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Preliminary Detection of Bearing Faults using Shannon Entropy of Wavelet Coefficients

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Abstract
In this work bearing faults of a three phase induction motor are detected using the information contents of stator current. The proposed methodology is implemented by taking Wavelet transform of the three phase currents of the induction motor. Finally the diagnosis is performed by employing the Shannon Entropy of the detailed wavelet coefficients at the decided level of decomposition. The work discusses some of the commonly occurring faults in the motor and a brief overview of Wavelet Transform. For different parameters the systems information and experimental results are demonstrated applying MATLAB toolbox. As a result the proposed methodology could improve the accuracy and reliability in the detection of induction motor faults.

Index Terms—entropy, fault diagnosis, Wavelet transform, decomposition level, detailed coefficients, bearing fault

I. Introduction

The ability to recognize a fault at an early stage is mandatory to prevent large system failures which may lead to huge losses and downtime of the machine. An induction machine's simplicity, robustness and its applications in countless industries has led to the increasing interest in the research of diagnosing various faults of induction motor. Using many techniques like noise and vibration monitoring, motor current signature analysis, condition monitoring, neuro-fuzzy inference systems, infrared recognition and temperature measurements research in different publications for the detection of various induction motor faults has become a challenging and tedious job. [3,4]. These faults include air gap eccentricity related faults, insulation failures, broken rotor bars, stator faults, bearing faults etc.

It is a well-known fact that techniques based on Fourier Transform are not sufficient to diagnose non-stationary signals like stator current of an induction machine [1]. In recent years many signal processing tools have provided advancement and optimal results in case of non-stationary signals. This work is all about finding a strategic and adaptive method to detect the broken rotor bar and bearing faults of an induction motor. Majority of the rotor failures take place due to the unavoidable magnetic, thermal, residual and environmental stresses. Due to the time varying conditions at different operating loads a training based algorithm is employed to recognize and distinguish between the normal and faulty operating modes.

II. INDUCTION MOTOR FAILURES

A. Bearing Faults

Bearing related faults constitute to around (4-50) % of the

total induction motor failures. The various faults that can be categorized are outer bearing race defect (f_{obd}), inner bearing race defect (f_{ibd}), ball defect(f_{bd}) and train defect (f_{td})[3];

$$f_{obd} = - \qquad - \qquad (1)$$

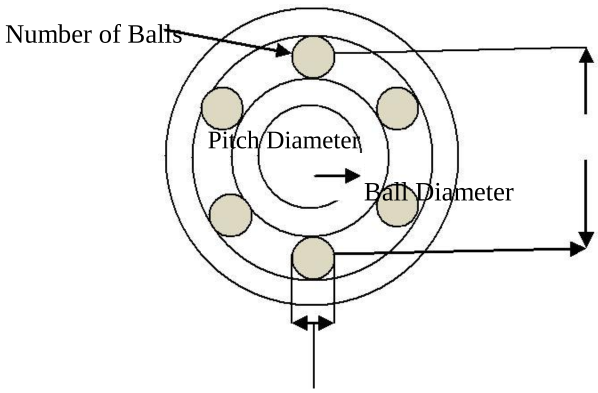


Figure1: Illustration of the bearing geometry showing the Ball diameter (b_d), Pitch Diameter (d_p) and the number of balls in the bearing (N)

f_{ibd}= (2)

f_{bd}= (3)

f_{td}= (4)

where f_r is the rotational frequency, N is the number of balls, b_d and d_p are the ball diameter and ball pitch diameter respectively, and β is the contact angle of the ball.

B. Air-gap Eccentricity related faults

One of the major faults that may occur is air-gap eccentricity related faults which occur due to the unequal air-gap between the stator and rotor of the motor. In practice including both types i.e. static air gap and dynamic air gap eccentricity approximately 10% of the total faults constitute to eccentricity based faults. Moreover a combined state of static and dynamic eccentricity is mixed eccentricity. The equation describing the frequency components for the purpose of detecting static and dynamic eccentricity

$$f_{eccen} = f\,[(k.Z \pm n_d) \quad] \qquad (5)$$

Where $n_d=0$ in case of static eccentricity and $n_d=1, 2, 3$...in case of dynamic eccentricity, f is the supply frequency, Z is the number of rotor slots, p is the number of pole pairs, $s$is the slip, k is any integer and v is the order of stator time harmonics[6].

C. Rotor and Stator Faults

The rotor failures constitute to (5-10) % of the total induction motor failures. The sequence of side-band components produced in order to detect the presence of broken rotor bars is given by

$$f_{br} = (1 \pm 2ns)\,f, \quad n = 1, 2\ 3,.... \qquad (6)$$

where f is the frequency of supply and s denotes the slip.

Primarily caused by insulation degradation the stator faults are around 30-40% of the total induction motor failures. They may also lead to inter-turn short circuits. [8]. The frequency components to detect the axial components of stator faults is given by

$$(k \pm n \quad) \qquad (7)$$

where p denotes the number of pole pairs, f the main frequency, s the slip and k=1, 3 [6]

III. INFORMATION ENTROPY

A system's disorder, instability, imbalance, uncertainty, etc. can be predicted by Entropy. Entropy has a direct relationship with disorder degree of the system. It describes the amount of information provided by a signal or event. Shannon defined entropy as a measure of the average information contents associated with a random outcome [5]. Considering a random event X with n possible outcomes $x1, x2, x3,\ldots, xn$, and every xi with a probability $p(\ )$, then the information entropy $E(X)$ of a random event X is given as in (8)

Coifman and Wickerhauser [9] proposed an algorithm based on entropy demonstrating that entropy is the best basis for selection of decomposition level in Wavelet Transform. The Wavelet Energy Entropy has been applied here to describe the complexities of different decomposition levels

III.WAVELET TRANSFORM (WT)

Wavelet transform of a time varying signal x(t) consists of computing coefficients that are the convolution of the signal x(t) with a family of wavelets (t) for various scale (dilation) a and location (translation) b:

$$, b \quad , a \qquad (6)$$

For any given signal x (t) $L^2(R)$, the discrete wavelet transform is defined as inner production of the wavelet function and the signal x (n):

(7)

Where $x(n)$is the discrete signal to be analyzed and is the discrete wavelet function at scale j and location k[6-7].

Selection of Wavelet

Choosing the type of mother wavelet according to its application is very important in any signal processing technique. A large number of known wavelet families and functions are available which can provide a rich space to search for a wavelet, which efficiently represents the signal of interest. The Wavelet families include Biorthrogonal, Coiflet, Haar, Symmlet, Daubechies etc. [6]. Actually there is no absolute way of choosing a wavelet. The Haar wavelet algorithm has some advantages like being simple and it can be understood easily, whereas the Daubechies algorithm is more complex conceptually but its computational overhead remains slightly higher. The details that are missed by Haar wavelet can be easily recognized with the help of Daubechies wavelet. Even if a signal is not represented properly by one member of the Daubechies family, it may still be efficiently represented by another member [6].

Selection of Decomposition Level

The objective of this study is to put forward a method of choosing the level of decomposition to develop the WT method. Moreover the proposed method of making choice of the decomposition level was based on the wavelet energy entropy. The decomposition of any series via wavelet transform consists of two types of wavelet coefficients sets, named as "approximation" (A_i) and "detailed" (D_i) coefficients at every level of decomposition. In 1988 Mallat produced a fast wavelet decomposition and reconstruction algorithm. In signal processing community the Mallat algorithm has produced a classical theme for decomposition of a signal using Discrete wavelet transform where at every stage the approximation coefficient is decomposed into the next level approximation and detailed coefficients.

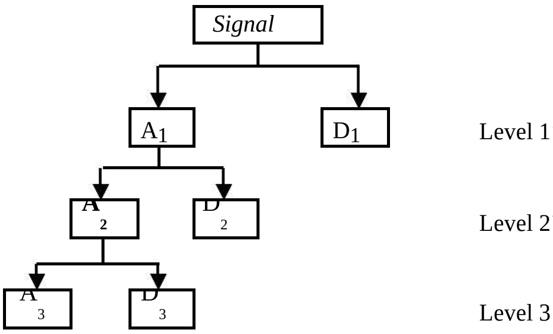


Figure2: Tree decomposition of the signal using Wavelet Transform

The theoretical maximum value of the level of decomposition for DWT can be calculated as

(6)

Where is the length *'m'* of series *f(t)* and the bracket [ ] represents that the integral part of is considered [8]

For accurate results, here in this work Shannon entropy of the wavelet coefficients has been used as a tool. As shown in Table I the signal was decomposed up to the 9^{th} level of decomposition and it was found out that maximum information was being obtained at the 6^{th} level. So the required tests were performed and results are obtained for the 6^{th} level of decomposition.

TABLE I
Comparative Shannon Entropy at Different Levels of Decomposition

Level of Decomposition	Shannon Entropy of Healthy signal	Shannon Entropy of 1 Faulty Bearing signal	Shannon Entropy of 2 Faulty Bearings signal
D1	219.5725	-7.9015e+003	239.5763
D2	143.7099	156.7663	152.2723
D3	-2.6087e+003	-1.0361e+004	-3.9163e+003
D4	-6.9512e+004	-1.0784e+005	-9.5893e+004
D5	-165.4558	-1.0833e+004	196.0081
D6	**-5.6430**	**-255.0836**	**-100.2836**
D7	-45.8708	-286.4791	-263.9899
D8	-116.5161	-603.9058	-567.4411
D9	-203.5321	-662.7562	-719.3437

IV.EXPERIMENTAL RESULTS

Feature Extraction

In this work a 4kW motor with sampling frequency 1 KHz is taken for operation. The tests have been performed for S=10,000 samples of stator current at No-load for a time duration of 60 seconds every time. Three cases have been considered for performing the tests i.e. when the signal is healthy, when one bearing is faulty and when two bearing are faulty. After exhaustive testing the wavelet level of decomposition was obtained using Shannon Entropy and hence features like RMS value, crest factor, skewness, maximum value, kurtosis and entropy are extracted for different orders (*db2, db3, db4...db7, db8*) of Daubechies wavelet for 6^{th} level detailed coefficients shown in Table 2. The RMS values of machine current are generally used to identify unbalanced supply conditions but it is also useful in giving information about the types of fault. The Crest factor, entropy and skewness have also proven to be good factors to diagnose rolling bearing faults [10]

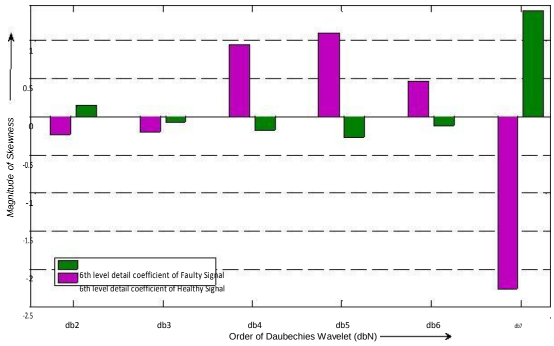


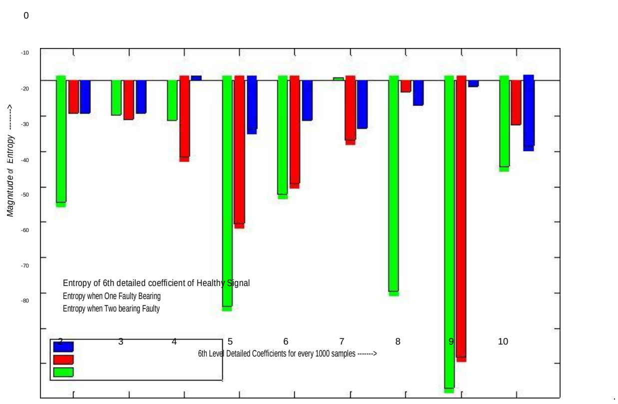
Figure 3: Comparative Skewness Factor of 'N' orders of Daubechies Wavelet

However, some authors showed that all these types of mother wavelets gave similar results. Due to the well-known properties of the orthogonal Daubechies family, we chose to use it to perform Wavelet Transform of the signal. From Figure 3, on comparing the skewness factors at different orders (*db2, db3…db7*) of Daubechies wavelet it was deduced that decomposition with 'db7' represents the maximum information for a healthy and faulty signal.

(a) 6th DETAILED coefficient of HEALTHY SIGNAL

The detailed coefficients at 6^{th} level of decomposition for a healthy as well as for a unhealthy signal taking DWT with Daubechies wavelet are shown in Figure 4

Table 1 clearly shows the variation in entropy at different levels and a noticeable change at the 6^{th} level. The Shannon entropy for every S=1000 samples for the tested 10,000 samples is shown is Figure 5. There is a remarkable difference in the entropy of a healthy signal and faulty signal. It can be seen the Shannon Entropy increases when a bearing fault occurs in the machine.



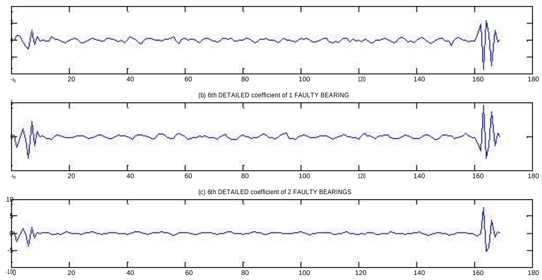


Figure 4: (a) Detailed coefficient of Healthy signal at 6^{th} level of decomposition (b) Detailed coefficient at 6^{th} level for 1 Faulty bearing (c) Detailed coefficient at 6^{th} level when 2 Faulty bearings

TABLE 2. EXTRACTED FEATURES OF HEALTHY AND FAULTY SIGNAL

		Entropy	RMS	Kurtosis	Skewness	Maximum value	Crest
db6	Healthy	-5.6430	6.5265	26.5246	-2.2684	2.3550	0.3608
	1 Faulty Bearing	-255.0836	12.3694	33.5794	1.3855	7.4833	0.6049
	2 Faulty Bearings	-100.2836	9.1010	22.2817	1.5146	4.6116	0.5067

Figure 5: Comparing 6^{th} Level Detailed Entropy of Healthy signal, One Faulty Bearing Signal and Two Faulty Bearing Signals for 1000 samples

V. CONCLUSION

Signal decomposition via wavelet transform provides a good approach of multi-resolution analysis. The decomposed signals are independent due to the orthogonality of the wavelet function. There is no redundant information in the decomposed frequency bands.

Based on the information from a set of independent frequency bands, mechanical condition monitoring and fault diagnosis can be effectively performed.

This work shows a new approach in detection of bearing faults in induction motor having only stator currents as input. The detection is based on the Discrete Wavelet Decomposition method. The results show the effectiveness of the proposed method for this kind of fault.

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