Fault Monitoring and Diagnosis of Induction Machines Based on Harmonic Wavelet Transform and Wavelet neural Network

Qianjin Guo1, Xiaoli Li2, Haibin Yu1, Xiangzhi Che1, Wei Hu1, Jingtao Hu1
1 Shenyang Inst. of Automation, Chinese Academy of Sciences, Liaoning 110016, China
2 Department of Resource Engineering, University of Science and Technology Beijing, Beijing 100083, China
guoqianjin@sia.cn

Abstract

The fault symptoms of stator winding inter-turn short circuit and rotor bar breakage are analyzed completely in this paper. And a new method for fault diagnosis of broken rotor bar and inter-turn short-circuits in induction machines is presented. The method is based on the analysis of the motor current signature analysis of induction machines using Zoom FFT spectrum analysis, generalized harmonic wavelet transform filter and hybrid particle swarm optimization (HPSO) based wavelet neural network. As an on-line current monitoring and non-invasive detection scheme, the presented method yields a high degree of accuracy in fault identification as evidenced by the given experimental results, which demonstrate that the detection scheme is valid and feasible.

1. Introduction

Induction motors are critical components in industrial processes. A motor failure may yield an unexpected interruption at the industrial plant, with consequences in costs, product quality, and safety. Early detection of abnormalities in the motors will help avoid expensive failures. Several diagnosis techniques for the identification and discrimination of the enumerated faults have been proposed. Temperature measurements, infrared recognition, radio frequency emissions, noise monitoring or chemical analysis are some of them [1]. References for coils to monitor the motor axial flux may be found in [2], vibration measurement, in [3]. Spectrum analysis of machine line current (called motor current signature analysis or MCSA) is referred to in [4], Park’s Vector currents (PVC) Monitoring, in [5,6], artificial intelligence based techniques are used in [7].

Among different detection approaches proposed in the literature, those based on stator current monitoring are advantageous due to its non-invasive properties. From all these approaches proposed in the literature, those based on stator current monitoring are advantageous because of its non-invasive feature. One of these techniques is the MCSA, in which motor faults become apparent by harmonic components around the supply frequency. The amplitude of these lateral bands allows dimensioning the failure’s degree [1].

This article presents the development of an on-line current monitoring system to perform the diagnosis task in a supervisory system. Firstly, the fault symptoms of stator winding inter-turn short circuit and rotor bar breakage are analyzed completely. Secondly, by thoroughly analyzing the fault symptoms, a novel scheme to detect induction machine fault, which perfectly blends Zoom FFT transform, harmonic wavelet filter (HMT), hybrid particle swarm optimization based wavelet neural network (WNN) technique together, and thus possesses high-sensitivity and high-reliability, is proposed in this paper. Finally, numerical simulation along with related experiments of broken rotor bar fault and short circuit are performed successfully.

2. On-line current monitoring scheme using HMT and WNN

In many situations, vibration monitoring methods were utilized for incipient fault detection. However, stator current monitoring was found to provide the same indication without requiring access to the motor. This paper describes an over-all scheme, based on current monitoring alone, that utilizes the harmonic wavelets filter approach, the Zoom FFT and the HPSO based wavelet network approach to determine if any one of a wide variety of fault conditions is developing in an induction machine. The harmonic wavelets filter and Zoom FFT approach provides a rule-based method for determining the spectral components which are of importance in condition monitoring. The wavelet neural network then detects changes from a learned normal condition of the machine by recognizing pattern changes in the frequency components designated by the harmonic wavelets filter and Zoom FFT system.

The unsupervised on-line current monitoring system contains the five processing sections illustrated in Figure 1. The sampler and Zoom FFT convert the time
domain stator current signal into a usable frequency domain spectrum. The harmonic wavelets filter and Zoom FFT determine which frequencies should be monitored by the wavelet neural network. The wavelet neural network determines if sufficient change has occurred in the current spectrum to indicate a possible fault condition in the monitored machine. The paper begins by discussing each of these sections followed by test results of the implemented system illustrating the operation of the overall system.

2.1. Generalized Harmonic Wavelets Filter

2.1.1. The generalized Harmonic Wavelets

Harmonic wavelet (HWT) is one of orthogonal wavelets, which is compact in the frequency domain, developed by Newland [8-13]. The basic idea behind HWT is to analyze a signal with a wavelet whose spectrum is confined exactly to a frequency band [8].

Deriving from the Fourier transform:

$$\psi_{mn}(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\psi}_{mn}(\omega) e^{i\omega t} d\omega$$

Newland obtained the following harmonic wavelet:

$$\psi_{mn}(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\psi}_{mn}(\omega) e^{i\omega t} d\omega$$

where $$m$$ and $$n$$ are the level parameters and $$1/\sqrt{n-m}$$ determines the scale of the wavelet. $$m$$ and $$n$$ are real and positive but not necessarily integers. It can be seen that $$\psi_{mn}(t)$$ is complex valued.

If we translate $$\psi_{mn}(t)$$ by step $$k/(n-m)$$, where $$k$$ is an integer, then we obtain the following translated harmonic wavelet:

$$\psi_{mn}(t-k/(n-m)) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\psi}_{mn}(\omega) e^{i\omega t} \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{\psi}_{mn}(\omega) e^{i\omega t} d\omega$$

The Fourier transform of $$\psi_{mn}(t-k/(n-m))$$ is given by:

$$\hat{\psi}_{mn}(\omega) = \left\{ \begin{array}{ll} 1/(n-m)2\pi, & m(2\pi) \leq \omega < (n/2)2\pi \\ 0, & \text{elsewhere} \end{array} \right.$$  \( (1) \)

$$\hat{\psi}_{mn}(\omega) = \left\{ \begin{array}{ll} 1/(n-m)2\pi, & m(2\pi) \leq \omega < (n/2)2\pi \\ 0, & \text{elsewhere} \end{array} \right.$$  \( (2) \)

Eq. (12) shows that $$\hat{\psi}_{mn}(\omega)$$ is identically zero except in the frequency band from $$2\pi m$$ to $$2\pi n$$ within which its modulus is constant. In addition, the Fourier transforms of the wavelets at adjacent frequency bands do not overlap each other. These properties make harmonic wavelets particularly useful when the accuracy of frequency analysis is of particular concern. Eqs. (1)- (4) give the definition of the generalized harmonic wavelets. If the level parameters are specified as $$m=2^j$$ and $$n=2^{j+1}$$; they will reduce to the classical form of harmonic wavelets. The spectra of the classical harmonic wavelets are confined exactly to octave bands [8]. They are therefore well suited for characterizing a signal composed of high-frequency components of short duration plus low-frequency components of long duration but do not necessarily work well for others. The generalized harmonic wavelets provide the possibility to overcome this shortcoming.

2.1.2. Application of Harmonic Wavelet Filter in the signal analysis of Induction Motor

In order to reduce the large amount of spectral information to a usable level, the general harmonic wavelet frequency filter eliminates those components that provide no useful failure information. General harmonic wavelet is an ideal band-pass filter, due to selecting frequency range discretely. The fault characteristic of induction machine can be extracted via integrating general harmonic wavelet and Zoom FFT technique. By the proposed method, the induction machine fault was detected.
The harmonic wavelet coefficients are practically calculated by the algorithm illustrated diagrammatically in Fig.2. The practical algorithm for the harmonic wavelet filter can be summarized as follows:

**Step 1:** The input signal \( f(t) \) is represented by the \( N \)-term series \( f_s, r = 0, 1, \ldots, N - 1 \) in the top box.

**Step 2:** The Fourier coefficients of a given signal are calculated by the fast Fourier transform (FFT). It is transformed from time to frequency by the FFT to give the Fourier coefficients \( F_0, F_1, F_2, \ldots, F_{N-1} \) in the second box.

\[
F_k = \frac{1}{N} \sum_{r=0}^{N-1} f_s e^{-j2\pi kr/N}, k = 0, 1, \ldots, N - 1 \tag{5}
\]

Where

\[
F_{N-k} = F_k^*, k = 1, 2, \ldots, N/2 \tag{6}
\]

**Step 3:** To identify the immersed impulses by filtering, the location and the shape of the frequency band corresponding to the impulses must be determined first. The scale \( j \) and frequency band \( B \) control the location and the shape of the daughter harmonic wavelet, respectively. As a result, a harmonic wavelet filter could be built by optimizing the two parameters for a daughter wavelet.

\[
B = 2^{-j} f_h \tag{7}
\]

\[
\begin{align*}
m &= sB \\ n &= (s + 1)B
\end{align*} \tag{8}
\]

where \( s = 0, 1, 2, \ldots, 2^j - 1; f_h \) is the highest analyzing frequency.

The harmonic wavelet transform functions as an ideal band pass filter so that the harmonic wavelet coefficient, \( a_{m,n}(t) \) for the wavelet in the frequency band \( B \), contains information only in the selective frequency band \((m2\pi, n2\pi)\).

**Step 4:** The multiplication operation is carried out.

\[
A_k(m,n,k) = F_k W_k^* (m,n,k) \tag{9}
\]

where the quantities \( A(\omega) \); \( S(\omega) \) and \( W(\omega) \) are the Fourier transform of corresponding quantities, harmonic wavelet coefficient \( a(t) \); input signal, \( s(t) \) and harmonic wavelet \( w(t) \).

Using the above \( W(\omega) \) in the HWT, the subband decomposition is done in frequency domain, unlike in time domain by a filter bank. This is achieved by applying a window \( W(\omega) \) in the frequency domain.

**Step 5:** The harmonic wavelet coefficients \( a_{m,n}(t) \) are generated by IFFT, and the real part of \( a_{m,n}(t) \) is the output signal of the bandpass filtering operation. These calculation procedures are repeated for all frequency blocks.

Harmonic Wavelet Decomposition is very much simpler compared to other methods. This is due to the fact that the subband signals are generated in frequency domain directly by mere grouping of the Fourier coefficients. The decimation and interpolation operations are built-in and no explicit decimation and interpolation are required. Further, the HWT does not use any antialiasing filter prior to down sampling and image rejection filter after up sampling and these are achieved by just grouping the Fourier transform coefficients.

### 2.2. Wavelet neural network for fault diagnosis

[Diagram of WNN topology structure]

The WNN employed in this study are designed as a three-layer structure with an input layer, wavelet layer (hidden layer) and output layer. The topological structure of the WNN is illustrated in Fig.3, where \( w_{jk} \) denotes the weights connecting the input layer and the hidden layer, \( u_{ij} \) denote the weights connecting the hidden layer and the output layer. In this WNN models, the hidden neurons have wavelet activation functions of different resolutions, the output neurons have sigmoid activation functions. A similar architecture can be used for general-purpose function approximation and system identification.

The activation functions of the wavelet nodes in the wavelet layer are derived from a mother wavelet \( \psi(x) \), suppose \( \psi(x) \in L^1(R) \), which represents the...
collection of all measurable functions in the real space, satisfies the\ admissibility condition [15]:
\[ \int_{-\infty}^{\infty} |\hat{\psi}(\omega)|^2 d\omega < \infty \]  (10)
where \( \hat{\psi}(x) \) indicates the Fourier transform of \( \psi(x) \).
The output of the wavelet neural network \( Y \) is represented by the following equation:
\[ y_j(t) = \sigma(x_k) = \sigma \left( \sum_{j=0}^{M} u_{ij} \psi_{ij} \left( \sum_{k=0}^{N} w_{jk} x_k(t) \right) \right) \]  (11)
\[ (i = 1, 2, ..., N) \]
where \( \sigma(x_k) = 1/(1 + e^{-x_k}) \), \( y_j \) denotes the \( j \)th component of the output vector; \( x_k \) denotes the \( k \)th component of the input vector; \( u_{ij} \) denotes the connection weight between the output unit \( i \) and the hidden unit \( j \); \( w_{jk} \) denotes the weight between the hidden unit \( j \) and input unit \( k \); \( a_j, b_j \) denote dilation coefficient and translation coefficient of wavelets in hidden layer respectively; \( L, M, N \) denote the sum of input, hidden and output nodes respectively.

The network is trained with a hybrid algorithm integrating PSO with gradient descent algorithm in batch way [14]. As a result, the network model in this paper is constructed by using HGDPSO as training algorithm and Morlet mother wavelet basic function as node activation function[14].

3. Experiments and Classification

A series of experiments have been done to verify the validity and effectiveness of the fault detection scheme presented in this paper. The current signals are used to find the cause of malfunction and to classify the conditions since the signals describe the dynamic characteristics of the induction motor. In order to classify the condition of the induction motor, the following four processes are required. These processes are data acquisition, feature calculation and extraction, data training and classification.

3.1. Data acquisition

In order to test and verify the performance of the condition classification system, motors were configured as the test experimental set. The experiments were carried out under the self-designed test rig which is mainly composed of motor, pulleys, belt, shaft and fan with changeable blade pitch angle as shown in Fig. 4. We performed experiments on an actual induction motor. The motor used in experimental tests was a three-phase, 50 Hz, 2-pole, 3kW, squirrel cage induction motor, type Y100L-2, rated at 380 V, 6.1 A, and 2880 rpm, driving a large DC motor via a flexible coupling. The DC motor acted as a generator and its power output was dissipated in a variable resistor bank.

Fig.4. Test bed used for experimental results

3.2. Feature Calculation

Initially, shorted turns were introduced in the stator a-phase winding while the rotor was normal. Subsequently, a faulty rotor substituted for the normal one while the shorted turns were removed. The corresponding results are given in Fig.5 to Fig.16, respectively. The stator three-phase currents were sampled by using a high-frequency multi-channel data acquisition device, type PXI4472, and delivered to LabView7.1 for thorough processing and analysis. The sampling interval is 0.1ms, the power supply frequency is 50 Hz.

The acquired data is stored on the hard disk of the PC, from which it can be retrieved for later processing. The processing involved several different routines each written for a specific task. The first task is to sort the data from the input channels into separate files. The Zoom Fast Fourier Transform (Zoom FFT) is then used to find the magnitude and phase of the harmonic components in the current and voltage waveforms. The output from the Zoom FFT is then scanned to determine if frequency components that characterize a particular fault type are present.

3.2.1. Broken rotor bars. Fig.5 shows the stator current in phase \( c \) with 1 broken rotor bar at 50Hz and 380V with torque 11.9Nm. Fig.6 shows the Zoom FFT of the stator current in phase \( c \) with 1 broken rotor bars at 50Hz and 380V with torque 11.9Nm. The spectrum obtained for the case of one broken rotor bar, clearly shows the existence of a spectral component at a frequency of \( 2sf_1 \). Fig.7 shows the stator current in phase \( c \) with 3 broken rotor bars at 50Hz and 380V with torque 11.9Nm. Fig.8 shows the Zoom FFT of the stator current in phase \( c \) with 3 broken rotor bars at 50Hz and 380V with torque 11.9Nm. The spectrum
obtained for the case of 3 broken rotor bars, more clearly shows the existence of a spectral component at a frequency of $2sf_1$.

Fig.5. Stator current in phase c with 1 broken rotor bars under 11.9N.m load

Fig.6. Zoom FFT of stator current at 50Hz with 1 broken rotor bars under 11.9N.m load

Fig.7. Stator current in phase c with 3 broken rotor bars under 11.9N.m load

Fig.8. Zoom FFT of stator current at 50Hz with 3 broken rotor bars under 11.9N.m load

As it was theoretically predicted, the spectrum obtained is practically clear from any spectral component, although, in practice, there still exists some negligible spectral components, due to the residual asymmetries that are inherent to any motor and to the voltage supply system. The occurrence of one broken rotor bar manifests itself in the Zoom FFT spectrum by the appearance of a spectral component at twice the rotor slip frequency, as can be seen in Fig.6. This characteristic component can be easily distinguished, since there are no other significant spectral components in its neighborhood. As comparison between Figures 6 and 8, it is clearly visible the increase in the amplitude of the spectral component directly related to the fault.

3.2.2. Inter-turn short circuit. Fig.9 shows the stator current in phase c with 1 turn shorted circuit at 50Hz and 380V under load 11.9Nm. Fig.10 shows the Zoom FFT of the filter stator current in phase c with 1 turn shorted circuit at 50Hz and 380V with torque 11.9Nm.

Fig.9. Stator current in phase c with 1 shorted circuits under 11.9N.m load

Fig.10. Zoom FFT spectral components for motor under 11.9N.m load in the case of 1 shorted circuits.

Fig.11 shows the stator current in phase c with 3 turn shorted circuits at 50Hz and 380V under load 11.9Nm. Fig.12 shows the Zoom FFT of the filter stator current in phase c with 3 turn shorted circuit with torque 11.9Nm.

Fig.11. Stator current in phase c with 3 shorted circuits under 11.9N.m load

Fig.12. Zoom FFT spectral components for motor under 11.9N.m load in the case of 3 shorted circuits.

As comparison between Figures 10 and 12 shows that the components at 100 and 150Hz have increased respectively with the shorted turn increased. The results obtained show that there is an increase in the value of the components at 100 and 150Hz with the extension of the fault, making it a good indicator about the condition of the machine, these components can be used as the severity indicator of shorted turns.

As regards the amplitude of these stator current components, they depend on three factors: the motor’s load inertia, the motor’s load torque, and the severity of the fault. So, the first two factors must be considered
in order to analyze, as independently as possible, the one of concern for the present application.

Fig. 13 and 15 show the stator current in phase with 1 and 3 turn shorted circuits at 50Hz and 380V under no-load operation respectively. Fig. 14 and 16 shows the Zoom FFT of the filter stator current in phase with 1 and 3 turn shorted circuit with no-load operation respectively.

As comparison between Fig. 14 and 16 shows that the components at 100 and 150Hz have increased respectively with the shorted turn increased. The results obtained show that there is an increase in the value of the components at 100 and 150Hz with the extension of the fault, making it a good indicator about the condition of the machine, these components can be used as the severity indicator of shorted turns.

3.3. Feature Calculation

The feature extraction of the signal is a critical initial step in any monitoring and fault diagnosis system. Its accuracy directly affects the final monitoring results. Thus, the feature extraction should preserve the critical information for decision-making. In this paper, the statistical information of time-base data and frequency-base data were used for obtaining the feature information from the measured signals (See Table.1).

When there are broken or even fissured bars, as it was theoretically and experimentally predicted, side bands reveal faults more clearly with high values of slip. Then it is recommended that the diagnosis were carried out with the motor running near its nominal load. Then, a severity factor can be defined as:

$$S_{RF} = \frac{I_{m(1+2\times s)f_1}}{I_{mf_1}}$$

where $S_{BF}$ is the severity rotor fault, $I_{m(1+2\times s)f_1}$ is the sum of amplitude of sidebands, and $I_{mf_1}$ is the amplitude of the fundamental component of the stator current.

When there are shorted turns fault, the severity factors can be defined as:

$$S_{SF1} = \frac{I_{m2f_1}}{I_{mf_1}}$$

$$S_{SF2} = \frac{I_{m3f_1}}{I_{mf_1}}$$

Where $S_{BF}$ and $S_{SF}$ are the severity shorted turns fault, $I_{m2f_1}$ is the amplitude of $2f_1$ sidebands, $I_{m2f_1}$ is the amplitude of $3f_1$ sidebands, and $I_{mf_1}$ is the amplitude of the fundamental component of the stator current.

3.4. Classification procedure

Once the frequency filter enters its monitoring stage, the magnitudes of the components listed in the table 1 form the inputs to the wavelet neural network for network training and fault sensing. The neural network is one of several clustering-type algorithms that are trained on the filtered frequency components during a network training period. During this time, it is assumed that the network will observe the performance of the motor long enough to be exposed to all the normal operating and load conditions. Just as in the case of the frequency filter, this training period is determined by the experience of the process operator and may range from only a few minutes to several days, depending on the application of the motor. The neural network forms clusters that represent valid motor operating conditions. As the wavelet neural network is exposed to more and varied operating conditions, the number of acceptable classifications.
increases. A simplified illustration of the wavelet neural network classifier is shown in Fig. 4.

At the end of the training period, when all of the operating conditions have been learned and classified, the network is switched to a fault sensing mode. When a spectral signature falls outside the trained clusters, it is tagged as a potential motor failure. Since a fault condition is not a spurious event but continues to degrade the machine, the postprocessor alarms the user only after multiple indications of a potential failure have occurred. In this way, the time history of the machine is incorporated into the monitoring system and protects the neural network from alarming on random signals that have been incorrectly identified.

Table 1: Feature extraction by stator current spectrum analysis

<table>
<thead>
<tr>
<th>Motor health status</th>
<th>Torque $T_e$ (N.m)</th>
<th>Slip ratio $s$ (%)</th>
<th>$S_{RF1}$ (%)</th>
<th>$S_{RF2}$ (%)</th>
<th>$S_{SF1}$ (%)</th>
<th>$S_{SF2}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>health</td>
<td>11.6</td>
<td>0.06</td>
<td>0.001</td>
<td>0.005</td>
<td>0.010</td>
<td>0.006</td>
</tr>
<tr>
<td>1 broken rotor bar</td>
<td>11.6</td>
<td>0.06</td>
<td>0.135</td>
<td>0.352</td>
<td>0.005</td>
<td>0.008</td>
</tr>
<tr>
<td>3 shorted circuits</td>
<td>11.6</td>
<td>0.06</td>
<td>0.010</td>
<td>0.012</td>
<td>0.201</td>
<td>0.125</td>
</tr>
</tbody>
</table>

4. Conclusions

This paper has introduced a new squirrel-cage induction motors on-line faults monitoring and diagnosis method based on the spectral analysis of the stator current. The method blends Zoom FFT transform, generalized harmonic wavelet transform filter, hybrid particle swarm optimization based wavelet neural network (WNN) technique together, which reduces the misdetection probability to a great extent. Theoretical analysis and experimental results have shown that the new approach is effective to detect broken rotor bars faults and inter-turn short circuit fault.

5. References


