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Wavelet Based Diagnosis and Protection of Electric Motors

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1. Introduction

Electric machines are electromagnetic energy conversion devices that convert one form of energy into another form. Electric machines have been playing important roles in the developments of modern industrial technology for over a century. Better understanding of energy conversion principles coupled with evolution of new and improved materials has contributed to the developments of machine designs. The applications of electric machines are increasing rapidly with increased technological advancements. The advances of modern digital computers and recent developments in power electronics and semiconductor devices have made revolutionary contributions on the design and control of electric machines. The direct current (dc), induction, and synchronous machines are the three major electric machines that serve industrial, commercial and household needs. The time-stepping finite element analysis has helped in further developments and design optimization of electric machines. Thus, new electric machines such as brushless dc (BLDC) motor, switched reluctance motor, permanent magnet hysteresis motor, permanent magnet synchronous motor, self-excited induction generator, and doubly fed induction generator are developed and implemented for household and industry applications (Rahman, 1980; Slemon, 1992).

The electric machines comes in many sizes and forms, and fulfill their function either independently or as part of a highly complex process in which all elements must function smoothly so that production can be maintained. The function of an individual electric machine is normally seen as separable from the rest of the electromechanical system. Not withstanding their high reliability, electric machines face various stresses including faults during different operating conditions. Hence the condition monitoring, faults diagnostic, and protection become necessary in order to avoid catastrophic failures of electric machines. The use of comprehensive monitoring schemes for the continuous assessment of electrical machines is becoming increasingly important. It is possible to provide adequate warning of imminent/incipient failures using new condition monitoring techniques. It is also possible to schedule future preventive maintenance and repair work in addition to present maintenance needs. This can result in minimum downtime and optimum maintenance schedules. Faults diagnosis allows a machine operator to have the necessary spare parts before the machine is stripped down, which also reduce machine outage times. If faults diagnosis is integrated into the maintenance policy, the usual maintenance at specified

intervals can be replaced by condition centered maintenance. This can also eliminate unnecessary maintenance (Vas, 1996). It is important to stress the fact that protection system for electric machines is basically designed to act only when a fault has occurred in order to initiate some remedial action. Virtually all electric machine protection systems embody some form of protective devices. In a typical machine, they are used in some or all of the following schemes

- Earth fault protection,
- over current protection,
- differential current protection,
- under and overvoltage protection,
- negative phase sequence protection,
- field failure protection,
- reverse power protection,
- over speed protection,
- excessive vibration protection,
- thermal overload protection, etc.

The executive action of a protection system is the disconnection of the piece of machinery of a plant from the supply. Such action is acceptable if the machine is readily dissociated from the process it is involved with, or if it exists substantially in isolation. However, if the machine is vital to the operation of a process, then an unscheduled shutdown of the complete process may occur. The losses involved may then be significantly greater than those resulting simply from the loss of output during a schedule shutdown. The capital cost of an individual electric machine is more often not small compared with the capital costs involved in a plant shutdown. Maintenance is most effective when it is planned to service many items in the course of a single outage. Therefore, condition monitoring of an electric machine is not necessarily aimed at the machine itself, but also at the wider health of the process involving the machines (Tavner et al., 2008).

2. State of the Art Faults Diagnostic and Condition Monitoring Technologies

Intensive research has been conducted to develop and implement new and reliable techniques for condition monitoring, faults diagnostic and protection of electric machines. The modern techniques are based on the application of advanced digital signal processing tools on stator currents. The signal processing tools include discrete Fourier transform (DFT), fast Fourier transform (FFT), wavelet transform (WT), and other high level frequency spectra analysis tools. The model reference adaptive system and artificial intelligence have also been used for faults diagnostic and protection of electric machines. In these non-invasive faults diagnostic techniques, either stator current or vibration signals of electric machines is used to detect a fault. The new faults diagnostic techniques for electric machines can be broadly classified into three categories: (a) artificial intelligence based techniques, (b) standard digital signal processing based techniques, (c) advanced digital signal processing based techniques. The artificial intelligence (AI) based techniques include the applications of expert systems (ES), genetic algorithm (GA), support vector machine (SVM), neural networks (NN), fuzzy logic (FL), and neuro-fuzzy. The standard digital signal processing

based techniques include the applications of discrete Fourier transform (DFT), fast Fourier transform (FFT), short time Fourier transform (STFT), and higher order spectra (HOS) such as bi-spectrum, tri-spectrum, etc. The advanced digital signal processing based techniques include the applications of continuous wavelet transform (CWT), discrete wavelet transform (DWT), wavelet packet transform (WPT), and wavelet neural network (WNN). The use of partial discharge (PD), and measurements of stator temperature and negative sequence impedance have also been documented in the literatures for faults diagnostic of electric machines. A state of the art review of various forms of condition monitoring and faults diagnostic techniques for squirrel cage and wound rotor induction motors, permanent magnet synchronous motors, interior permanent magnet (IPM) motors, separately excited synchronous generators, etc, are given in the following subsections.

2.1 Application of artificial intelligence

The artificial intelligence (AI) is the study of system conditions through the use of computational models. The AI tools are of great practical significance in engineering to solve various complex problems, which require human intelligence. Recently, significant efforts have been made on the use of artificial intelligence tools to develop condition monitoring and faults diagnostic techniques for electric machines. Filippetti et al., (1988), have outlined an expert system (ES) based on the knowledge representation for faults diagnostic of induction motors. The knowledge based ES uses instantaneous line currents, line voltages, and rotor speed as input variables. Leith et al., (1988), have presented an on-line real time ES for diagnosing faults in induction motors. The knowledge base consists of a failure tree, an observation tree, and a case tree. The proposed ES require theoretical and practical studies of fault mechanisms, and case histories of fault analyses. This method is vulnerable to uncertainty and is not quite suitable from computational point of view. Pöyhönen et al. (2002), have implemented support vector machine (SVM) based faults diagnostic and classification technique for an inverter fed squirrel cage induction motor. The magnetic field analysis is used to get virtual data of the healthy and faulty operating conditions of the induction motor. The power spectra of stator current are used as inputs to the SVM based classifier to distinguish healthy condition from normal unfaulted condition. However, the technique may fail if two separate classes get equal amount of votes. In addition, it did not consider the possible redundancy from pair-wise outputs of the classifier. Chow et al. (1991), have implemented a three-layer feed forward neural network for condition monitoring of induction motors in real time. The stator inter-turn and motor bearing faults are investigated at constant load torque. The stator currents and rotor speed are used as inputs during the off-line training of the network. The network is implemented in real time using a digital signal processor board. The network showed satisfactory performances with higher number of hidden nodes. However, the technique is not quite accurate due to the dynamic nature of machine parameters. In addition, it requires large number of training data set in order to cover all the operating conditions including the faulted and unfaulted conditions of the motor. Lasurt et al. (2000), have implemented a fuzzy logic based condition monitoring and faults diagnostic technique for induction motors. The proposed technique implemented the higher order statistical (HOS) analysis of the machine vibration signal. The fuzzy logic procedures are then applied to the HOS signatures in order to enable diagnosis of a machine fault. Park et al. (2004), have presented an adaptive neuro-fuzzy inference system (ANFIS) based faults diagnostic technique for an

inverter fed pulse width modulated induction motor drive system. The proposed technique involves data acquisition and feature extraction of fault currents, and then use of adaptive neuro fuzzy inference system (ANFIS) for faults diagnostic. The technique used the mean values of direct and quadrature axis phase currents as the input pattern for the ANFIS.

2.2 Application of standard digital signal processing techniques

The standard signal processing tools such as DFT, FFT, STFT, etc are widely used for condition monitoring and faults diagnostic of electric machines in last fifteen years. These techniques have traditionally been applied separately in time and frequency domains. The time domain analysis focuses particularly on statistical characteristics of vibration, temperature, and stator currents, which include peak level, standard deviation, kurtosis, skewness, and crest factor of the diagnostic signal. The frequency domain approach uses Fourier methods to transform the time domain signal in the frequency domain, where further analysis is carried out. The use of either domain implicitly excludes the direct use of information present in other domain (Yang et al., 2003).

Yang et al. (2003), have used vibration analysis based on bi-spectra and wavelet transform for the diagnostic of induction motor rolling element bearing faults. The singular value decomposition (SVD) technique is applied to extract the most significant features from vibration signatures. The features are used as inputs to an artificial neural network to identify the type of fault. Roux et al. (2003), have investigated two condition monitoring techniques in order to detect rotor faults in surface mounted type permanent magnet synchronous motor. The first technique is based on harmonic spectra analysis of stator voltage and current in the natural reference frame. The second technique is based on spectra analysis of d-q axis voltage the rotor reference frame. The static and dynamic eccentricity, broken magnets, and rotor misalignments are investigated. The harmonic spectra analysis method based on fast Fourier transform (FFT) was able to differentiate all faults except the static eccentricity from the normal case. Therefore, the harmonics of the negative sequence component of the stator current were used for the detection of static eccentricity, and it successfully distinguished the static eccentricity from the normal case. However, the main disadvantage of FFT based harmonic spectra analysis is the impact of side lobe leakage due to windowing of finite data sets.

Zanardelli et al. (2007), have implemented the short time Fourier transform (STFT) of the torque producing current component in order to diagnose faults in surface mounted permanent magnet synchronous motor. The field oriented d-q axis currents are used in this analysis. The energy of the STFT coefficients is used to detect a fault in the motor, and linear discriminator analysis is used to classify faults. However, the STFT based technique uses stationary and periodic basis functions. But fault currents are often non-stationary and non-periodic. As a result, the performances of the technique are limited due to the constraint on the window size. In addition, the performances of the proposed technique have not been investigated in real time. Schoen et al. (1995), have implemented motor current spectral analysis (MCSA) for diagnostic of rolling element bearing in induction motors. The vibration and current frequencies are modeled in order to detect incipient bearing failures. Yazici et al. (1999), have developed an adaptive statistical time–frequency approach for diagnostic of broken bars and bearing faults in induction motors. The proposed technique has four stages such as preprocessing, training, testing, and post processing. In the preprocessing stage, analog current data are filtered by low pass circuit in order to prevent

aliasing in the frequency domain. Next, the time–frequency spectra of the digital data are computed and used as inputs of a neural network. In the training stage, fault frequencies are determined, and a window with frequency components near to the estimated frequencies is applied to form a feature vector. Next, feature vectors are segmented into homogenous sections along the time axis in time–frequency space. Segmentation is performed by a statistical method, which divided the time–frequency spectra into statistically homogenous regions along the time axis. However, the proposed technique shows strong interactions between machine operating conditions and machine variables.

2.3 Application of advanced digital signal processing techniques

Majority of the signal processing based faults diagnostic techniques involve the analyses of vibrations signal or stator currents in either time or frequency domains assuming stationary and periodic nature of fault currents. Thus these techniques are not fully suitable for localizing and identifying short duration dynamic phenomena. Therefore, the applications of advanced signal processing techniques are required, which include signal modeling, filtering, and time-frequency analysis. Among the latter, the wavelet transform algorithms are the recent mathematical tools adopted and implemented for faults diagnostic and protection of electric machines (Dalpiaz & Rivola, 1997).

Zanardelli et al. (2005), have developed a failure prognosis technique for surface mounted permanent magnet synchronous motor drives based on undecimated discrete wavelet transform (UDWT) of torque current components. The energy of the UDWT coefficients of normal unfaulted and faulted currents is used to detect a fault in the motor. The linear discriminator analysis is used to classify faults. The same authors (Zanardelli et. al., 2002) have made a comparative analysis of wavelet based faults diagnostic and protection techniques in electric machines. Khan & Rahman (2009), have developed and implemented a novel fault diagnostic and protection technique for interior permanent magnet (IPM) synchronous motors using wavelet packet transform (WPT) and artificial neural network (ANN). In the proposed technique, the line currents of different faulted and normal conditions of an IPM motor are preprocessed by the WPT. The second level wavelet packet transformed coefficients of line currents are used as inputs of a three-layer feed forward neural network. The proposed protection technique is successfully simulated and experimentally tested on a line-fed and an inverter-fed IPM motors. [a]Khan & Rahman (2008), have developed a wavelet transform based diagnostic and protection technique for inverter faults of IPM motor drives. The proposed technique is implemented in real time for a voltage source inverter fed IPM motor. The WPT coefficients of motor currents are used as inputs of a three-layer wavelet neural network (WNN) for detecting inverter faults in the drive system. A feature vector based on the energy of WPT coefficients is used to classify different faulted conditions. [b]Khan & Rahman (2008), have developed and implemented a WNN based diagnostic and protection algorithm for inverter faults in vector controlled induction motor drive system. The proposed technique is tested on-line for a laboratory 1-hp induction motor drive using the digital signal processor board ds1102. [a]Khan et al. (2007), have developed and implemented a novel wavelet power based faults diagnostic and protection algorithm for separately excited synchronous generator. The proposed algorithm is based on the comparison of instantaneous wavelet power of terminal voltage and current of a synchronous generator for different faulted and normal (unfaulted) conditions. The wavelet power of second level high frequency details (dd^2) of fault currents and voltages

using a selected mother wavelet show distinctive features between different faulted and normal conditions. The proposed technique is tested on-line on a laboratory 1.6 kW three-phase synchronous generator. The WPT based diagnostic and protection technique is implemented in ([b]Khan et al., 2007) for three-phase induction motors. The WPT coefficients at second level of resolution using a selected mother wavelet are compared with a fault threshold in order to detect a fault in induction motor. The proposed technique is tested on both squirrel cage and wound rotor induction motors. The proposed protection technique initiated a trip signal almost at the instant or within one cycle of fault current in all cases of investigated faults. [c]Khan & Rahman (2007), have developed and implemented a hybrid WPT and ANN based faults diagnostic and protection technique for three-phase IPM motors. The proposed technique is compared with discrete Fourier transform (DFT) based protection algorithm at dynamic operating conditions. The proposed technique showed better performances than the DFT based technique. [d]Khan et al. (2007), have developed and implemented a wavelet power based diagnostic and protection technique for stator faults in synchronous generators. The stator phase unbalance, line to ground (L-G), line-to-line (L-L), and turn-to-turn faults are investigated to evaluate the performances of the proposed technique.

Kim et al. (2002), have developed a model based faults diagnostic technique based on recurrent dynamic neural networks and multi-resolution signal decomposition for predicting transient response and extracting features of fault currents in induction motors, respectively. The transient model is used to generate residual fault current. Then, the wavelet packet transform based decomposition algorithm is implemented on residuals in order to generate decoupled fault indicators. The wavelet transform is applied in (Chow et al., 2004) for extracting vibration spectra, which contain features of critical frequencies for faults diagnostic in induction motors running at different speeds. The wavelet basis functions are matched with related signals through careful selection of basis function parameters. An on-line fault detection approach based on the continuous wavelet transform of vibration signals for detecting bearing faults in induction motors has been reported in (Luo et al., 2003). Douglas et al. (2004), have developed a new faults diagnostic algorithm based on the signature analysis of starting currents of induction motors. The proposed algorithm estimated the amplitude, frequency, and phase of a single sinusoid signal of the non-stationary fault current waveforms. The DWT is applied to residual current vector in order to discriminate a healthy motor from the damaged motor. However, the proposed technique is used to detect passive faults rather than incipient failures in induction motors. Toliyat et al. (2003), have implemented WPT for detecting defects in railroad track. The energy of WPT coefficients is used to detect a fault. The experimental results showed deviation of energy of the DWT coefficients in the faulted motor from the healthy motor. Yen et al. (2000), have outlined a systematic procedure for selecting best WPT features, which exploit specific differences among interesting signals. In this method the signal is first decomposed via the wavelet packet transform (WPT) in order to extract the time–frequency information. Several feature components, which contain little discriminator information are discarded with the help of a statistic based feature selection criterion. Zhengjia et al. (1996), have implemented WPT for condition monitoring and faults diagnostic of turbo generators. The proposed method successfully diagnosed weak defects and looseness in ball bearings of inside the bearing terminal of a 50MW turbine generator.

There have been many condition monitoring and faults diagnostic techniques for electric machines. The artificial intelligence, motor current signature analysis, and finally time-frequency analysis based on short time Fourier transform or wavelet transforms are widely used in last twenty years. The wavelet transform is a relatively new technique for condition monitoring and faults diagnostic of electric machines. It replaces other condition monitoring techniques because of its better frequency resolution and time localization properties. It is free from any learning or training of the experimental data covering all operating conditions of the motor. In addition, desirable basis function related to a specific application can be chosen in wavelet transform based faults diagnostic technique whereas in Fourier transform based diagnostic technique the basis functions are fixed to sinusoid or cosine function.

3. DFT, STFT, and NN Based Faults Diagnostic and Protection

The discrete Fourier transform (DFT), short time Fourier transform (STFT), and neural network are implemented for faults diagnostic and protection of three-phase interior permanent magnet (IPM) motors. At the beginning the discrete Fourier transform (DFT) is implemented using the fast Fourier transform (FFT) based algorithm to estimate the spectra of fault current in order to differentiate normal conditions from abnormal conditions. The short time Fourier transform (STFT) based faults diagnostic algorithm is implemented after the DFT based technique. Finally a pattern recognition technique based on three-layer feed forward neural network is implemented for faults diagnostic of laboratory 1hp IPM motor. A short analysis and real time implementation of each type are given for diagnostic and protection of faults in electric motors.

3.1 Application of Discrete Fourier Transform (DFT)
The DFT analysis and synthesis equations can be expressed as

$$X[k] = \sum_{n=0}^{N-1} x[n] W_N^{kn}, \quad 0 \le k \le N-1 \tag{1}$$

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] W_N^{-kn}, \quad 0 \le n \le N-1 \tag{2}$$

where,
$$W_N = e^{-j\frac{2\pi}{N}} \tag{3}$$

For the case of non-periodic and non-stationary fault current signals, the windowed DFT is normally used. If a signal is sampled with sampling interval of Δt such that there are $N/\Delta t$ samples per cycle, then the DFT basis function coefficients can be calculated as (Khan, 2006)

$$S_k = \frac{2}{N} \sum_{n=1}^{N-1} x[n] \sin\left(\frac{2\pi kn}{N}\right) \tag{4}$$

$$C_k = \frac{2}{N} \sum_{n=1}^{N-1} x[n] \cos\left(\frac{2\pi kn}{N}\right)$$ (5)

The Fourier harmonic coefficients can be calculated as

$$F_k = \sqrt{S_k^2 + C_k^2}$$ (6)

where F_k is the kth harmonic Fourier coefficient, and $x[n]$ is the sampled sequence of the continuous signal $x(t)$. Three types of electrical faults such as single phasing, stator winding line to ground (L-G), and stator winding line to line (L-L) faults are investigated. The DFT is implemented to determine the spectra of stator current of different faulted and normal unfaulted conditions.

Figure 1 shows the DFT based spectra of stator current of different unfaulted and faulted conditions of a laboratory 4-pole 1-hp IPM motor. The fundamental harmonic (30Hz) is found significant in all the operating conditions of the IPM motor of Figs. 1(*a*)-1(*d*). The fundamental spectrum varied between faulted and normal unfaulted (healthy) conditions and also within disturbances. The normalized magnitude of fundamental spectrum varied between 0.5 and 0.6 for the case of unfaulted operating conditions of the motor. It showed peak values of greater than 0.69 and less than 0.3 for the cases of disturbances. Based on the observations it can be asserted that the DFT based spectra analysis of fault currents can detect and classify possible disturbances in IPM motors. However, the DFT based technique is not suitable for non-stationary and non-periodic signals. In addition, faults cannot be localizes in time domain using DFT based technique.
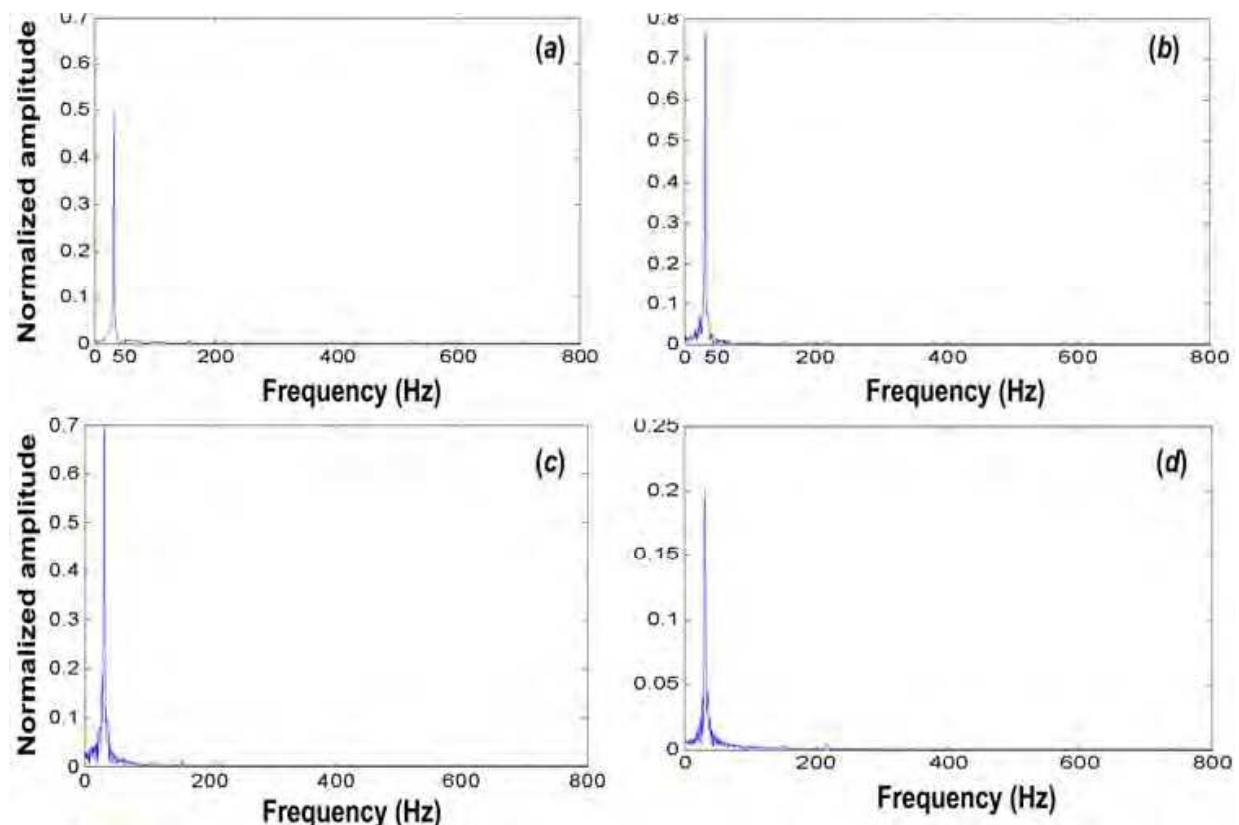
Fig. 1. The DFT of stator current of the 1hp IPM motor: (*a*) normal healthy operation, (*b*) stator winding line to ground (L-G) fault, (*c*) stator winding line to line (L-L) fault, (*d*) single phasing.

3.2 Application of Short Time Fourier Transform (STFT)

The short time Fourier transform (STFT) is an extension of fast Fourier transform (FFT), which is able to analyze non-stationary and non-periodic signals. In the STFT, the discrete signal is divided into segments, and each segment is analyzed using the FFT. The results of the STFT are intuitive and easy to correlate with the original signal. The tiling of the STFT is shown in Fig. 2. The tiling shows how the spectrum of a signal changes with time in the STFT. In the implementation of the STFT, a design tradeoff is normally made between time and frequency resolution. This is due to the uncertainty principle, which limits the lower bound of the time-bandwidth product. Figure 3 shows the block diagram of the STFT algorithm. In Fig. 3, nfft is the length of the FFT, noverlap is the number of overlap samples, and window is a weighting vector applied to the FFT input. The spectrogram is the graphical way to display the output of the STFT.

The STFT based spectrogram of stator current of the 1hp IPM motor for the case of normal unfaulted and faulted conditions are shown in Figs. 4(*a*)-4(*d*). In the detailed analysis, a 512-point FFT with 475 overlap samples between data segments is used to estimate the frequencies of discrete signal. A 500-point Kaiser window (Mathworks, 2007) is applied in each data segment. The analysis generated 257 frequency points in 141 time-axis values. The energy concentration of the fundamental harmonic (30 Hz) of the 4-pole IPM motor is uniform over the entire time axis of the spectrogram for the case of healthy operating condition of the IPM motor of Fig. 4(*a*). However, the concentrations of energy of the fundamental, third, fifth, and seventh harmonics are different than those of the healthy motor during the inception and clearing of faults of Figs. 4(*b*)-4(*d*). Based on the analysis performed, it can be asserted that the STFT based algorithm can detect faults in the IPM motors in both time and frequency domains. However, the STFT based technique does not provide good energy resolution for a specific point of the data signal as the length of the window is fixed in each of the data segment of the discrete signal. In addition, the frequency analysis is performed using the sinusoidal basis functions.
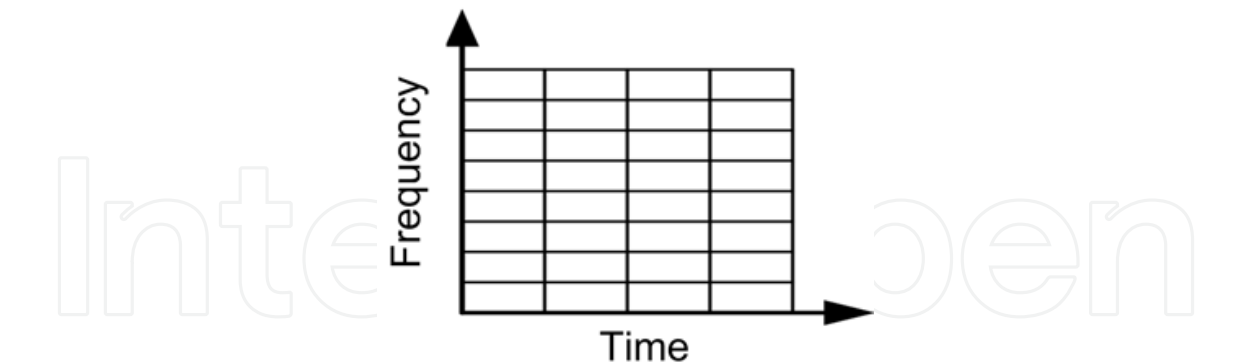

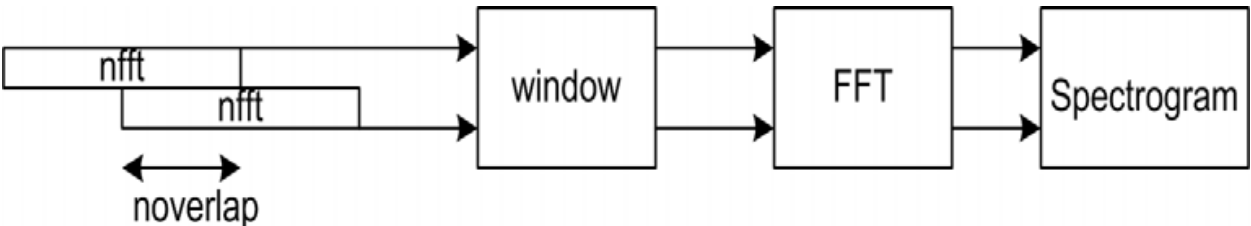Fig. 2. Time-frequency distribution of the STFT.

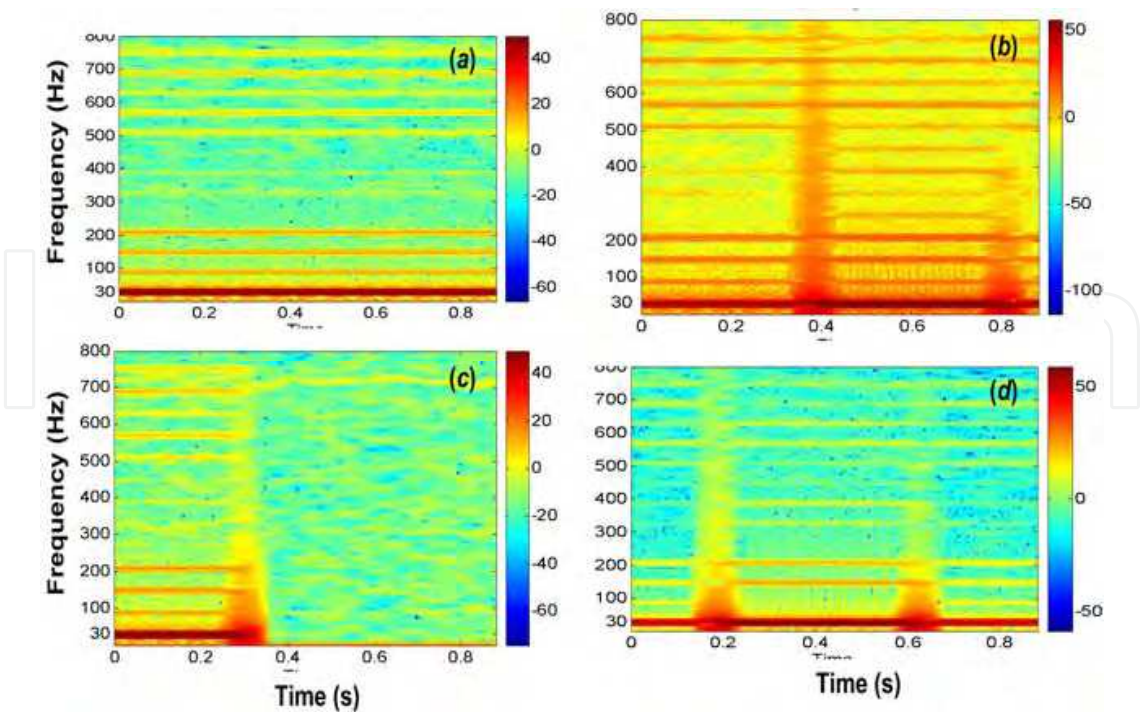Fig. 3. Block diagram of the STFT algorithm.

Fig. 4. STFT based spectrogram of stator current of the 1hp IPM motor: (*a*) normal healthy operation, (*b*) stator winding line to ground (L-G) fault, (*c*) single phasing, (*d*) stator winding line to line (L-L) fault.

3.3 Application of artificial neural network (NN)

The primary step in developing and implementing artificial neural network (NN) based faults diagnostic and protection technique for electric motors is to choose a suitable network structure. A three-layer feed forward network with three neurons in the hidden layer and one neuron in the output layer is chosen in this work for the NN based faults diagnostic of IPM motors. The numbers of neurons in the hidden layer are selected by trial and error, which ensured stability and higher convergence rate. The Nguyen-Widrow initialization algorithm (Mathworks, 2007) is used in order to initialize weights and biases of the network. The activation function *log-sigmoid* (Mathworks, 2007) is used in both hidden and output layers of the network.
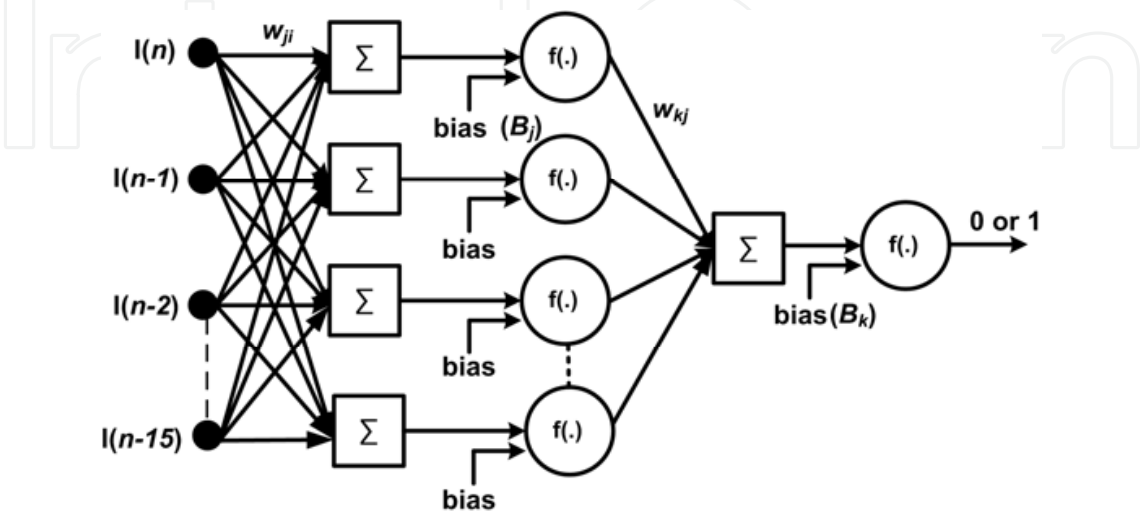

Fig. 5. Specific structure of a three-layer feed forward neural network (FFNN).

The specific structure of a three-layer feed forward neural network is shown in Fig. 5. The network is trained off-line in a supervised manner with the back propagation function *traingdm* (Mathworks, 2007), which updates weight and bias values of the hidden and output layers according to the gradient descent with momentum. In the NN based faults diagnostic algorithm for an IPM motor, the stator currents are used as inputs to the neural network. The discrete data of normal unfaulted and faulted conditions are used to train the network so that it can differentiate normal conditions from the abnormal conditions. In order to generate the realizable training patterns for the NN based faults diagnostic, samples of the squared summation of three-phase stator currents are compared with a predefined threshold to convert it a binary value of either 1 or 0, depending on whether the value is greater or smaller than the threshold, respectively. In this way each training pattern became a different combination of 1 and 0. It is expected that the starting current and fault currents data would not have same training pattern. The elements of the target vector for the case of normal unfaulted (both no load and full load) and starting current samples are chosen equal to binary '0'. On the other hand, the elements of the target vector are equal to binary '1' for the case of fault current samples. After training the network with one set of training pattern, which includes the samples of the normal unfaulted and faulted currents, and starting currents, the network is tested off-line in the MATLAB environment with the different set of testing pattern. Figure 6 shows the off-line test results of NN based faults diagnostic and protection algorithm of the 1hp IPM motor.
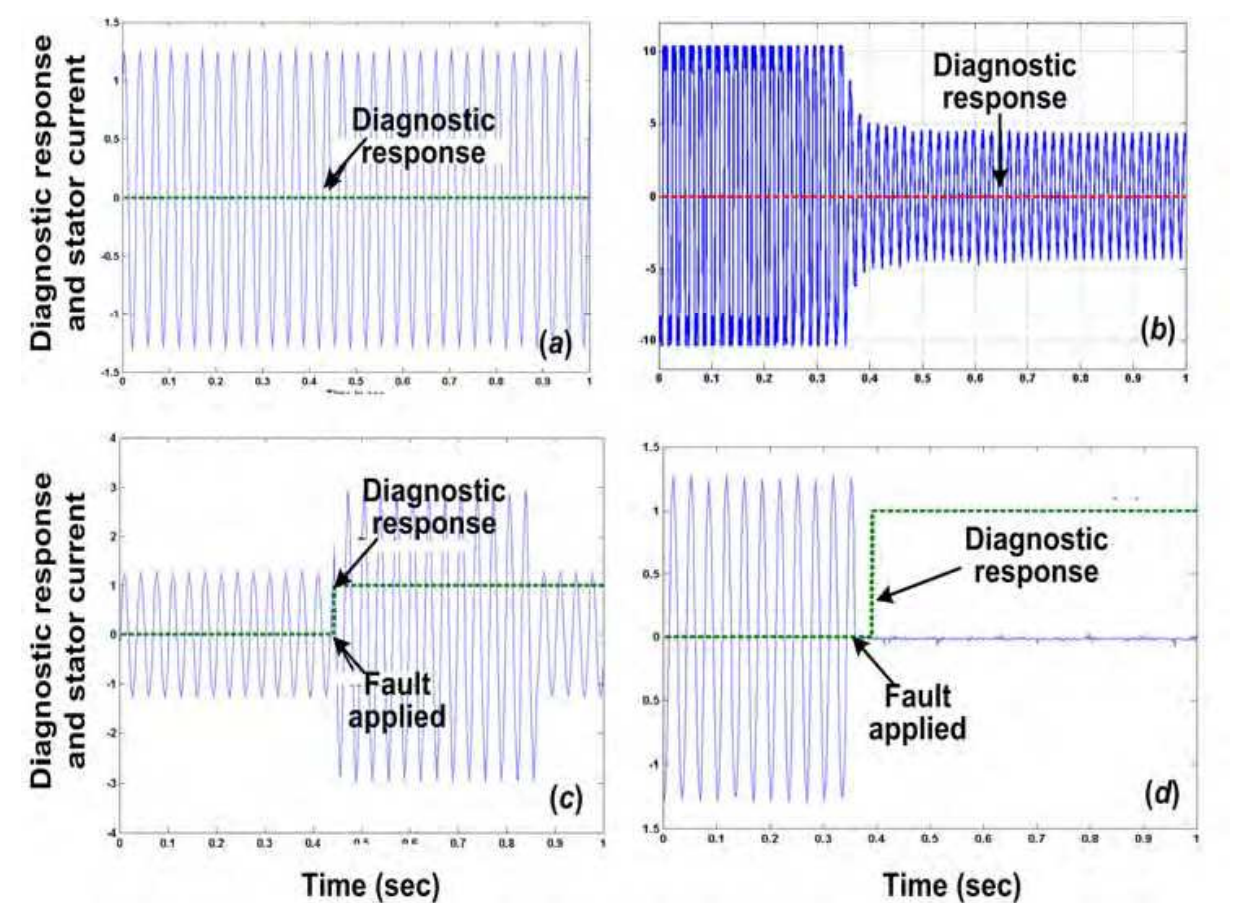

Fig. 6. NN based faults diagnostic response and stator current of the 1hp IPM motor: (*a*) normal unfaulted condition, (*b*) normal starting condition, (*c*) stator winding line to ground (L-G) fault, (*d*) single phasing.

Figures 6(*a*)–6(*b*) show the NN based faults diagnostic response and stator current of the 1hp IPM motor for the case of normal (unfaulted) and starting conditions. The neural network (NN) based diagnostic algorithm identified these as normal conditions and did not generate any trip signal. The stator current with the associated trip signal for the case of stator winding line to ground (L-G) fault and single phasing are shown in Figs. 6(*c*)–6(*d*). The algorithm identified these properly and initiated a trip signal almost at the instant of the fault occurrence. However, the technique needs a large number of data files to train the network effectively. In addition, number of hidden layers may have to be increased to improve the accuracy. Therefore, more memory may be needed to accommodate the weights and biases of the new layers, and as a result, many trials are required to determine the learning rate, so as to improve the functionality of the NN based diagnostic algorithm.

4. Wavelets and Wavelet Transforms

The wavelet transforms analyze a signal simultaneously in time and frequency domains. The wavelet transforms are very useful in analyzing non-stationary, non-periodic, intermittent, and transient signals. Therefore, a number of wavelet based techniques are developed and implemented for signal manipulation and interrogation. The wavelet transforms are applied in the investigation of diverse physical phenomena such as climate analysis, financial market analysis, heart monitoring, condition monitoring and protection of rotating machines, de noising of seismic signal and astronomical images, characterization of crack surface and turbulent intermittency, compression of video image and medical signal records, etc. The wavelets are little waves of short duration. These have finite energy and decay quickly in time. The wavelets also have oscillating feature, which comes along with the location in time and frequency. These basic features make wavelets highly adequate for signal representation. The wavelet functions of orthogonal type have a companion function, which is known as the scaling function. It is responsible for generating basis functions, which are required during the decomposition or reconstruction of a signal. Figures 7(*a*) and 7(*b*) show the *Daubechies* ('*db*3') wavelet function and its scaling function, respectively. In certain application, it is necessary to use real and symmetric wavelets. One way to get the symmetric wavelets is to construct two sets of bi-orthogonal wavelets, which are wavelet function $\psi_{m,n}(t)$ and it's dual $\hat{\psi}_{m,n}(t)$. The first set is used during the decomposition, and the other one is used during the reconstruction process. Figures 8(*a*)–8(*d*) show the *spline* bi-orthogonal ('*bior*2.6') wavelet functions and their scaling functions during the decomposition and reconstruction of a signal.
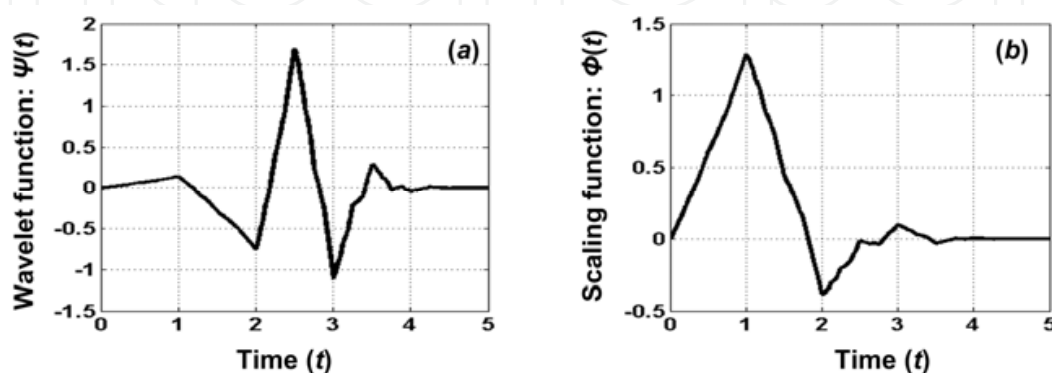

Fig. 7. The *Daubechies* ('*db*3') wavelet: (*a*) mother wavelet function and (*b*) scaling function.
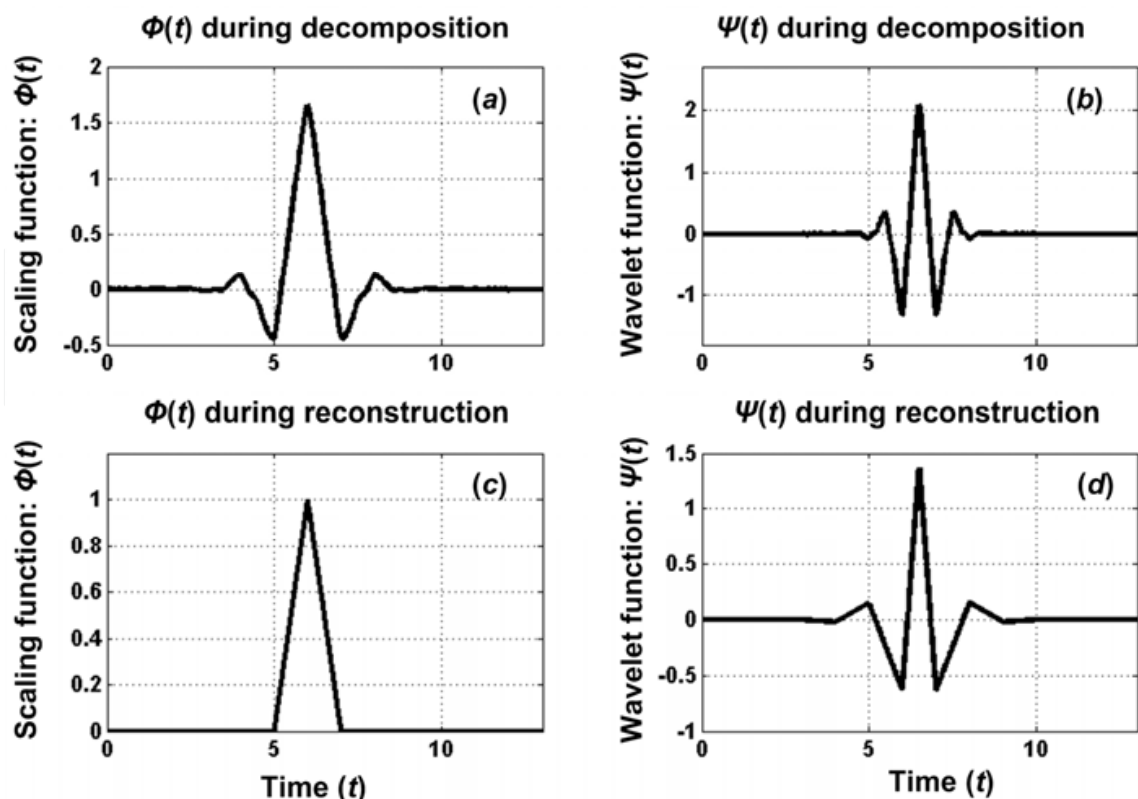
Fig. 8. The *Spline* bi-orthogonal ('*bior*2.6') wavelet: (*a*) scaling function during decomposition, (*b*) mother wavelet function during decomposition, (*c*) scaling function during reconstruction, and (*d*) mother wavelet function during reconstruction.

The wavelet transforms use little wavelike functions, which are known as wavelets. Wavelets are used to transform a signal under investigation into another representation of a more useful form. From the mathematical point of view, the wavelet transform is a convolution of the wavelet function with the signal. The wavelet function is manipulated in two ways: it is moved to various locations on the signal, and it is stretched or squeezed. If a wavelet function matches the shape of a signal well at a specific scale and location, then a large transformation value will be generated. On the other hand, if the wavelet function and signal do not correlate well, then a low value of transformation will be generated (Addison, 2002). The wavelet transform can be applied to both continuous and discrete signals. In the following subsections, different forms of wavelet transforms and their mathematical formulations are briefly presented.

4.1 Continuous wavelet transform

The wavelet transform of a continuous signal $x(t)$ with respect to the wavelet function $\psi(t)$ can be defined as

$$T(a,b) = w(a)\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \qquad (7)$$

where $w(a)$ is the weighting function, a and b are the dilation and translation parameters, respectively. The asterisk indicates that the complex conjugate of the wavelet function is used in the transformation. The wavelet transform can be thought of as the cross correlation

of a signal with a set of wavelets of various widths. Typically, $w(a)$ is set to $1/\sqrt{a}$ for the reason of energy conservation. It ensures that wavelets at each scale have identical energy. If one sets $w(a) = 1/\sqrt{a}$, then the wavelet transform of the continuous signal $x(t)$ can be rewritten as

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt. \tag{8}$$

The equation (8) is known as the continuous wavelet transform (CWT) of the signal $x(t)$. It contains both dilated and translated wavelets $\psi((t-b)/a)$, and the continuous signal $x(t)$. The signal $x(t)$ may be a beating heart, an audio signal, a financial index, the gearbox vibration signal, a spatial signal such as crack profile or land surface heights. The normalized wavelet function can be written more compactly as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a} \right) \tag{9}$$

where the normalization is in the sense of wavelet energy. Now the transform integral of equation (9) can be rewritten as

$$T(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^*(t) \, dt \tag{10}$$

The dilation and contraction of the mother wavelet function is governed by the dilation parameter a, which is the distance between center of the wavelet function and its crossing on the time axis. The movement of the wavelet function along the time axis is governed by the translation parameter b. Figure 9 shows the stretching (double) and squeezing (half) of the Mexican Hat wavelet function on the time axis. Figure 10 shows the translation of the Mexican Hat wavelet function on the time axis from b_1 via b_2 to b_3.
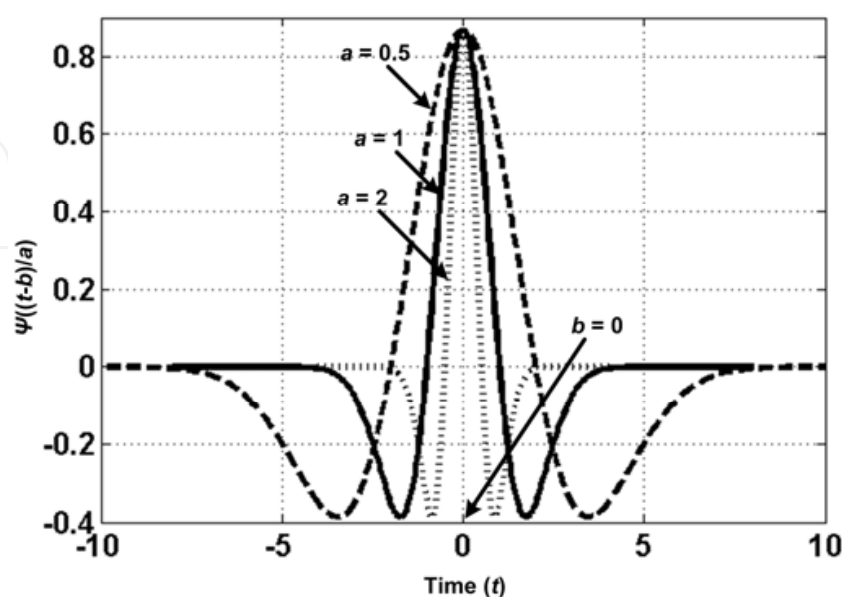

Fig. 9. Stretching ($a = 0.5$) and squeezing ($a = 2$) of the Mexican Hat wavelet function.
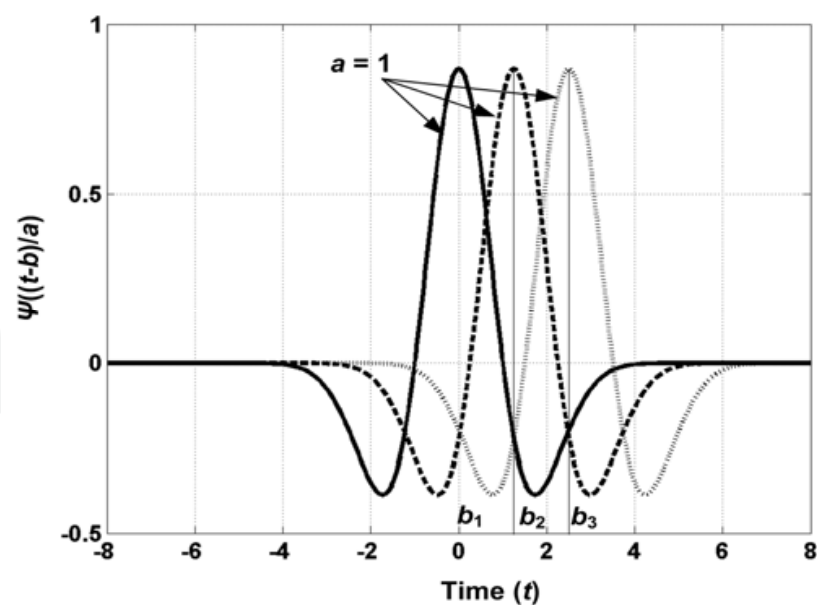
Fig. 10. Translation (b_1 via b_2 to b_3) of the Mexican Hat wavelet function.

4.2 Discrete wavelet transform

In the continuous wavelet transform (CWT), the mother wavelet is dilated and translated continuously over a real continuous number system $(\mathbb{R})$. Therefore, it can generate substantial redundant information. The mother wavelet can be dilated and translated discretely by replacing $a = a_0^m$ and $b = n b_0 a_0^m$, where a_0 and b_0 are the fixed constants with $a_0 > 1$, $b_0 > 0$, and $m, n \in \mathbb{N}$. Here $\mathbb{N}$ is the set of positive integers. Then, the discretized mother wavelet function can be defined as (Addison, 2002)

$$\psi_{m,n}(t) = a_0^{-m/2} \, \psi\left(\frac{t - n b_0 a_0^m}{a_0^m} \right)$$ (11)

and the corresponding discrete wavelet transform (DWT) can be defined as

$$DWT_\psi x(m,n) = \int_{-\infty}^{\infty} x(t) \psi_{m,n}^*(t) \, dt$$ (12)

In the DWT, the family of dilated wavelets constitutes an orthonormal basis by careful selections of a_0 and b_0. There are several implications of the orthonormal basis. The orthonormality ensures no information redundancy among the decomposed signals. With the optimal choices of a_0 and b_0, there exists an elegant algorithm known as the multiresolution signal decomposition. It decomposes a signal into various scales with different time and frequency resolutions. In the DWT, the procedure starts with passing the discrete signal x[n] of length N through a digital low pass filter with impulse response g[n] and a digital high pass filter with impulse response h[n]. The low pass and high pass filters are called scaling and wavelet filters, respectively. The outputs from the low pass filter are approximation coefficients of the discrete signal at first level of resolution of the DWT. The

outputs from the high pass filter are detail coefficients of the discrete signal at first level of resolution of the DWT. The output of these filters consists of N wavelet coefficients. This constitutes first level of decomposition of the discrete signal and can be mathematically expressed as

$$a^1[n] = \sum_{k=0}^{N-1} g[k] x[n-k] \tag{13}$$

$$d^1[n] = \sum_{k=0}^{N-1} h[k] x[n-k] \tag{14}$$

The approximation coefficients (a^1) at first level of resolution are used as inputs for another pair of wavelet filters (identical with the first pair) after being down sampled by two. The filters at second level of resolution generate sets of approximations and details coefficients of length $N/2$. This constitutes second level of decomposition of the discrete signal and can be mathematically expressed as

$$a^2[n] = \sum_{k=0}^{N/2-1} g[k] a^1[2n-k] \tag{15}$$

$$d^2[n] = \sum_{k=0}^{N/2-1} h[k] a^1[2n-k] \tag{16}$$

Figure 11(*a*) shows the two-level decomposition of a discrete signal of the discrete wavelet transform. It uses the high pass filters (*H*) and the low pass filters (*G*) in the decomposition process.

4.3 Wavelet packet transform

The wavelet packets are alternative bases, which can be formed from the linear combinations of usual wavelet functions. These bases inherit properties such as orthonormality and time-frequency localization from their corresponding wavelet functions. A wavelet packet function is a function of three indices *j*, *k* and *n*, and is defined as

$$W_{j,k}^n(t) = 2^{j/2} W^n(2^j t - k) \tag{17}$$

where the integers *j* and *k* are the indices for scale and translation operations, respectively. The index *n* is defined as the modulation or oscillation parameter. The first two wavelet packet functions are the scaling function and mother wavelet function, and these are defined as

$$W_{0,0}^0(t) = \varphi(t) \tag{18}$$

$$W_{0,0}^1(t) = \psi(t). \tag{19}$$

The wavelet packet functions for *n* = 2,3,… can be computed as

$$W_{0,0}^{2n}(t) = \sqrt{2} \sum_k g(k) W_{1,k}^n(2t - k) \tag{20}$$

$$W_{0,0}^{2n+1}(t) = \sqrt{2}\sum_{k} h(k) W_{1,k}^{n}(2t - k) \tag{21}$$

where $g(k)$ and $h(k)$ are the quadrature mirror filters associated with the predefined scaling and mother wavelet functions. To measure specific time-frequency information of a signal, one simply takes the inner product of the signal with a particular basis function. The wavelet packet decomposition (WPD) involves applying both high pass and low pass filters to a discrete signal, and then recursively to each intermediate signal. The procedure is illustrated in Fig. 11(b) up to the second level of resolution. The first level of decomposition of the discrete signal $x[n]$ of length N in the wavelet packet transform (WPT) generates two-frequency sub-bands, which are the approximation coefficients $a_n^1 = \begin{bmatrix} a_0^1 & a_1^1 & a_2^1 \dots a_{N-1}^1 \end{bmatrix}$ and detail coefficients $d_n^1 = \begin{bmatrix} d_0^1 & d_1^1 & d_2^1 \dots d_{N-1}^1 \end{bmatrix}$. The second level of decomposition generates four-frequency sub-bands using same set of filters of the first level of resolution. These are defined as

$$aa^2[n] = \sum_{k=0}^{N/2-1} g[k] a^1[2n - k] \tag{22}$$

$$ad^2[n] = \sum_{k=0}^{N/2-1} h[k] a^1[2n - k] \tag{23}$$

$$da^2[n] = \sum_{k=0}^{N/2-1} g[k] d^1[2n - k] \tag{24}$$

$$dd^2[n] = \sum_{k=0}^{N/2-1} h[k] d^1[2n - k] \tag{25}$$

The frequency sub-band aa^2 is defined as second level low frequency approximations of original signal. The frequency sub-band ad^2 is defined as second level low frequency details of original signal. The frequency sub-band da^2 is defined as second level high frequency approximations of original signal. The frequency sub-band dd^2 is defined as second level high frequency details of original signal.
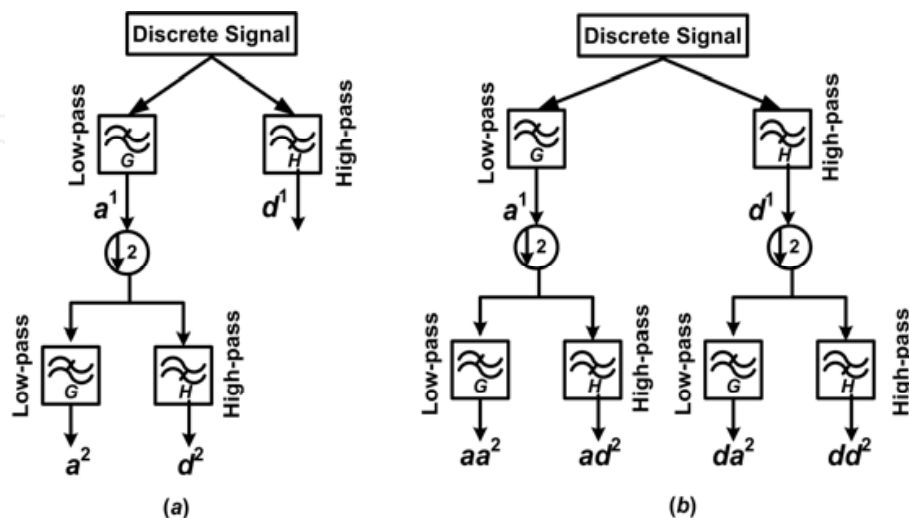

Fig. 11. (a) Two-level decomposition of a discrete signal of the discrete wavelet transform (DWT) and (b) two-level decomposition of a discrete signal of the wavelet packet transform (WPT).

272 Fault Detection

5. Wavelet Transform Based Faults Diagnostic and Protection

One of the primary tasks of wavelet based faults diagnostic technique for electric machines is to develop experimental setup and to collect stator current of faulted and normal unfaulted conditions. The collected data are to be employed for selecting optimum mother wavelet and optimal levels of resolution, and for off-line testing of the proposed technique. In the data acquisition setup, the current transformers (CTs) are connected in series with motor terminals to collect different faulted and normal unfaulted stator currents. The CTs are rated at 200/5 A (rms) and 15 V (max.). The data acquisition instrument consists of DSP controller board ds1102, which includes a floating-point digital signal processor TMS320C31. The digital data are acquired through on-board three-channel analog-to-digital (A/D) converters. The data are collected at the sampling rate of 8 kHz, and stored in a personal computer through dSPACE TRACE module. Then, these data are converted to ASCII format for further processing. The wavelet based faults diagnostic and protection technique is tested on laboratory prototype electric machines. These include 1hp and 5hp interior permanent magnet (IPM) motors, 1hp squirrel cage induction motor (IM), 1.5hp wound rotor induction motor (IM), and 1.6 kW separately excited synchronous generator. Electric machines may experience different type of faults. The majority of these faults are stator faults such as turn-to-turn fault, which appears as phase-to-phase or phase-to-ground faults later, loss of a phase or field faults, and rotor faults such as static eccentricity, dynamic eccentricity, broken bars, and defects in buried permanent magnets or field windings. Faults such as stator inter-turn, loss of supply (single phasing), line to ground (L-G), and line-to-line (L-L) faults are considered in this work.

5.1 Feature extraction using WPT coefficients

The wavelet packet transform (WPT) is suitable for detection of high frequency components superimposed on the fundamental frequency. In addition, a feature can be extracted by the existence of details or approximations coefficients of a signal at any level of resolution of the wavelet packet tree, and such feature can be used to identify the type of a fault. The collected data of different faulted and unfaulted conditions of an IPM motor are decomposed up to the second level of resolution of the WPT using the selected mother wavelet '*db3*'. The minimum description length data criterion (Hamid et al., 2002) is used for the selection of optimum mother wavelet from a set of orthogonal and non orthogonal wavelet functions. Figures 12–13 show the second level WPT coefficients of normal and fault currents of an inverter-fed 1-hp IPM motor. The second level WPT coefficients of stator current for the case of faulted condition in Fig. 13 are larger than those of unfaulted condition in Fig. 12 at the inception of fault occurrence. Therefore, these feature coefficients can be used for faults diagnostic and protection of IPM motors. A feature vector *F* is defined using the de noised second level WPT components of stator currents. The feature vector F is defined as (Khan & Rahman, 2009)

$$F = \left[W_{aa^2} \; W_{ad^2} \; W_{da^2} \; W_{dd^2} \right] \qquad (26)$$

$$W_{aa^2} = \sqrt{\sum_{n=1}^{N} aa^2(n) \, / \, N} \qquad (27)$$

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Fig. 12. Second level WPT coefficients of normal current: (*a*) low frequency approximations (aa^2), (*b*) low frequency details (ad^2), (*c*) high frequency approximations (da^2), and (*d*) high frequency details (dd^2).
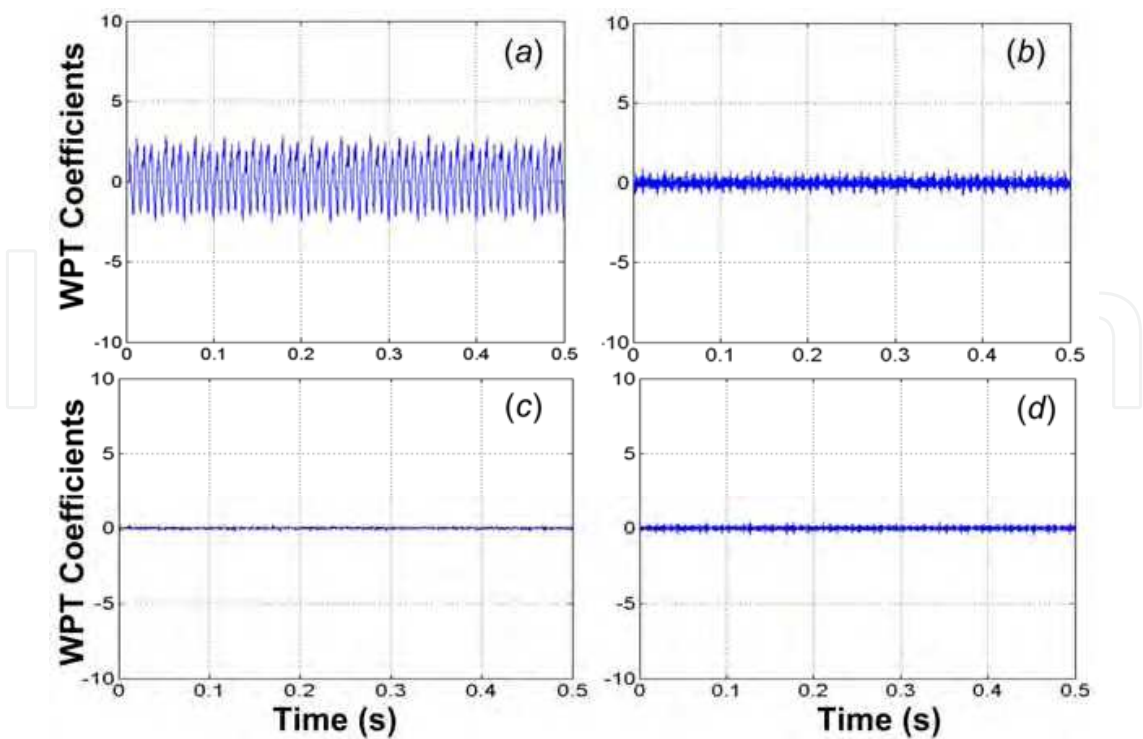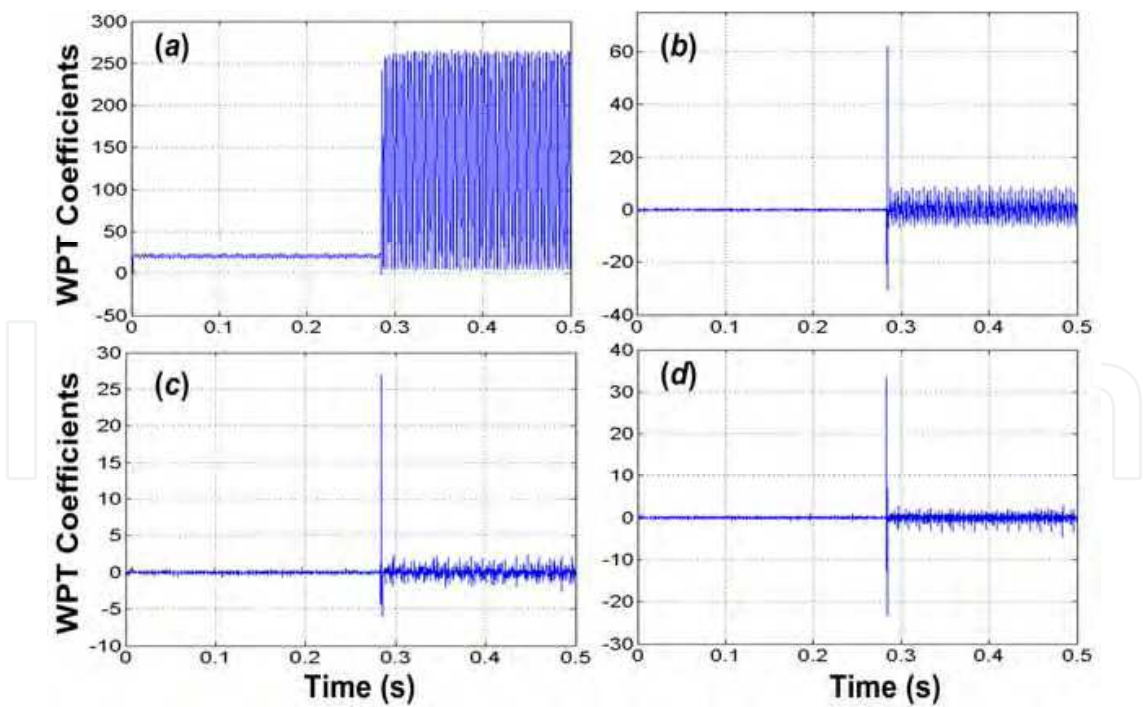

Fig. 13. Second level WPT coefficients of fault current: (*a*) low frequency approximations (aa^2), (*b*) low frequency details (ad^2), (*c*) high frequency approximations (da^2), and (*d*) high frequency details (dd^2).

$$W_{ad^2} = \sqrt{\sum_{n=1}^{N} ad^2(n) / N} \qquad (28)$$

$$W_{da^2} = \sqrt{\sum_{n=1}^{N} da^2(n) / N} \qquad (29)$$

$$W_{dd^2} = \sqrt{\sum_{n=1}^{N} dd^2(n) / N} \qquad (30)$$

where N denotes total number of coefficients in a certain node of wavelet packet tree. Table-I shows the comparisons of feature vector calculated using equations (26)-(30) between faulted and normal conditions of an IPM motor. The feature vectors clearly differentiate faulted conditions from normal conditions and also within faulted conditions.

Type of faults	W_{aa^2}	W_{ad^2}	W_{da^2}	W_{dd^2}
Normal	17.31	0.2757	0.0479	0.1222
Inter-turn	30.33	0.3654	0.1125	0.1854
L-G	34.34	0.4164	0.1278	0.2039
L-L	114.75	0.7929	0.2588	0.3607
Single phasing	21.88	0.7485	0.1036	0.2671

Table 1. Feature vector

5.2 Feature extraction based on signature analysis of WPT coefficients

The signature analysis technique is used for feature extraction of fault currents of the proposed wavelet based faults diagnostic technique for induction motors. The discrete signal of stator current is decomposed up to the second level of resolution of the wavelet packet tree using the selected mother wavelet '$db3$'. The second level high frequency details (dd^2) of stator currents are used to analyse the signatures of various faults in an induction motor as most of the fault current signals contain high frequency components superimposed on the fundamental frequency. The 2nd level high frequency details (dd^2) of stator currents of different faulted and normal unfaulted conditions are given in Figs. 14(a)–14(d). The details (dd^2) of stator current of Figs. 14(c)–14(d) showed high density of color strips between the faulted region as compared to those of normal currents (loaded or unloaded) of Figs. 14(a)–14(b). Therefore, the significant features for faults detection can be extracted based on the density of WPT coefficients (dd^2) of stator currents.

5.3 Wavelet based faults diagnostic algorithm

The new faults diagnostic and protection algorithm is developed by combining the features of wavelet packet transform (WPT) coefficients and neural network (NN) algorithm. A three-layer feed forward neural network with four inputs and one output is used.
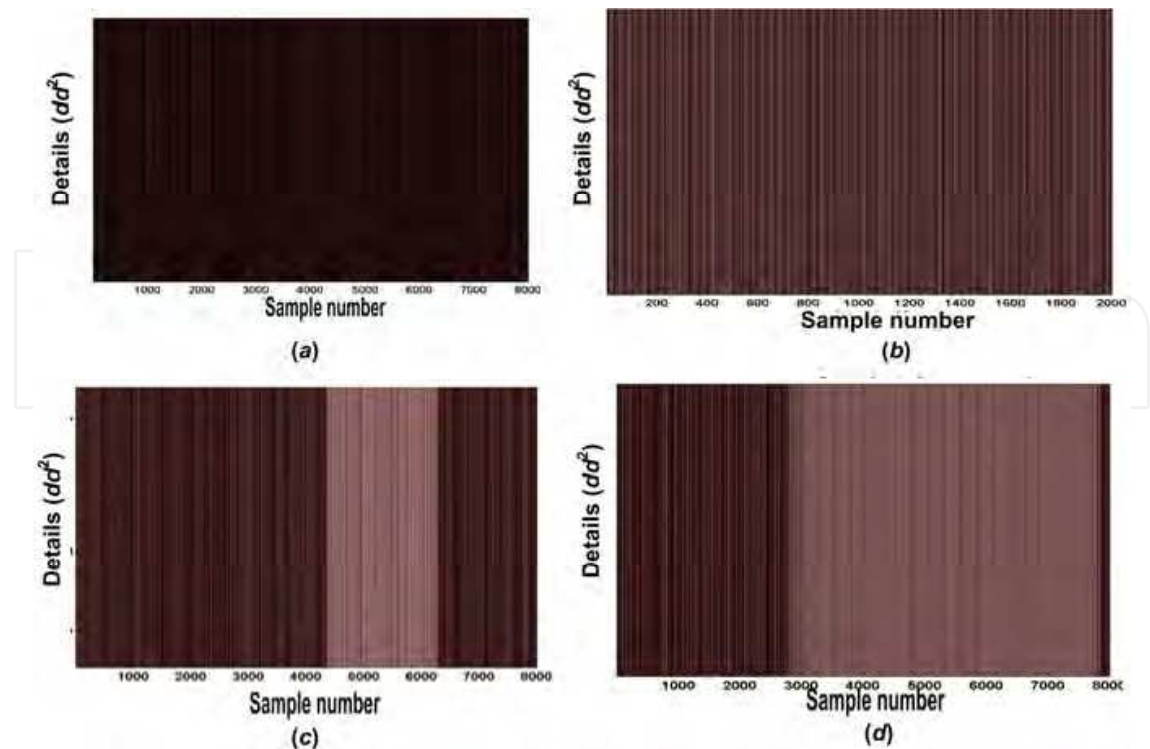
Fig. 14. Second level high frequency details (dd^2) of stator current of the 1hp induction motor: (a) unloaded current, (b) full load current, (c) stator winding phase to ground fault current, and (d) single phasing current.
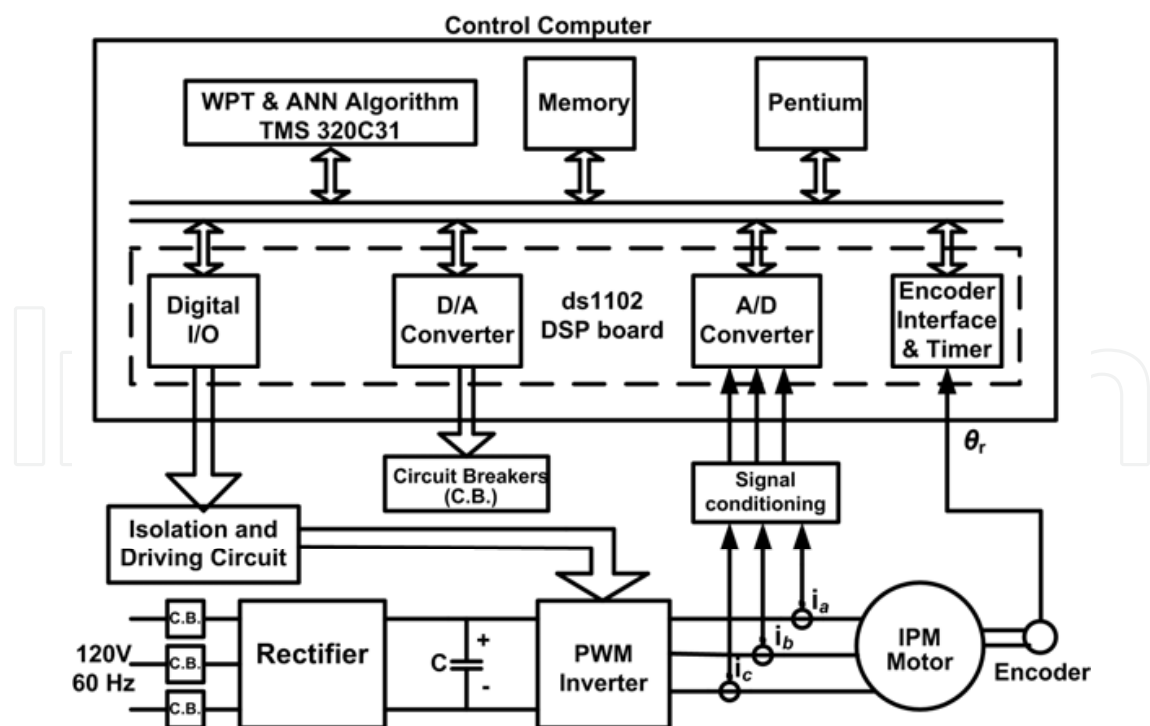

Fig. 15. Experimental setup of the proposed WPT and NN based faults diagnostic and protection algorithm for inverter fed IPM motor using the DSP board ds1102.

```
                           ┌─────────────────┐
                           │    Start DSP    │
                           └─────────────────┘
                                    │
                    ┌───────────────────────────────────┐
                    │   Initialize DSP timer (timer0)   │
                    │     Initialize inputs/outputs     │
                    │     Load filter coefficients,     │
                    │    network weights and biases     │
                    │             DAC(1)=0              │
                    └───────────────────────────────────┘
                                    │
                    ╭───────────────────────────────────╮
                    │      Read Iₐ from ADC(1)          │
                    │      Read I_b from ADC(2)          │
                    │      Read I_c from ADC(3)          │
                    ╰───────────────────────────────────╯
                                    │
                    ┌───────────────────────────────────┐
                    │   X=Iₐ*Iₐ+I_b*I_b+I_c*I_c         │
                    │        Perform WPT on X           │
                    │     Determine feature vectors     │
                    └───────────────────────────────────┘
                                    │
                    ┌───────────────────────────────────┐
                    │       Execute ANN algorithm       │
                    │       using feature vectors       │
                    └───────────────────────────────────┘
                                    │
     No            ◇───────────────────────────────────◇            Yes
   ◄───────────────    Network O/P > Threshold          ────────────►
                      ◇───────────────────────────────◇
                                                                     │
                                                    ┌──────────────────┐
                                                    │    DAC1(1)=1     │
                                                    │   Stop timer0    │
                                                    └──────────────────┘
                                                                     │
                                                    ╭──────────────────╮
                                                    │       End        │
                                                    ╰──────────────────╯
```
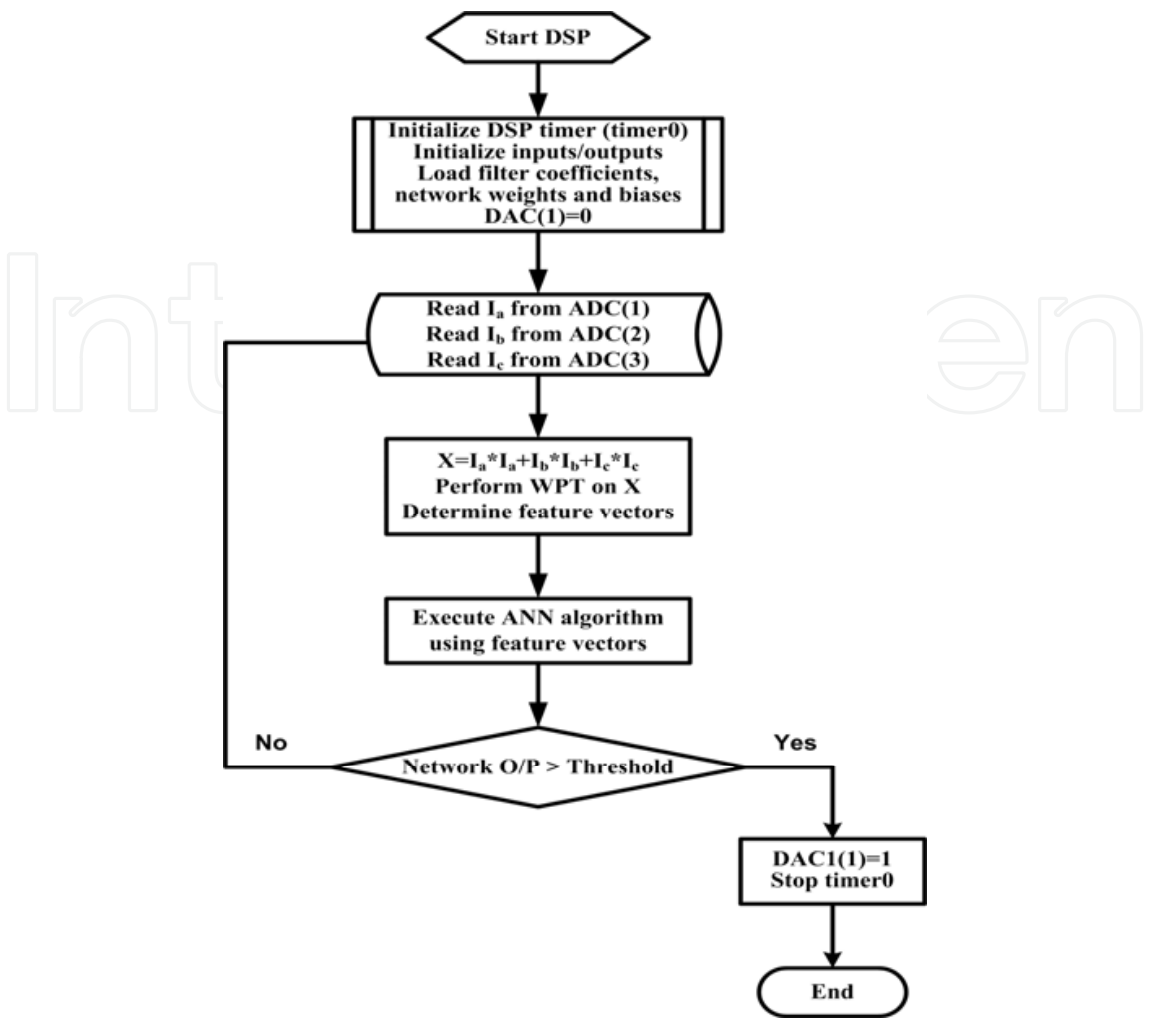
Fig. 16. Flow chart of the new WPT and NN based faults diagnostic and protection algorithm for electric motors.

In the proposed faults diagnostic and protection technique, the inputs of the NN are feature vectors of second level WPT coefficients of faulted and normal currents. The outputs are binary values of 0 or 1 to indicate whether the measured current is a normal current or a fault current, respectively. The proposed wavelet based diagnostic and protection technique for inverter fed interior permanent magnet (IPM) motors using the DSP board ds1102 is shown in Fig. 15. The proposed WPT and NN based faults diagnostic algorithm is written in the turbo C language. The algorithm uses a set of initialization and input/output (I/O) functions in order to initialize TMS320C31's on-chip timers and to access the ds1102's on board A/D and D/A converters. When a timer is started, the A/D converters of the DSP board continuously sample stator currents at the rate of 8 kHz. The samples of stator currents are sent to the memory of the DSP by the host PC, where they are squared and summed into one sample. This sample is placed into a circular buffer of size six. The six current data are processed using the filter coefficients of the mother wavelet '*db3*', and the biases and weights of the NN algorithm.

The procedure to implement the proposed WPT and NN based faults diagnostic algorithm using the DSP board ds1102 is shown in the flow chart of Figure 16. In the proposed

technique, samples of three-phase stator currents are squared and summed into one sample at the beginning for minimizing the computational burden. The WPT is applied on squared samples of stator currents, and the feature vectors are calculated from the WPT coefficients. The feature vectors are given as inputs to the neural network. The NN algorithm determines the values of the network output using the trained weights and biases, and checks whether it is greater than the threshold or not in order to generate the trip signals for the circuit breakers.

5.4 Laboratory implementation of wavelet based faults diagnostic algorithm

The proposed wavelet based faults diagnostic technique is tested in real time using the experimental setup of Fig. 15. The experimental responses of the wavelet based faults diagnostic technique for supply and inverter fed IPM motors are shown in Figs. 17–19. Figures 17(a) and 17(b) show the test results for the case of single phasing of a supply fed IPM motor. Figures 17(c) and 17(d) contain the test results for the case of L-L fault of a supply fed IPM motor. The proposed faults diagnostic algorithm generated trip signal almost at the instant of fault occurrence without any delay. The experimental responses of the wavelet based faults diagnostic technique for inverter fed IPM motor are shown in Figs. 18(a)–18(d). It is clear from Figs. 18(a)–18(d) that for all fault cases disturbances are identified promptly and properly. However, the trip signal is initiated after three cycles of fault occurrence for the case of single phasing of inverter fed IPM motor of Figs. 18(a)–18(b). In addition, the algorithm generated trip signal after one cycle of fault occurrence for the case of line to line fault of Figs. 18(c)–18(d). These delays are due to the fact that the response time includes the executions of the proposed protection algorithm, the speed control algorithm, and the vector control algorithm for generation of logic signals of inverter switches. Figure 19(a) shows the phase-a current and experimental response of no trip signal of the hybrid wavelet packet transform (WPT) and neural network (NN) based faults diagnostic algorithm for step increase and step decrease of command speeds of the inverter fed IPM motor. Figure 19(b) shows the phase-a current and experimental response of no trip signal of the hybrid diagnostic algorithm for the sudden change of load torque of the inverter fed IPM motor. The hybrid algorithm identified these unfaulted conditions of Figs. 19(a)–19(b) as normal conditions and did not change the status of trip signal. Thus the proposed WPT and NN based hybrid algorithm correctly and promptly detected faulted and normal currents of both supply fed and inverter fed IPM motors.

The wavelet based faults diagnostic technique is also implemented on a three-phase, Y-connected, 1705 rpm, 1hp squirrel cage induction motor. The proposed algorithm is based on the identification of WPT coefficients of stator currents of different faulted and normal unfaulted conditions. The experimental responses of the faults diagnostic algorithm and three-phase stator currents are shown in Figs. 20(a)–20(d). Figures 20(a)–20(b) show the test results for single phasing, and Figures 20(c)–20(d) show the test results for line to ground fault of supply fed induction motors. The proposed WPT based faults diagnostic algorithm correctly and promptly classified faulted and normal currents of induction motor.
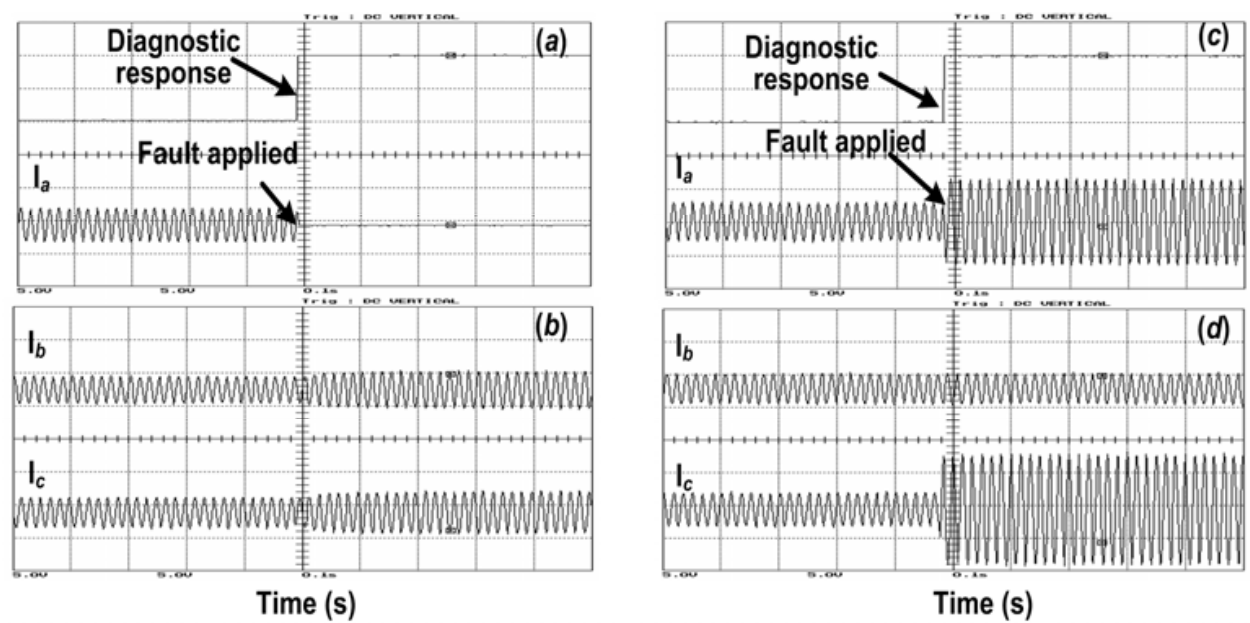
Fig. 17. Experimental responses of the WPT and NN based faults diagnostic technique for supply fed IPM motor: (*a*)-(*b*) single phasing condition and (*c*)-(*d*) line to line fault condition. (time: 0.1 s/div., trip signal: 5 V/div., I_a: 4.172 A/div., I_b: 4.66 A/div., and I_c: 4.82 A/div.)
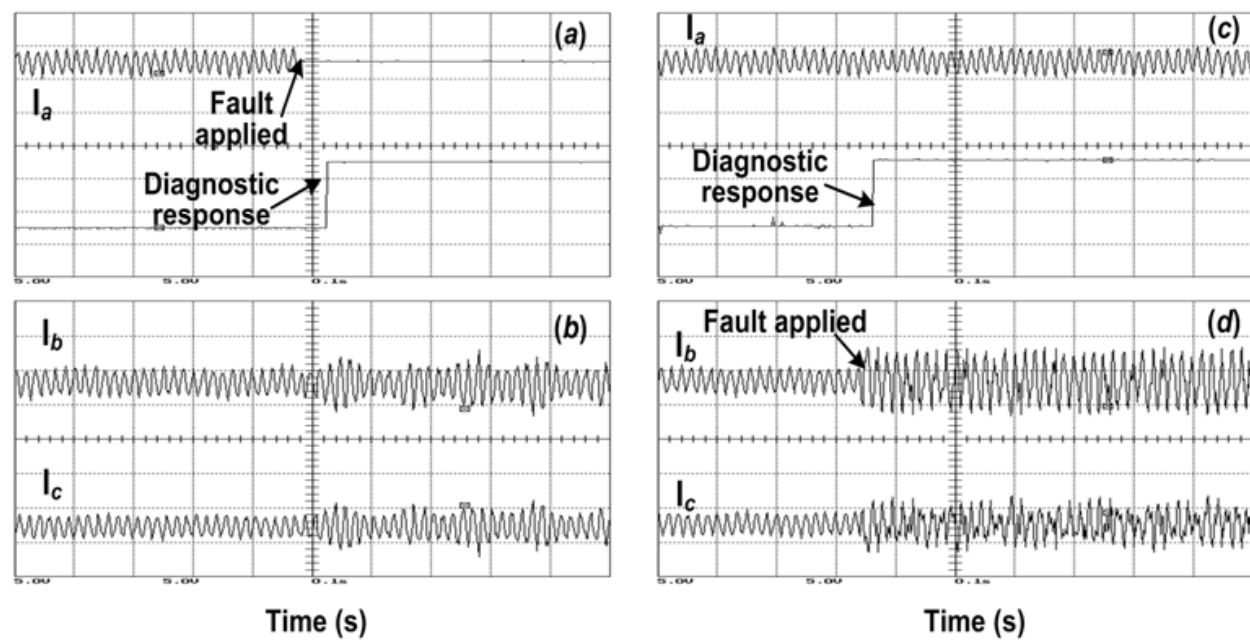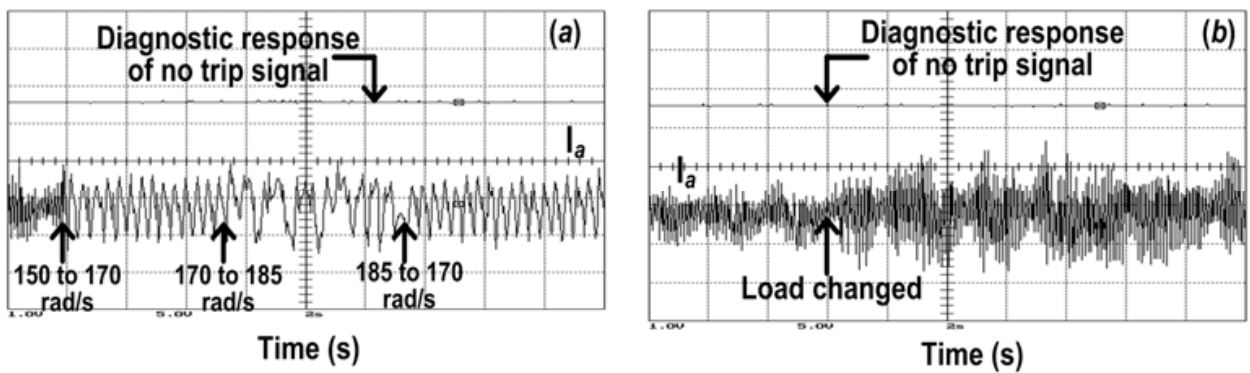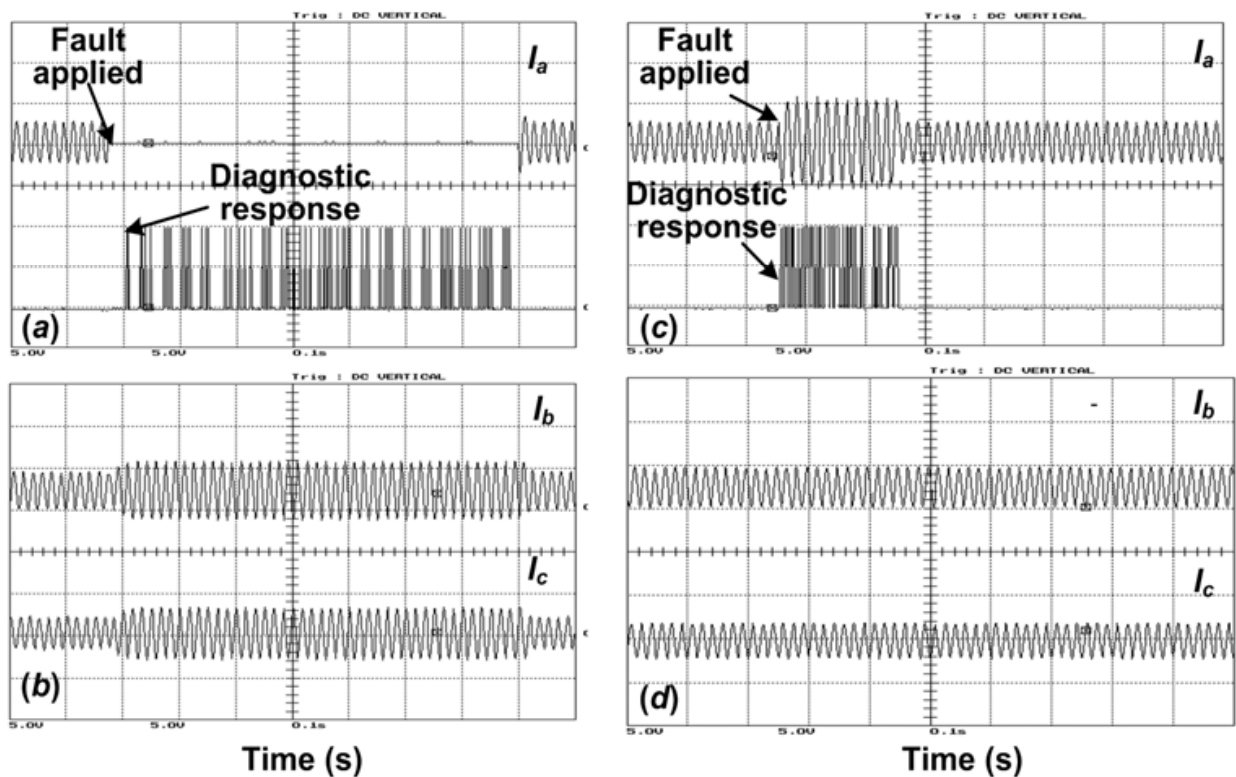

Fig. 18. Experimental responses of the WPT and NN based faults diagnostic technique for inverter fed IPM motor: (*a*)-(*b*) single phasing condition and (*c*)-(*d*) line to line fault condition. (time: 0.1 s/div., trip signal: 5 V/div., I_a: 4.172 A/div., I_b: 4.66 A/div., and I_c: 4.82 A/div.)

Fig. 19. Experimental responses of the WPT and NN based faults diagnostic technique for inverter fed IPM motor: (*a*) step changes of speed condition and (*b*) change of load torque condition. (time: 2 s/div., trip signal: 1 V/div., I$_a$: 4.172 A/div., I$_b$: 4.66 A/div., and I$_c$: 4.82 A/div.)

Fig. 20. Experimental responses of the WPT based faults diagnostic technique for supply fed induction motor: (*a*)-(*b*) single phasing condition and (*c*)-(*d*) line to ground fault condition. (time: 0.1 s/div., trip signal: 5 V/div., I$_a$: 4.172 A/div., I$_b$: 4.66 A/div., and I$_c$: 4.82 A/div.)

6. Conclusions and Remarks

In this chapter, a short review of conventional Fourier transforms and new wavelet based faults diagnostic and protection techniques for electric motors is presented. The new hybrid wavelet packet transform (WPT) and neural network (NN) based faults diagnostic algorithm is developed and implemented for electric motors. The proposed WPT and NN

faults diagnostic algorithm based protection technique is implemented in real time using the DSP board ds1102 for both supply fed and inverter fed IPM motors. In the proposed faults diagnostic technique, the WPT feature coefficients of stator currents are used as inputs to a two-layer feed forward neural network. The WPT based faults diagnostic algorithm is developed and implemented for a squirrel cage induction motor. The performances of both hybrid and WPT based diagnostic algorithm are found satisfactory. The proposed techniques do not require any harmonic contents analysis, and these are independent of motor equivalent circuit model parameters. The wavelet based technique is quite fast and easy to implement. It also requires less computational memory for the on-line implementation.

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