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Diagnostics Of Faults In Induction Motor Via Wavelet Packet Transform

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Abstract: *This paper deals with fault diagnosis of induction machines based on the discrete wavelet transform. By using the wavelet packet decomposition, the information on the health of a system can be extracted from a signal over a wide range of frequencies. This analysis is performed in both time and frequency domains. The HAAR wavelet is selected for the analysis of the stator current. Wavelet components appear to be useful for detecting different electrical faults.*

Index Terms—*Broken rotor bars, data-dependent selection (DDS) and data-independent selection (DIS) of the decomposition level, fault diagnosis, induction machines (IMs), motor-current signature analysis (MCSA), wavelet transform.*

I. INTRODUCTION

Electrical machines are a necessary part of our daily life. As important elements in electromechanical energy conversion, they are used in many fields, such as power generation, the paper industry, oil fields, manufacturing, etc. Among electrical machines, induction motors are the most widely used in industry because of their rugged configuration, low cost, and versatility. With their great contributions, induction motors are called the workhorse of industry. Because of natural aging processes and other factors in practical applications, induction motors are subject to various faults. Those faults disturb the safe operation of motors, threaten normal manufacturing, and can result in substantial cost penalties. The field of motor condition monitoring recognizes those problems, and more and more relative research is being devoted to it by industry and academia. With condition monitoring, an incipient fault can be detected at an early stage. Appropriate maintenance can then be scheduled at a planned downtime, avoiding a costly emergency. An induction motor is constructed with elements of copper, steel, and aluminium. They are very reliable, occasional breakdown of these machines used in critical applications can lead to plant shutdown and hence heavy revenue losses.

II. TYPES OF FAULTS IN INDUCTION MOTOR

Induction motors are susceptible to many types of fault in industrial applications. A motor failure that is not identified in an initial stage may become catastrophic and the induction motor may suffer severe damage.

The motor faults are due to mechanical and electrical stresses. Mechanical stresses are caused by overloads and abrupt load changes, which can produce bearing faults and rotor bar breakage. On the other hand, electrical stresses are usually associated with the power supply. Induction motors can be energized from constant frequency sinusoidal power supplies or from adjustable speed ac drives.

Extra voltage stress on the stator windings, the high frequency stator current components, and the induced bearing currents, caused by ac drives. Electrical stresses may produce stator winding short circuits and result in a complete motor failure.

The major faults of electrical machines can broadly classified by the following:

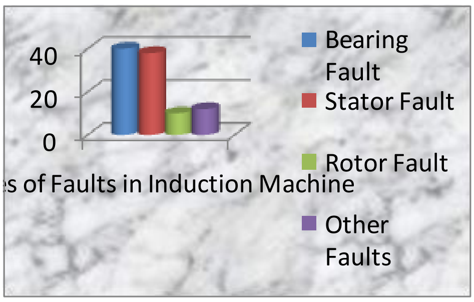

Fig 1 Percentage of faults in induction machine

- Stator faults resulting in the opening or shorting of one or more of a stator phase winding
- Abnormal connection of the stator windings
- Broken rotor bar or cracked rotor end-rings
- Static and /or dynamic air-gap irregularities
- Bent shaft (akin to dynamic eccentricity) which can result in a rub between the rotor and stator, causing serious damage to stator core and windings
- Shorted rotor field winding
- Bearing and gearbox failures

III. DIAGNOSTIC METHODS

The diagnostic methods to identify the above faults may involve several different types of fields of science and technology. They can be described as**:**

- Electromagnetic field monitoring, search coils, coils wound
- Around motor shafts (axial flux related detection),
- Temperature measurements,
- Infrared recognition
- Radio frequency (RF) emissions monitoring
- Noise and vibration monitoring,
- Chemical analysis,
- Acoustic noise measurements,
- Motor current signature analysis (MCSA).

Among existing methods in induction motor condition monitoring, motor current Signal analysis **(MCSA)** is the most commonly used technique. The advantages of this Scheme include low cost and easy operation. In most applications, the stator current of an induction motor is readily available to protect machines against destructive over-currents, ground currents, etc.

IV. CONDITION MONITORING

Condition monitoring of electric machinery can significantly reduce the cost of maintenance and the risk of unexpected failures by allowing the early detection of potentially catastrophic faults. In condition based maintenance, one does not schedule maintenance or machine replacement based on previous records or statistical estimates of machine failure. Rather, one relies on the information provided by condition monitoring systems assessing the machine's condition. Thus the key for the success of condition based maintenance is having an accurate means of condition assessment and fault diagnosis.

Fig. 2 shows a block diagram of on-line condition monitoring system is consist of the following blocks. Different types of sensors can be used to measure signals to detect these faults. Various signal processing techniques can be applied to these sensor signals to extract particular features which are sensitive to the presence of faults. Finally, in the fault detection stage, a
decision needs to be made as to whether a fault exists or not.

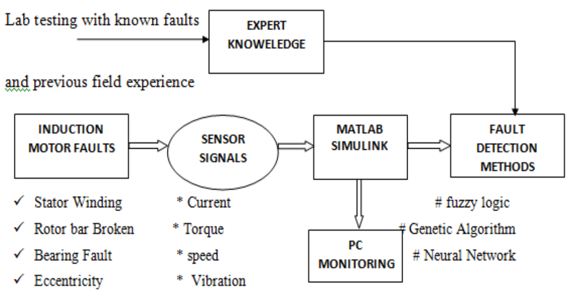

FIG.2 ON-LINE MONITORING PROCESS

V. RELATED WORKS

Mohamed A. Awadallah, et al., attracted by An Overview on Application of AI Tools in Fault Diagnosis of Electrical Machines and Drives. Correct diagnosis and early detection of incipient faults result in fast unscheduled maintenance and short down time for the machine under consideration. It also avoids harmful, sometimes devastative, consequences and helps reduce financial lossNon-invasive motor current signature analysis (MCSA) has been the most preferable technique. Advantages of the paradigms applied to the field include emulating and employing human expertise, automating the diagnosis process, and gaining earlier and more precise detection.

Loredana cristaldi, et al., suggested that a Neuro-Fuzzy Application for AC Motor Drives Monitoring System. An industrial applications require suitable monitoring systems able to identify any decrement in the efficiency involving economical losses. This paper confirm the possibility to design a diagnostic system for an AC drives starting from current measurement on the input side.

Loredana Cristaldi, Antonello Monti Sqior and Ferdinanda Ponci described that Integrated Development of Diagnostic Systems Based on Virtual Systems . This paper describes an experience on the with the help of a virtual environment if suitable interfaces development of virtual procedures for diagnostic system testing The authors describes the possibility of an open platform for simulation to accomplish this task. The application of the virtual environment simplifies the data-training phase as well as the testing of the diagnostic system before the on-line application.

Fiorenzo Filippetti, et al., presented a review on Recent Developments of Induction Motor Drives Fault Diagnosis Using artificial intelligence (AI) Techniques. It covers the application of expert systems, artificial neural networks (ANNs), and fuzzy logic systems that can be integrated into each other and also with more traditional techniques. GA-assisted neural- and fuzzy-neural systems may also be used more extensively for machine condition monitoring, e.g., in self-repairing electrical drives.

Rastko Fiser, et al., presented that the application of a finite element method for predicting the performance of induction motor having electric and magnetic asymmetry of rotor cage due to some broken rotor bars. Magnetic vector potential, flux density, force components, rotor and stator currents, mutual and leakage inductance also determined. The FEM was used to calculate magnetic field of induction motor with symmetrical (healthy) and asymmetrical (faulty) rotor cage.

Loredana Cristaldi., et al., discussed a Virtual Environment for Remote Testing of Complex Systems. Complex systems, realized by integration of several components or subsystems, pose specific problems to simulation environments. This paper presents a methodology for remote model validation. The effectiveness of the approach is experimentally verified locally and remotely.

Olaf Moseler et al., proposed that the Application of Model-Based Fault Detection to a Brushless DC Motor. In comparison to classical dc motors, brushless dc motors are very reliable. They may fail, caused by, e.g., overheating or mechanical wear. This paper proposes a parameter estimation technique for fault detection on this type of motor. Simply by measuring the motor’s input and output signals, its parameters also estimated.

Randy R. Schoen, et al., investigated that Motor Bearing Damage Detection using stator Current Monitoring. Vibration monitoring of mechanical bearing frequencies is currently wed to detect the presence of a fault condition. Since these mechanical vibrations are associated with variations in the physical air gap of the machine, the air gap flux density is modulated and stator currents are generated at predictable frequencies related to the electrical supply and vibration frequencies. Air gap eccentricities cause variations in the air gap flux density that produce visible changes in the stator current spectrum at predictable Frequencies.

Arfat Siddique, et al., investigated thathe Applications of Artificial Intelligence Techniques for Induction Machine Stator Fault Diagnostics . This paper reviewed that the applications of four of these tools, namely, knowledge based systems, fuzzy logic, artificial neural network and genetic algorithm for stator fault diagnostics of induction machines.

VI. PROPOSED SYSTEM

Wavelet analysis can reveal aspects of data that other signal analysis techniques fail to spot, such as trends, breakdown points, discontinuities in higher derivatives, and self-similarity. The discrete version of the wavelet transform, DWT, consists of sampling the scaling and shifted parameters but not the signal or the transform. This leads to high-frequency resolution at low frequencies and high-time resolution at higher frequencies.

A discrete signal $x[n]$ could be decomposed as,

$$X[n] = \Sigma a_{jo},k\Phi_{jo},k[n] + \Sigma \ d_{j,k\Psi j,}k[n]$$

Where Φ[n] is the scaling function, and Ψ[n] is the mother wavelet, Φjo, k[n]=2jo/2Φ(2jon-k) is the scaling function at a scale of $s = 2j0$ shifted by k, j, $k[n] = 2j/2(2jn - k)$ is the mother wavelet at a scale of $s = 2j$ shifted by k, $aj0,k$ are the approximation coefficients at a scale of $s = 2j0$, dj, k are the detail coefficients at a scale of $s = 2j0$ and $N = 2J$, where N is the number of $x[n]$ samples.

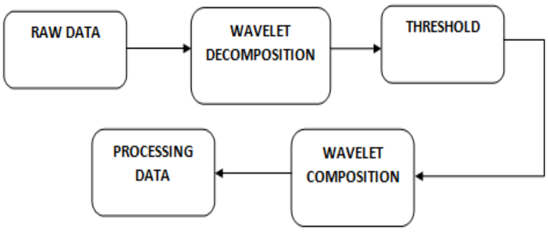

Fig 3 Data Analysis

DISCRETE WAVELET TRANSFORM

The basic concepts of the DWT will be introduced in this section along with its properties and the algorithms used to compute it.

Dilations and translations of the "Mother function," or "analyzing wavelet" $\Phi(x)$ define an orthogonal basis, our wavelet basis:

$$\Phi_{\{sf\}}(\chi) = 2^{\frac{-s}{2}}\Phi(2^{-s}\chi - l)$$

The variables *s* and *l* are integers that scale and dilate the mother function $\Phi(x)$ to generate wavelets, such as a Daubechies wavelet family. The scale index *s* indicates the wavelet's width, and the location index *l* gives its position. Notice that the mother functions are rescaled, or "dilated" by powers of two, and translated by integers. What makes wavelet bases especially interesting is the self-similarity caused by the scales and dilations. Once we know about the mother functions, we know everything about the basis.

To span our data domain at different resolutions, the analyzing wavelet is used in a scaling equation:

$$W(x) = \sum_{k=-1}^{N-2}(-1)^k c_{k+1}\Phi(2x+k)$$

where *W(x)* is the scaling function for the mother function Φ (x), and C_k are the *wavelet coefficients.* The wavelet coefficients must satisfy linear and quadratic constraints of the form, $\sum_{k=0}^{N-1} c_k = 2$, $\sum_{k=0}^{N-1} c_k\, c_{k+2i} = 2\delta_{l,0}$ where δ is the delta function and *l* is the location index.

HAAR WAVELET

A Haar wavelet is the simplest type of wavelet [11]. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. The Haar transform serves as a prototype for all other wavelet transforms. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two subsignals of half its length. One subsignal is a running average or trend; the other subsignal is a running difference or fluctuation.

Advantages Of Haar Wavelet Transform

- It is conceptually simple.
- It is fast.
- It is memory efficient, since it can be calculated in place without a temporary Array.

WAVELET PACKET

The wavelet transform is known as multi scale decomposition process [22].The wavelet transform is actually a subset of a far more versatile transform, the wavelet packet transform. Wavelet packets are particular linear combinations of wavelets. They form bases which retain many of the orthogonality, smoothness, and localization properties of their parent wavelets.

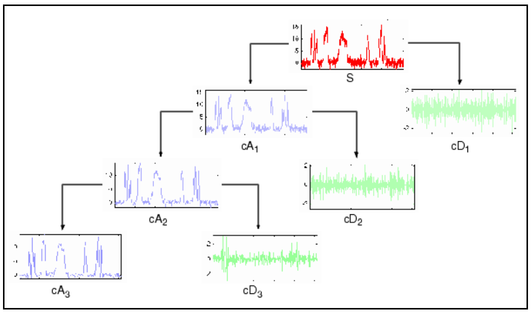

Fig 5 Multilevel Decomposition

ALGORITHM FOR COEFFICIENTS

Starting from a signal s, two sets of coefficients are computed: approximation coefficients CA1, and detail coefficients CD1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for detail, followed by dyadic decimation.

The length of each filter is equal to 2N. If n = length(s), the signals F and G are of length n + 2N - 1, and then the coefficients CA1 and CD1 are of length,

Floor (n-1/2)+N

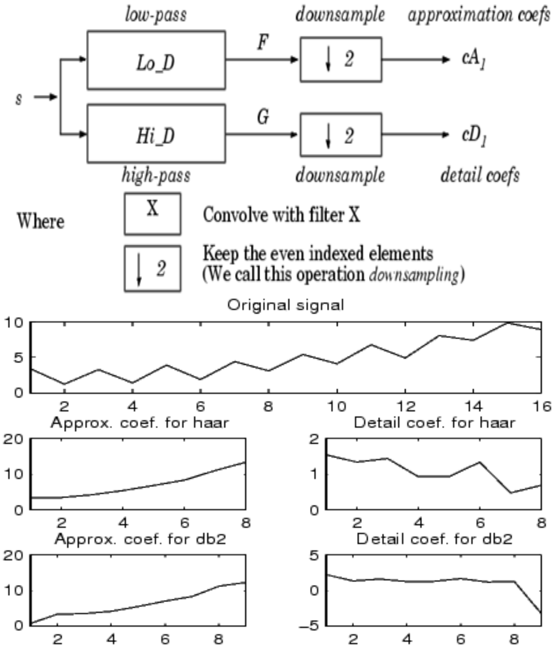

Fig 4.14 Approximation and detailed coefficient curves

VII. EXPERIMENTAL RESULTS

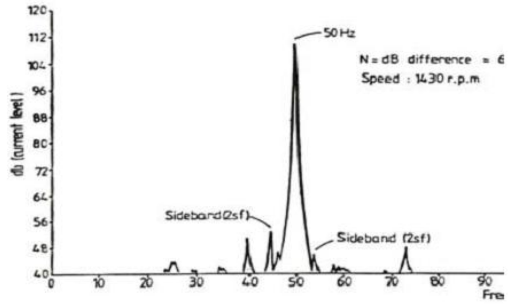

Fig 4.1 Current Spectrum for healthy induction machine

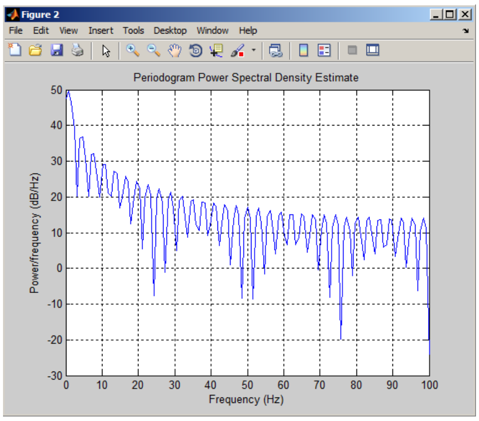

Fig 4.2 Current Spectrum for bearing faulty induction machine

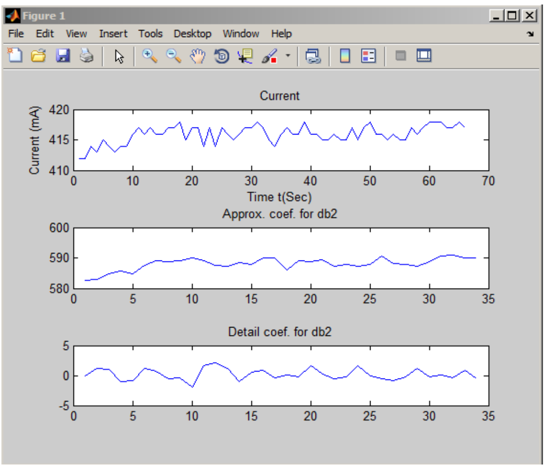

Fig 4.3 Wavelet coefficients of faulty current in induction machine

DETAILS	SPECIFICATION
POWER RATING	**0.5HP**
VOLTAGE RATING	**230V**
CURRENT RATING	**400mA**
SPEED	**1500rpm (1800)**

Table 1 Motor ratings

VIII. CONCLUSIONS

Signal decomposition via wavelet transform and wavelet packets provides a good approach of multiresolution 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.

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