are analysed using Fourier transformations that transform time domain signals into frequency domain. This work proposes the use of time-frequency (T-F) transforms to analyse vibration data in motors.
Keywords: Induction motors; bearings; fault diagnosis; vibrations; time-frequency domain

I. INTRODUCTION

Bearings are extensively used in various types of machines ranging from simple induction motor to complex manufacturing machines. However, during the operation there are several types of faults viz., faults related to stator, faults related to rotor, faults related to bearing , gear box, air gap eccentricity faults and shaft misalignment that conclusively lead to machine failure. Among these faults, bearing faults are a common cause of machinery failures that contribute about 41% of the induction motor faults. Thus, diagnosis of bearing failures is a revolutionary issue for scientists and research scholars. In this paper, a new approach for fault detection and diagnosis system is studied for induction motors.

The motor condition monitoring science is moving toward an automated computerized scheme, trying to remove human experts from the condition monitoring process [1]. The purpose of monitoring system is to record the vibration signals from the bearing housing of the motor and to analyse these data using signal processing techniques such as time domain, frequency domain and time-frequency domain techniques [2].It is vibration analysis that makes the detection of the fault quantitatively. The vibration analysis methods for bearing fault detection can be classified into time-domain, frequency-domain, and time-frequency approaches [3,4]. The condition monitoring and fault diagnosis of induction motors have received significant attention recently and become an integrated part of various maintenance strategies.The fault detection process is based on vibration signals using time–frequency analysis that include the wavelet transform which is one of the new and powerful tools in the field of health monitoring. Since the vibration of the induction motor is the basic cause of motor faults, the vibration signal can be analysed to indicate the state of the motor. To prevent this unpredicted damage, it is essential to predict these faults at aboriginal stage.There are many condition monitoring techniques, including; vibration, temperature [5], chemical, and current monitoring [6].

II. VIBRATION SIGNATURE ANALYSIS

Vibrations are created by the oscillation of mechanical parts and are generally produced in every rotating machine.Vibration is one of the mechanical feature of machine that if not controlled at due time can cause minor or major, unsatisfactory operational performance. Machine vibration is the prime component for machine condition monitoring. Hence, it has become necessary to analyse and scale the particular machine vibrations for improving operational efficiency, structural reliability and to enhance the performance of the machine.

The vibration signature of a machine is the characteristic pattern of vibration it generates when in operation which forecast the severity of the machine before any unexpected breakdown and to diagnose the fault as early as possible. Vibration signature analysis is the most extensive method used for monitoring, detecting and analyzing the structural condition in real time. The amplitude signal analysis of vibration gives the indication of severity of the problem and the frequency indicates the origin of the defect [7]. Due to non-destructive nature, vibration monitoring plays a vital role for the structural condition monitoring in industrial process without interfering the actual operation.

III. BEARING RELATED FAULTS

Bearings act as a source of vibration due to either fluctuating pliability or the presence of structural defects during manufacture or their usage. The accuracy of the motor system is highly dependent on the effective performance of the motor bearings for system monitoring and control. Therefore detection of these bearingrelatedfaults is important for condition monitoring as well as eminent assessment of bearings. Bearing faults are one of the prominent causes that instigate the failures in induction motors.Different methods are used for detection and diagnosis of bearing related faultslike vibration and acoustic measurements, temperature and wear debris analysis. Bearing defects may be categorized as ‘distributed’ or ‘local’. The distributed defects include surface roughness, waviness, misaligned races and off-size rolling elements.Single-point defects are lo-calized and can be classified according to the following affected element: outer raceway defect, inner raceway defect,ball defect and cagedefect [8].Stack JR et al. [9] categorized bearing defects into single-point defects and generalized roughness. Single-point defects are usually created off-line in a factory, by drilling a hole in either part of the bearing. Generalized roughness is most often generated on-line by the bearing surfaces degradation, but they do not necessarily show distinguishing defects.

Rolling bearings consist of two concentric rings with a set of rolling elements with two rings called as the outer raceway and inner raceway. Rolling elements comprises of the shapes like the ball, cylindrical roller, needle roller, tapered roller, and symmetrical and unsymmetrical barrel roller. Any fault of inner race, outer race and rolling elements will results in modulation in vibration signals.The root cause of machinery faults in rotating machinery is faulty rolling element bearing [10]. Rolling bearing faults result in a mechanical impulse of higher order amplitude with respect to healthy bearing during normal operation.

IV. HEALTHY BEARING ANALYSIS

Healthy bearing can be analysed on the basis of noise orvibration monitoring. Bearing damages can be detected by a loud running noise or by using continuous vibration monitoring. Damaged bearing element will generate a mechanical impulse of higher frequency as compared with the healthy bearing element. Analysis of the vibration spectrum is done to detect damages in different parts of the bearing. When a damaged bearing is detected, it should be immediately checked out before the overall destruction takes place.

V. RECORDING OF VIBRATION SIGNAL

Vibration measurement is a virtous and relevant technique to monitor the status of the machine during origination, normal operations and shutdowns. Methods to analyse vibration signals are probabilistic analysis, frequency-domain signal analysis and waveform analysis. Vibration sensors are considered as the crux of structural health monitoring systems. Sensor based monitoring methodology has acquire an effective role in determining the best signal for data acquisition system. This methodology provides a precise signal and also has a capability of interpreting what the signal means. These vibration sensors convert the mechanical vibration signals to equivalent electrical signals by detecting the vibration parameter from that particular machine. Once the signal obtained, they are analysed by various signal processing and feature extraction techniques to assess the characteristic features of vibrations. These features include displacement, speed, amplitude, frequency, acceleration, period and phase. The selection of sensors is an important criteria for particular vibration measurement. Numerous sensors have been invented to quantify the data procurement for betterment of the results. These signals so obtained are compared with the base results for interpreting the results. The ISO establishes universally acceptable metric units for machinery vibration.

VI. VIBRATION SIGNAL ANALYSIS IN TIME DOMAIN

The simplest approach in the time domain is to measure the overall root mean square (RMS) level and crest factor ie., the ratio of peak value to RMS value of acceleration .This method has been applied with limited success fr the detection of localised defects, some statistical parameters such as probability density, upper wound value of histogram, lower wound value of histogram and kurtosis have been proposed for bearing fault detection.

6.1 Standard deviation

Standard deviation is the dispersion of a group of data with respect to the mean, and its magnitude equals to the arithmetic mean value of the variance. High standard deviation indicates that the data points are spread out over a large range of values, whereas a low standard deviation shows that the data point tend to be very close to the mean.

SD= $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{\mathrm{i}} - \bar{X})^{2}}$ ……(1)

Where, SD is the Standard Deviation, ‘x’ is mean value of the time series ‘x_i, ‘i’ is the sample number and ‘N’ is total number of samples.

6.2Root mean square value

Root mean square shows the energy of the vibration signal and has a positive effect on wear fault and a weak sensitivity to early fault.

RMS= $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{\mathrm{i}})^{2}}$ ………….(2)

Where, RMS is the Root Mean Square Value, ‘i’ is sample number and ‘N’ is total number of samples.

6.3Peak value

Peak level is indicative of occurrences of impacts. For low-level fault, peak level is good indicator. It is the maximum amplitude used to detect breakdown accompanied by occurrence of sudden impact.

Pv=max(Xi) ………………………..(3)

Where, Pv is the peak value, ‘Xi’ is the time series and ‘i’ is the sample number.

6.4 Crest factor

The crest factor is defined as the ratio of peak value to the RMS value. It is a measure of pectinessof a signal. Crest factor of radial vibration signal is frequently used to signify the rolling bearing faults. Crest factor for healthy bearing is more as compared to that of damaged bearing. The threshold value to judge physical condition of bearing is approximately 1.5 and if exceeds then there is a local defect The crest factorprimarily increases with fault level but it decreases with the increase in fault extremeness after a certain level.

Crest Factor=$\frac{\text{Peak Value}}{\text{RMS Value}}$ ……………..(4)

6.5 Kurtosis

Kurtosis is the characteristic of random variable distribution. Kurtosis comprises of whether the data is are peaked or flat with respect to normal distribution. High kurtosis implies a "peaked" distribution and low kurtosis implies a "flat" distribution near the mean value. A uniform distribution would be the rare case. , the value of kurtosis varies between 3 and 4. If the value is up to4 it indicates that there is a certain degree of defect. The kurtosis value increases considerably up to low level ball defect however it decreases back to value corresponding to healthy case.

Kv=$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\bar{X}}{RMSValue}\right)^4$ ……………….(5)

Where, Kv is the kurtosis, 'x' is mean value of the time series 'x_i, 'i' is the sample number and 'N' is total number of samples.

6.6 Skewness

Skewness is the characteristic parameter to attribute asymmetry degree of probability density curve relative to the mean. It is the characteristics of symmetry. A distribution is said to be symmetric if both the left and the right of the center point of Gaussian distribution appears the same. Negative and positive values of Skewness indicate that the data are skewed left and right respectively. The skewness is found as the consistent parameter with respect to fault severity.

$S_w=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-X}{RMSValue}\right)^2$ ….(6)

Where S_w, is the skewness, 'x' is mean value of the time series 'x_i, 'i' is the sample number and 'N' is total number of sample

6.7 Clearance factor

It is the ratio of peak value of the signal to the square of the average of square root of the absolute value signal.

Clf=$\frac{PeakValue}{(\frac{1}{N}\sum_{i=1}^{N}\sqrt{|X_i|})^2}$ …………………………(7)

Where, Clf is the clearance factor, 'x' is mean value of the time series 'x_i, 'i' is the sample number and 'N' is total number of samples.

6.8 Impulse factor

The ratio of peak value of the signal to average of the absolute value of the signal is impulse factor.

Imf=$\frac{PeakValue}{\frac{1}{N}\sum_{i=1}^{N}|X_i|}$ ………………………..(8)

Where, Imf is the impulse factor, 'x' is mean value of the time series 'x_i, 'i' is the sample number and 'N' is total number of samples.

6.9 Shape factor

The ratio of root mean square value of the signal to the absolute value of the signal is shape factor.

Shf=$\frac{RMSValue}{\frac{1}{N}\sum_{i=1}^{N}|X_i|}$ ……………………….. (9)

Where, Shf is the shape factor, 'x' is mean value of the time series 'x_i, 'i' is the sample number and 'N' is total number of sample.

VII. VIBRATIONSIGNAL ANALYSIS IN FREQUENCY DOMAIN

In frequency-domain, non-stationary signals are analysed. Frequency-domain or spectral analysis of the vibration signal is a universal approach used for bearing defect detection.Analysis in the frequency domain allows not only detection of the bearing damage but also recognition of the type of damage[11].Here the Fourier transformations are employed to transform time domain signals into frequency domain. Modern fast fourier transform analysers have made the narrow band spectra easier and more efficient. Both low and high frequency ranges of the vibration spectrum are of importance in computing the condition of the bearing. A new and powerful tool in the field of signal processing known as wavelet transform has been invented which overcomes the problem that other techniques face in the processing of non-stationary signals. Non-stationary signals comprises of discontinuities and shape spikes. It allows the use of long time intervals, where more precise low-frequency information is required. It also permits the use of shorter time intervals where accurate high-frequency information is expected. Wavelets have the ability to scrutinize non-stationary signals. The continuous wavelet transform is a time-frequency representation of signals.

7.1 Discrete wavelet transforms (DWT)

The DWT analyses the signal at different frequency bands with different resolutions by disintegrating the signal into an unrefined approximation and detail information. It employs two sets of functions viz., scaling and wavelet functions, associated with low pass and high pass filters, respectively.

7.2 Continuous wavelet transforms(CWT)

Wavelet Transform can be implemented using Continuous Wavelet Transform CWT and Discrete Wavelet Transform DWT. CWT is a time-frequency representation of signals. Continuous wavelet transform (CWT) used to extract the local
information content of the data has several advantages over the
morecommonly used DWT [12] which uses a set of orthogonal wavelet bases to obtain the most compact representation of the data mainly useful for image compression.Mathematically, the CWT is given by:

$\Psi_{s,\tau}$ (t)=$\frac{1}{\sqrt{s}}\Psi\left[\frac{t-\tau}{s}\right]$…………(10)

CWT_{Ψ} x(s,τ)=W_x (s,τ)=$\int_{-\infty}^{+\infty} x\ (t)\Psi_{s,\tau}(t)$dt…….(11)

For a given wavelet mother function "ψ" the Continuous Wavelet Transform (CWT) of the signal x (t) is defined by aboveequationwhere ψ* represents the conjugated transpose of the mother wavelet function, "S" is a scale factor and "τ" is the translation factor.The different steps involved in the CWT are:

- deciding a wavelet,
- matching it to the section at the time of starting of the signal,
- Calculating continuous wavelet transform coefficients, to measures the similarity between the wavelet and the section of the signal.
- Shifting the wavelet to the right by translation factor"τ".
- Repeating the steps 1to 3 and calculatingthe values of CWT coefficients for all translations.
- Scaling the wavelet, and repeating steps 1to 4 above.
- Repeating step 5 for all scales.

From the above, it reveals that wavelet based techniques are most effective for extraction of features. The CWT coefficients computed as above, form a matrix at the different scale and translation values; the higher value of coefficients suggest a high correlation between the portion of the signal and that version of the wavelet [13].The continuous wavelet transform has been applied to healthy bearing along with bearings with inner race, outer races, cage and ball faults and continuous wavelet transform plots are obtained.

VIII. BEARING DEFECT EVALUATION

In machine condition monitoring, much attention is generally given to bearing condition because it is the most common component; the rotational movement in bearing elements generates vibrational excitation at a series of discrete frequencies [14].The bearing condition can be analysed with machine vibration. When machine is under operation and if any fault is present in the rolling bearing element it will generate a mechanical impulse of higher amplitude as compared with the healthy bearing element. The bearing failure increases the rotational friction of the rotor under normal operating conditions such as balanced load and good alignment, fatigue failure begins with small fissures, below the surfaces of the raceway and rolling elements, which gradually propagate to the surface generating detectable vibrations and increasing noise levels. Most bearing fault detection techniques for induction motors are intended for detecting single point defects. To detect such faults, vibration analysis is widely used. Bearing faults, whether single point defects or generalized roughness, will typically produce consecutive and periodic impulse terms in working motor vibration caused by passing the ball bearing through the defect points. The period of these terms can be calculated by knowing the rotating velocity, position of faults and bearing dimensions [15].

Single-point defects produce one of the four characteristic fault frequencies in machine vibration spectrum depending on which bearing surface contains the fault.These fault frequencies are inner race, outer race, cageand ball defect frequencies respectively. In case of awell-definedbearing configuration- inner race, outer race and rolling bearing element faults generate vibration spectra with unique frequency components. These frequencies, termed as the defect frequencies, depend on the running speed of the machine and ratio of the pitch diameter to ball diameter of the bearing. Outer and inner race frequencies are linear functions on the number of balls in the bearing element. For a stationary outer ring and rotating inner ring, the fundamental frequencies are obtained from the bearing geometry. The characteristic vibrating frequencies due to these faults can be calculated using equations. (12)– (15), (Frosini et all , 2010)[16].

The vibration frequency due to outer race fault, f_{out} is given by

$$f_{out} = \frac{n}{2} f_r \left(1 - \frac{BD}{PD} cos\emptyset\right) \ldots\ldots\ldots\ldots\ldots\ldots....(12)$$

The vibration frequency due to inner race fault, f_{inn} is given by

$$f_{inn} = \frac{n}{2} f_r \left(1 + \frac{BD}{PD} cos\emptyset\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

The vibration frequency due to ball defect, f_{ball} is given by

$$f_{ball} = \frac{PD}{2\mathrm{BD}} f_r \left(1 - \left(\frac{BD}{PD}\right)^2 cos^2\,\emptyset\right) \ldots\ldots\ldots (14)$$

The vibration frequency due to cage fault, f_{cage} is given by

$$f_{cage} = \frac{1}{2} f_r \left(1 - \frac{BD}{PD} cos\emptyset\right) \ldots\ldots\ldots\ldots\ldots\ldots..(15)$$

Where n is the number of balls, θ is the contact angle, PD is the pitch diameter, BD is the ball diameter of the bearing and$f_r$is the rotor frequency in Hz.

XI. CONCLUSION

Different methodologies based on vibration analysis have been used so far for identifying specific faults in induction motors. Vibration in the time domain can be measured through parameters such as overall root mean square level, crest factor, probability density and kurtosis while the vibration measurement in the frequency domain has the advantage that it can detect the location of the defect. This paper has presented an approach to detect the incipient state of bearing faults in induction motor in time- frequency domain. From a review of studies on vibration measurement techniques for the detection of bearing faults by using time, frequency and time- frequency domain based analysis, emphasis is given on time-frequency based analysis.CWT is a time-frequency representation of signals, that extract the local information content of the data and is easier to interpret since its redundancy tends to reinforce the traits and makes all information more visible. Traditional techniques like Fast Fourier Transform (FFT) used for analysis of the vibration signal is not appropriate to analyze signals that have a transitory characteristic and is dependent on the machine load as well requires a very high resolution data for correct identification of fault frequency components. Thus CWT is very important distinct informative feature extraction technique used for fault detection.

REFERENCES

[1] Mikhail Tsypkin,"Induction Motor Condition Monitoring: Vibration Analysis Technique - a Practical Implementation", IEEE International Electric Machines & Drives Conference, 2011.

[2] S.Wadhwani, S.P. Gupta, V.Kumar, "Wavalate Based Vibration Monitoring for Detection of Faults in Ball Bearing of Rotating Machines", IE(I) Journal-EL, 86, 2005.

[3] Sheng Fu, Kun Liu, YonggangXu, and Yi Liu, "Rolling Bearing Diagnosing Method Based on

Time Domain Analysis and Adaptive Fuzzy C-Means Clustering", Hindawi Publishing Corporation, Shock and Vibration, ID 9412787, 8 pages Volume 2016.
[4] LotfiSaidia,n, JaouherBenAli a, MohamedBenbouzidb,c, EricBechhoefer d, "The use of SESK as a trend parameter for localized bearing fault diagnosis in induction machines",ISA Transactions ,63, 436–447, 2016.
[5] Márton L, van der Linden F, "Temperature Dependent Friction Estimation: Application To Lubricant Health Monitoring", Mechatronics, 2012.
[6] Nandi S et al.,"Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review", IEEE Trans Energy Convers, vol.20, pp.719–29, 2005.
[7] G.G. Yen, K.-C. Lin, "Wavelet Packet Feature Extraction for Vibration Monitoring", IEEE Transactions on Industrial Electronics, vol. 47 (3), pp. 650–667, 2000.
[8] Ahmed Alwodai1, Tie Wang, Zhi Chen, Fengshou Gu1, Robert Cattley, Andrew Ball, "A Study of Motor Bearing Fault Diagnosis using Modulation Signal Bispectrum Analysis of Motor Current Signals",Journal of Signal and Information Processing, 4, pp72-79, 2013.
[9] Stack JR et al., "Fault Classification and Fault Signature Production for Rolling Element Bearings in Electric Machines", IEEE Trans IndAppl vol. 9, pp, 40-735, 2004.
[10] MadhavendraSaxenaa*, Olvin Oliver Banneta, ManojGuptaa, R.P. Rajoriaa,Bearing Fault Monitoring Using CWT Based Vibration Signature,12th International Conference on Vibration Problems, ICOVP 2015,Procedia Engineering 144 (2016) 234 – 241.
[11] JacekDybała, "Diagnosing of Rolling-Element Bearings Using Amplitude Level-Based Decomposition of Machine Vibration Signal", Measurement, may 2018.
[12] Commander Sunil Tyagi, A comparative study of SVM classifiers and artificial neural networks application for rolling element bearing fault diagnosis using wavelet transform preprocessing, in: Proceedings of World Academy of Science, Engineering and Technology, vol. 33, September, 2008, pp. 319–327.
[13] Chen, J., Zi, Y., He, Z., & Yuan, J.. Compound faults detection of rotating machinery using improved adaptive redundant lifting multiwavelet,Mechanical Systems and Signal Processing, vol. *38*, pp.36–54, 2013.
[14] Juan Jose Saucedo-Dorantes et all, "Multiple-Fault Detection Methodology Based on Vibration and Current Analysis Applied to Bearings in Induction Motors and Gearboxes on the Kinematic Chain",Hindawi Publishing Corporation, Shock and Vibration ID 5467643,February 2016.
[15] Siddique A et al, "A Review of Stator Fault Monitoring Techniques of Induction Motors", IEEE Trans Energy Convers, vol.20, pp.106–14, 2005.
[16] Frosini, L., Bassi, E., "Stator Current and Motor Efficiency as Indicators for Different Types of Bearing Faults In Induction Motor", IEEE Trans.Ind. Electron. Vol. 57(1), pp. 244–251, 2010.

