SIGNAL PROCESSING BASED SVM CLASSIFIER FOR MIXED FAULT DETECTION IN INDUCTION MOTOR

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Abstract-
Use of induction motor is widespread in industry. Early detection of faults is crucial for reliable and economical operation of induction motor in industries. In this study fault diagnosis of induction motor under mixed fault including stator inter turn and broken rotor bar is introduced. The base structure of study consists of current signature analysis, feature extraction, SVM and diagnosis algorithm. Motor current signals are recorded for healthy and faulty conditions of motor. To get sight of the effects of current signals that are in time domain is transformed into time frequency domain via discrete wavelet transform (DWT). Five types of wavelets are used for signal processing to demonstrate the superiority of Db4 over other standard wavelets for accurate fault classification. Features extracted using DWT are applied to SVM which is used as a fault classifier. Results obtained prove the suitability of proposed method.

Keywords: *Induction motor, discrete wavelet transforms, Signal Processing, Support vector machine, mixed fault detection*

INTRODUCTION

It is well known that interruption of a manufacturing process due to mechanical and electrical problems induce a significant financial loss for the firm. Interruptions can be caused by rotor faults (broken rotor bars), stator faults (stator interturn faults), or bearing failures .Approximately 36 % of Induction motor failures are caused by failure of stator winding and if remain undetected, progress to catastrophic phase to phase or phase to ground faults. To achieve prior warning of failure shorted turns within the stator winding coil must be predicted to avoid catastrophic failure. Rotor bar crack rarely causes immediate failures especially in large multipole motors [1]. However if there are enough broken rotor bars, motor may not start as it may not be able to develop sufficient accelerating torque. The presence of broken rotor bar precipitates deterioration in other components that can result in time consuming and expensive fixes. Thus above mention faults produced symptoms such as unbalanced air gap voltages and line currents, increased torque pulsations, increased losses, reduction in efficiency and excessive heating. The diagnostic methods to identify above involve several different types of field of science and technology. The trend is to monitor the rotary machine using voltage, current signals because of their low cost. Rangel et al [2] detected cracked rotor bar analyzing vibrations through FFT. Another approach to detect interturn and rotor bar fault is based analysis of motor line currents using Park's vector approach. [3, 4, 5]. This method is based on identification of stator current Concordia pattern. This enables the identification of motor fault and its extension by pattern recognition method. Park's vector approach can be used to detect faulty motor based on the shape of its pattern. Lazarevic and Petrovic [6] use wavelets and decomposition of stator current to detect broken bars. Combastel et al.[7]apply wavelet to stator currents and coil short circuit on the basis of models of motor based on Park's transformation. Ondel et al [8] have proposed k nearest neighbor method for broken rotor bar faults. Ayden et al [9] have proposed a time series data mining algorithm for broken rotor bar faults. Detection of broken rotor bars and interturn short circuit in stator windings based on analysis of three phase current envelopes of induction motor using reconstructed phase space transform is proposed in [10].Artificial Intelligence play a dominant role in field of conditioning monitoring and different techniques such as neural network, fuzzy inference systems, expert system, adoptive neural fuzzy inference system and genetic algorithm are being widely used for feature extraction and classification purpose [11-13]. It can be summarized that there are countless techniques for diagnosis and prognosis of specific induction motor faults, most of these techniques are applied offline, which demands a generalized technique that allows online multiple fault detection. In this paper signal processing algorithm based on SVM is proposed for detection of rotor bar crack and stator interturn fault in induction motor. Line currents recorded from motor terminals are processed using different wavelet transforms to obtain judicious features corresponding to different fault conditions. An attempt is made to investigate five different types of wavelets to establish the superiority of Db4 wavelet over other standard wavelets namely Biorthogonal (Bior1.3, Bior3.1) and Symlets (Sym2, Sym3). Spectral energies contained in d3-d5 level of DWT decomposed stator currents are selected as inputs to SVM. SVM is implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs which fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data which share complex boundaries .Experimentation results obtained prove the suitability of proposed technique for mixed fault detection in induction motor.

1. WAVELET TRANSFORM

Wavelet analysis is about analyzing the signal with short duration finite energy functions which transform the considered signal into another useful form. This transformation is called Wavelet Transform (WT). Let us consider a signal *f*(t), which can be expressed as-

$$f(t) = \sum_{l} a_l \varphi_l(t) \qquad (1)$$

Where, *l* is an integer index for the finite or infinite sum. Symbol a_l are the real valued expansion coefficients, while $\boldsymbol{\varphi_l(t)}$ are the expansion set.

If the expansion (1) is unique, the set is called a basis for the class of functions that can be so expressed. The basis is orthogonal if-

$$\langle \varphi_l(t), \varphi_k(t) \rangle = \int \varphi_l(t)\varphi_k(t)dt = 0 \quad k \neq l \quad (2)$$

Then coefficients can be calculated by the inner product as-

$$\left\langle f(t), \varphi_k(t) \right\rangle = \int f(t)\, \varphi_k(t)\, dt \qquad (3)$$

If the basis set is not orthogonal, then a dual basis set $\varphi_k(t)$ exists such that using (3) with the dual basis gives the desired coefficients. For wavelet expansion, equation (1) becomes-

$$f(t) = \sum_{k}\sum_{j} a_{j,k}\, \varphi_{j,k}(t) \qquad (4)$$

In (4) j and k are both integer indices and φ_{jk} (t) are the wavelet expansion function that usually form an orthogonal basis. The set of expansion coefficients a_{jk} are called Discrete Wavelet Transform (DWT).

There are varieties of wavelet expansion functions (or also called as a Mother Wavelet) available for useful analysis of signals. Choice of particular wavelet depends upon the type of applications. If the wavelet matches the shape of signal well at specific scale and location, then large transform value is obtained, vice versa happens if they do not correlate. This ability to modify the frequency resolution can make it possible to detect signal features which may be useful in characterizing the source of transient or state of post disturbance system. In particular, capability of wavelets to spotlight on short time intervals for high frequency components improves the analysis of signals with localized impulses and oscillations particularly in the presence of fundamental and low order harmonics of transient signals. Hence, Wavelet is a powerful time frequency method to analyze a signal within different frequency ranges by means of dilating and translating of a single function called Mother wavelet.

The DWT is implemented using a multiresolution signal decomposition algorithm to decompose a given signal into scales with different time and frequency resolution. In this sense, a recorder-digitized function a0(*n*), which is a sampled signal of *f*(t), is decomposed into its smoothed version a1(*n*) (containing low-frequency components), and detailed version d1(*n*) (containing higher-frequency components), using filters h(*n*) and g(*n*), respectively. This is first-scale decomposition. The next higher scale decomposition is now based on signal a1(*n*) and so on, as demonstrated in Figure.1

The analysis filter bank divides the spectrum into octave bands. The cut-off frequency for a given level j is found by –

$$fc = fs \,/\, 2^{j+1} \qquad (5)$$

where *fs* is the sampling frequency. The sampling frequency in this paper is taken to be 10 kHz.

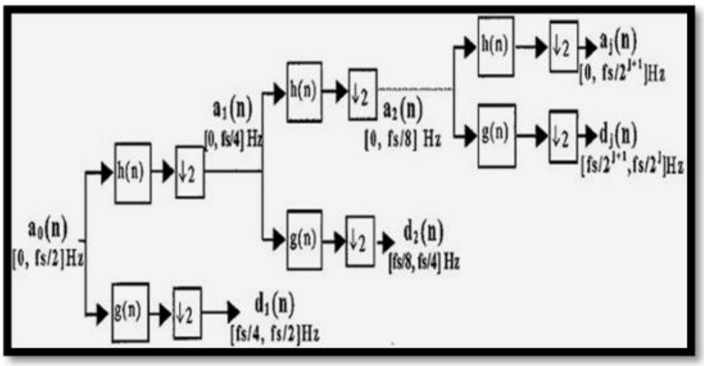

Figure 1: Multiresolution signal decomposition

2. SUPPORT VECTOR MACHINE

In recent years, SVM has proved to perform as an advanced tool for classification or pattern recognition problems.[14] SVM has found to surpass other contemporary classification schemes, including advanced statistical decision methods, as accurate classifications can be achieved with smaller number of support vectors, with the consequent benefit of computational cost [15]. The SVM technique, developed by Vapnik was found to be useful to deal with non-linearly separable cases. Given a set of points that belong to either of two different classes, SVM finds the hyperplane placing the largest possible number of points of the same class on same side, while maximizing the distance of either class from the hyperplane. To find the best hyperplane, the concepts of Empirical Risk Minimization (ERM) can be used. The principle of Structural Risk Minimization (SRM) imposes structure on the optimization process by suitably placing the hyperplanes based on a margin. The optimal hyperplane is the one which maximizes the margin while minimizing the empirical risk .Real-world classification problems, such as the present one; typically involve data that can only be separated using a nonlinear decision surface. Optimization on the input data in such cases will involve the use of a kernel-based transformation. K is a kernel unction such that for all input x, z∈ X where x, z are input and X is input space, φ is a mapping from X to an (inner product) feature space F

$$K(x,z) = \left\langle \ddot{}(x) \bullet \ddot{}(z) \right\rangle \qquad (6)$$

A kernel-based decision function has the form

$$f(x) = \sum_{i=1}^{l} \sim_i y_i K(x, x_i) + b \qquad (7)$$

where b is bias, y is output,~ Lagrange multiplier and *l* is training set size.

Kernel Adatron Algorithm:

Support vector machines work by mapping training data for classification tasks into a high dimensional feature space. In the feature space they then find a maximal margin hyperplane which separates the data. This hyperplane is usually found using a quadratic programming routine which is computationally intensive and non trivial to implement. In this section the (K–A) algorithm for SVM classification is explained briefly. The algorithm is simple and can find rapid solution for SVM classification with an exponentially fast rate of convergence (in the number of iterations) towards the optimal solution as follows.

Step-1: Initialize Lagrangian parameters $\sim_i$=1.

Step-2: Starting from pattern i = 1, for labeled points $\{(x_i, y_i)\}$ Calculates

$$z_i = y_i \sum_{j=1}^{p} \sim_i y_i K(x_{i,} x_j) \qquad (8)$$

Step-3: For all patterns i calculate

$$¥_i = y_i z_i \qquad (9)$$

and execute steps 4–5 below.

Step-4:Let

$$¢\sim^i = ¦\,(1 - ¥^i) \qquad (10)$$

Step-5.1: If $(\sim^i + ¢\sim^i) \le 0$ then the proposed change to the multipliers would result in a negative $\sim^i$ Consequently to avoid this problem we set $\sim^i = 0$.

Step-5.2: If $(\sim^i + ¢\sim^i) > 0$ then the multipliers are updated through the addition of the $¢\sim^i$ i.e $\sim^i = \sim^i + ¢\sim^i$.

Step-6: Calculate the bias b from

$$b = \frac{1}{2}(\min(z_i^+) + \max(z_i^-)) \qquad (11)$$

Where z_i^+ are those patterns i with class label +1 and z_i^- are those with class label -1.

Step-7: If a maximum number of presentations of the pattern set has been exceeded then stop, otherwise return to step 2.

3. EXPERIMENTATION & DATA COLLECTION

For experimentation and data generation a 2 H.P, 3 phase, 4 pole, 415 volts, 50 Hz squirrel cage induction motor is used for staging different faults on the motor. Experimental set up is shown in Figure 2.Motor used for experiment has 24 coils and 36 slots. Each phase comprising of 8 coils has 300 turns. Each phase is tapped where tapping is made after 10 turns, starting from star point (neutral). Tapings are drawn from coils where each group comprises of approximately 70 to 80 turns. Spring and belt arrangement is used for mechanical loading of motor. With 10 Khz sampling frequency 200 samples per cycle are recorded for different load conditions and at different mains supply conditions for following cases.

A. Healthy: 2 H.P motor is fed from three phase balanced supply. Load on the motor is varied from 75 % of full load to full load with spring and belt arrangement .Stator current signals and phase voltages are captured for no load, 75 % of full load up to full load conditions.

B: Stator Interturn Short Circuit: For this case study, stator winding of induction motor is modified to have several accessible tappings that can be used to introduce inter turn short circuits. For this experimentation phase A is tapped, where each tapping is made after 10 turns. Different experimentations are conducted with 10 turns, 20 turns and 30 turns short circuited in phase A of motor and for different loading conditions, phase voltage and stator current signals are recorded.

C: Broken Rotor bars: Induction motor under test has 32 rotor bars. To carry out rotor broken bar test, two rotor bars are broken at both sides of end rings and stator current signals are captured at different loading conditions.

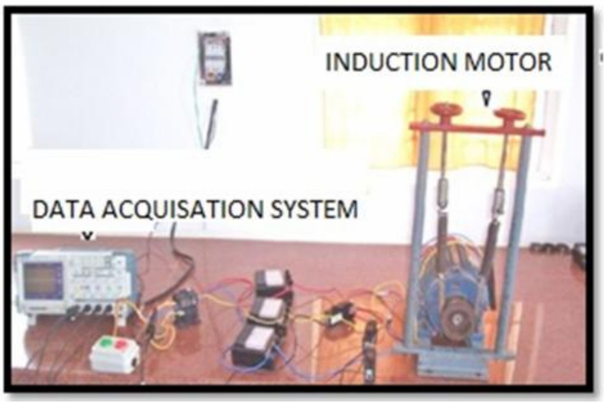

Figure.2: Experimental set up

4. FEATURE EXTRACTION USING DWT.

Current signals obtained for abnormal conditions of motor are similar to normal motor signals. Data acquired does not directly reveal any information usable for fault detection. From time domain no conspicuous differences exist among different fault conditions. There is a need to come up with feature extraction method for fault classification. For feature extraction Db4 is used as a mother wavelet since it has good performance results for fault analysis. To demonstrate the effectiveness of Db4 for accurate fault classification four different wavelets are used. Based on sampling rate of 10 KHz, current signals are decomposed into five levels using different wavelet transforms to obtain MRA coefficients. Table 1 gives range of frequency band for detail coefficients up to five levels.

Table 1: Frequency levels of Wavelet Functions Coefficients

Level No.	Wavelet component	Component type	Frequency band (Hz)
1	d1	Detail	5000-2500
2	d2	Detail	2500-1250
3	d3	Detail	1250-625
4	d4	Detail	625-312.5
5	d5	Detail	312.5-156.25
5	a5	Approximation	0-156.25

Figure 3 shows the decomposition of stator current for db4 wavelet up to fifth level for healthy and for different fault conditions. These wavelet coefficients extracted from raw transient signal contains large amount of information. Though this information is useful, it is difficult for ANN to train that large data, another alternative is to input the energy content in the detailed coefficient according to Parseval's theorem. Parseval's theorem relates the energy of current signal to the wavelet coefficient. Norm of energy of signal can be partitioned in terms of expansion coefficients. The energy of signal is partitioned at different resolution levels in different ways depending on the signals to be analyzed. Energy contents in the detail coefficients of signal is given as

$$\int f(t)^2 dt = \sum_k Cj(k)^2 + \sum_{x=1:j} \sum_k dx(k)^2 \qquad (12)$$

Where $f(t)$ signal to be decomposed using DWT, Cj approximation of the DWT at level j., dx detail number x of the DWT

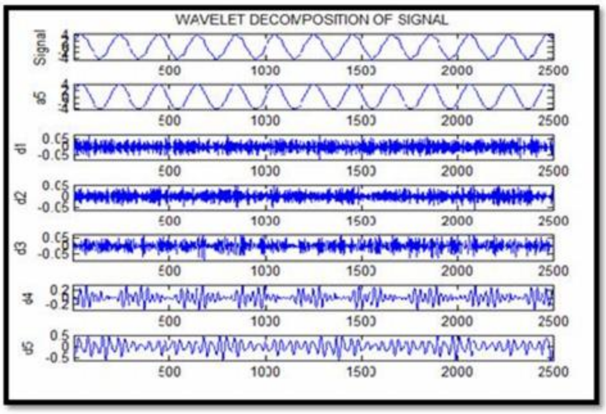

Figure 3.a Wavelet decomposition of stator current for healthy state of Motor

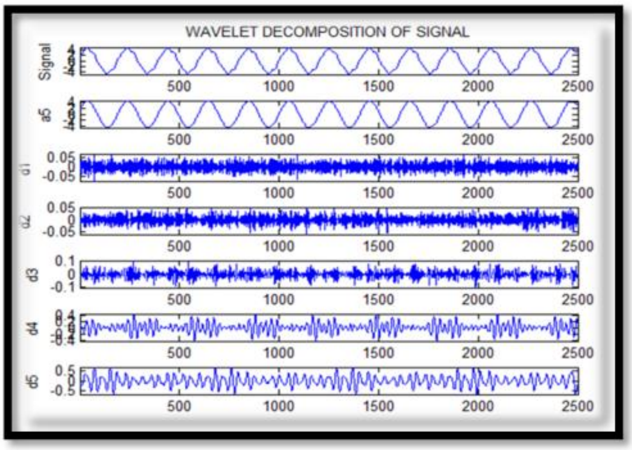

Figure 3.b Wavelet decomposition of stator current for the motor under stator interturn fault

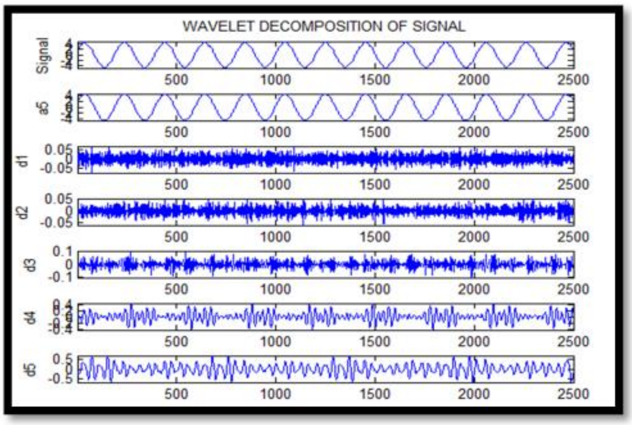

Figure 3.c Wavelet decomposition of stator current for the motor under rotor bar crack

Amongst different decomposition level levels d3-d5 in MRA are seen to be the most dominant band hence feature extraction from these levels could be effectively realized using MRA analysis technique. Energies of level d3-d5 are computed and used as input to SVM. Network is trained and further used for induction motor fault classification.

5. RESULTS AND DISCUSSION

A Support Vector Machine (SVM) is implemented using the **kernel Adatron algorithm** which constructs a hyperplane or set of hyperplanes in a high dimensional space, which can be used for classification, regression or other task. In this paper SVM is network is selected with input layer consisting of nine processing elements which corresponds to energies of detailed levels d3-d5 of stator currents. Output layer consists of three processing elements representing healthy condition, stator interturn short circuit and rotor bar crack .Network is trained with maximum epochs of 1000, training data 60%, testing data 40%, step size is 0.01. With these assumptions percentage accuracy of classification for healthy and abnormal conditions of motor is obtained. In order to demonstrate the superiority of Db4 wavelet, detail analysis of fault classification is obtained using various wavelets. Results tabulated in Table 2 validate the efficacy of Db4 for fault classification. From the tabulated results it is apparent that with Db4 wavelet 100% fault classification accuracy is obtained whereas other wavelets fails to give 100 % percentage accuracy. Figure 4 shows the graph for the same.

Table 2: Percentage Classification Accuracy for various Wavelets with SVM as fault Classifier

Mother Wavelet	Healthy condition	Interturn fault	Rotor bar crack
Daubechies (Db4)	100	100	100
Biorthogonal (Bior 1.3)	60	80	66
Biorthogonal (Bior 3.1)	50	100	100
Symlet (Sym2)	100	100	50
Symlet (Sym 3)	33	100	100

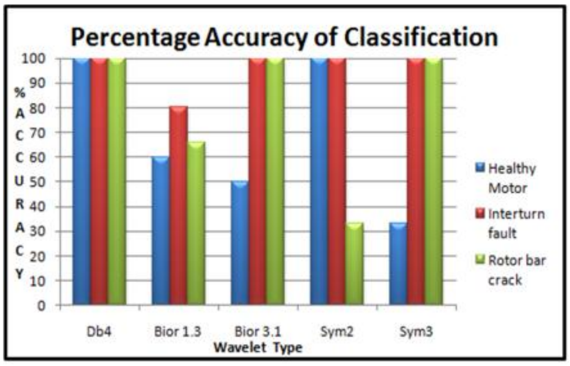

Figure 4: Variation of Percentage Classification Accuracy for various Mother wavelet

6. CONCLUSION

This paper proposes new approach to fault detection and classification of three phase induction motor, validating its effectiveness through different cases of study that considered the motor under diverse fault conditions like stator interturn fault and rotor bar crack. Line current signals recorded under healthy and faulty conditions are passed through series of signal processing procedures .Subsequently DWT is utilized to extract the features which derive rich information about the fault from stator current signals. Since selection of particular wavelet plays an important role for extracting dynamic features of generated harmonics, therefore an investigation is carried out using five wavelets to establish the efficacy of Db4 over other wavelets. Thus feature extraction using mother wavelet Db4, and SVM based classifier works as an elegant classifier for fault diagnosis of three phase induction motor.

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