Abstract- In this paper, a wavelet neural network (WNN) based diagnostic algorithm is developed and implemented in real-time for the identification and detection of inverter faults in the vector controlled induction motor drives. The phase currents of an induction motor (IM) drive of different faulted and unfaulted conditions are preprocessded by the wavelet packet transform (WPT) algorithm in order to minimize the structure and timing of the proposed diagnostic technique using the WNN algorithm. The WPT coefficients are used as the inputs of a three-layer WNN. The performance of the proposed diagnosis scheme is evaluated by simulation and experimental results. The proposed technique is evaluated and tested on-line for a laboratory 1-hp IM motor drive using the ds1102 digital signal processor (DSP) board. In all the tests carried out, the type of fault is identified promptly and properly, and the tripping action is initiated almost at the instant or within one cycle of the fault occurrence.

Index terms-Digital signal processor, fault diagnosis, induction motor protection, inverter faults, wavelet neural network, wavelet packet transform.

I. INTRODUCTION

With the development of power electronics and microprocessor, induction motors are predominantly fed from pulse width modulation (PWM) inverters for variable speed operation. PWM inverter fed motors are usually more reliable than those fed directly on-line. However, these induction motor (IM) drive systems are sensitive to different types of fault occurring at the input rectifier, or at the power inverter stage, or at the control sub-system. In general, when one of these faults occurs, the drive system has to be stopped for maintenance [1]. To introduce fault diagnostics in motor drive systems as practical entities, hardware and software must perform the following tasks:

1) fault detection;
2) fault identification;
3) remedial actions.

A basic requirement to all fault diagnostics development is a comprehensive understanding of the regular system operation so that its behavior can be compared to those at the onset of faults [2]. Based on the idea of keeping the IM drive operating after fault detection, several authors [4]-[8] have been proposing fault-tolerant operating strategies, which are based on the principle of systems redundancy. The use of induction motors with a redundant number of phases, the availability of the motor stator winding neutral connection, or the use of inverters with a redundant number of controlled power switches are among the solutions provided. However, the use of some of these techniques may cause the occurrence of some additional problems such as flowing of zero-sequence currents where the neutral point is connected or increasing of both motor line currents and electromagnetic torque oscillations [3].

In order to implement appropriate remedial actions against faults, the drive system must incorporate suitable fault diagnostic techniques that would aid in detecting, identifying, and isolating the faulty elements. An online diagnostic algorithm for the detection of intermittent misfiring of the switching devices in a voltage-fed PWM inverter fed IM drive is reported in [9]. It is based on the time-domain response analysis of the motor current space vector in addition to the application of a pattern recognition algorithm. This paper only concentrates on the intermittent misfiring fault. Two strategies are proposed in [10] for providing compensations against open-circuit and short circuit failures occurring in the converter power devices. The compensation scheme is based on the integration of a fault-tolerant system, which allows a continuous free operation of the drive under inverter faulty conditions. In the past, several studies concerning the detection of stator winding and air gap eccentricity faults in PWM fed IM drive are accomplished. In [11], a high frequency carrier-voltage is superimposed on the fundamental excitation for the on-line detection of stator winding faults in inverter fed induction motors. It is based on the measurement of dc component of the resulting negative sequence current. Stator voltages and currents are used in [12] to detect air gap eccentricity fault in a vector-controlled induction motor drive. The diagnostic scheme utilized a neural network based diagnostic algorithm to aid in analyzing the fault current.

The objective of this paper is to develop and implement a new diagnostic technique for inverter faults in the PWM inverter fed induction motor drive. The inverter single phasing and shoot through faults are investigated in this work. The proposed technique involves the development of a wavelet neural network (WNN) based diagnostic algorithm and its on-line testing on a three-phase squirrel cage induction motor. The proposed technique is tested on-line on a laboratory 1-hp IM using the ds1102 digital signal processor (DSP) board. Simulation and experimental results are presented to demonstrate the effectiveness of the proposed diagnostic technique.
II. WNN

The WNN employed in this work are designed as a three-layer structure with an input later, wavelet layer (hidden layer), and output layer. The hidden neurons have wavelet activation functions of different resolutions. The output neurons have sigmoid activation functions. The modified Morlet wavelet [13]-[14] has been chosen to serve as an adoption basis function for the hidden layer of the network. The modified Morlet wavelet can be expressed as

\[ \psi_{\alpha,\beta}(t) = \cos(1.75t) e^{-\frac{(t-\beta)^2}{\alpha}} \]

where \( \theta \) is the wavelet width, \( a \) and \( b \) are the dilation and translation coefficients of wavelets in the hidden layer, respectively. Figure 1 shows the specific structure of a three-layer WNN for fault diagnostics in IM drives. The output of the WNN is represented as

\[ y(t) = \sigma(x) = \frac{1}{1 + e^{-\frac{\sum_{j=1}^{M} w_{jk} x(t)}}} \]

where \( y \) is the output, \( x \) is the \( k \)th component of the input vector, \( v \) is the connection weight between output and hidden \( (j) \) units, \( w_{jk} \) is the weight between hidden \( (j) \) and input \( (k) \) units, \( L \) and \( M \) are sum of input and hidden nodes, respectively.

A. Training Algorithm

The network is trained with back propagation algorithm in batch way [15]-[16]. The wavelet node parameters \( (a, b, \theta) \) and the network weights \( (v, w) \) are adjusted to minimize the least square error. For the \( d^p \) as the desired target output of \( p \)th input pattern, the cost function is defined as

\[ E = \frac{1}{2} \sum_{k=1}^{L} (d^p - y^p)^2. \]

The error propagations in layers of the WNN are defined as

\[ \delta_{v} = \frac{\partial E}{\partial v} = -\frac{\sum_{j=1}^{M} w_{jk} x(t)}{E} \]

\[ \delta_{w} = \frac{\partial E}{\partial w_{jk}} = -\frac{\sum_{k=1}^{L} w_{jk} x(t)}{E} \]

\[ \delta_{a} = \frac{\partial E}{\partial a} = -\frac{\sum_{j=1}^{M} w_{jk} x(t)}{E} \]

The parameters are updated as

\[ w_{jk} (t+1) = w_{jk} (t) + \eta \delta_{a} \]

\[ a(t+1) = a(t) + \eta \delta_{v} \]

\[ k(t+1) = k(t) - \eta \delta_{w} \]

\[ \theta(t+1) = \theta(t) - \eta \delta_{a} \]

III. FEATURE EXTRACTION

The collected data of different faulted and normal unfaulted conditions are decomposed up to the second level of resolution of the wavelet packet transform (WPT) using the mother wavelet ‘db3’ [17] for faults identification and classification. The digital data are acquired through the three-channel A/D converter of the ds1102 DSP board. Figures 2(a), 2(b), and 2(c) show normal current, inverter single phasing current, and shot through fault current of a IM drive system, respectively. The WPT coefficients of the second level of resolution for normal and fault currents of a vector controlled IM drive are shown in Figs. 3(a)-3(d). The WPT coefficients of these frequency sub-bands for the case of faulted condition in Figs. 3(b) and 3(d) are larger than those of normal (unfaulted) condition in Figs. 3(a) and 3(c) at the inception of fault occurrence. Therefore, these feature coefficients can be used to train neural networks, which will provide accurate and reliable diagnosis of fault currents. It is to be noted that number of coefficients that can be used for the purpose of training is very high. So, the input data vector of WPT coefficients are scaled in order to have a finite-dimensional vector, which is more convenient for training and validation of the WNN. In this work, a feature vector \( F \) is defined using the second level WPT components of line currents from equations (6)-(7) for different faulted and normal currents as

\[ F = \left[ \begin{array}{c} W_{aa} W_{ad} W_{da} W_{dd} \end{array} \right] \]

\[ W_{aa} = \frac{\sum_{n=1}^{N} a^2 (n) / N}{N} \]

\[ W_{ad} = \frac{\sum_{n=1}^{N} ad (n) / N}{N} \]

\[ W_{da} = \frac{\sum_{n=1}^{N} da^2 (n) / N}{N} \]

\[ W_{dd} = \frac{\sum_{n=1}^{N} dd^2 (n) / N}{N} \]

where \( N \) is the total number of coefficients in a certain node of the wavelet packet tree. Table-I shows the comparisons of feature vector between faulted and normal conditions using equations (6)-(7). These feature vectors are used to train the WNN of the proposed fault diagnostics scheme.
<table>
<thead>
<tr>
<th>Type of faults</th>
<th>$W_a$</th>
<th>$W_{a^2}$</th>
<th>$W_{a^3}$</th>
<th>$W_{a^4}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single phasing (phase-a)</td>
<td>9.267</td>
<td>3.0522</td>
<td>3.1825</td>
<td>3.3112</td>
</tr>
<tr>
<td>Single phasing (phase-c)</td>
<td>78.9099</td>
<td>4.3334</td>
<td>3.3966</td>
<td>3.7618</td>
</tr>
<tr>
<td>Shot through (phase-a)</td>
<td>119.5608</td>
<td>4.0422</td>
<td>3.8339</td>
<td>4.5404</td>
</tr>
<tr>
<td>Shot through (phase-b)</td>
<td>28.8702</td>
<td>6.3491</td>
<td>6.1513</td>
<td>8.8314</td>
</tr>
<tr>
<td>Shot through (phase-c)</td>
<td>49.6368</td>
<td>4.5118</td>
<td>3.5153</td>
<td>4.6276</td>
</tr>
</tbody>
</table>

Fig. 2. Current responses of the IM drive system: (a) normal currents, (b) inverter single phasing currents, and (c) inverter shot through fault currents.

Fig. 3. Second level WPT coefficients: (a) high frequency approximations ($da^2$) of normal current, (b) high frequency approximations ($da^3$) of fault current, (c) high frequency details ($dd^2$) of normal current, and (d) high frequency details ($dd^3$) of fault current.

IV. HYBRID DIAGNOSIS SCHEME USING WPT AND WNN

The most critical task in using the WNN algorithm for any particular system is to formulate the problem. Finding inputs and outputs is the first step of the problem formulation. In the proposed diagnosis scheme, the inputs 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. In the proposed scheme, a three-layer WNN with four inputs and one output is used. The proposed diagnosis scheme is shown in Fig. 4.

The procedure to implement the proposed hybrid WPT and WNN algorithm based diagnosis and protection technique using the ds1102 DSP board is shown in the flow chart of Figure 5. In the proposed technique, samples of three-phase line currents are squared and summed into one sample at the beginning for minimizing the computational burden. The hybrid algorithm checks the values of the network output using the trained weights and biases, and determines whether it is greater than the threshold or not in order to generate the tripping action.

Fig. 4. System diagram of the proposed hybrid diagnosis scheme.

Fig. 5. Flow chart of the proposed hybrid algorithm based diagnostic and protection technique for IM drives.
V. IMPLEMENTATION AND RESULTS

The real-time implementation of the proposed protection technique involves the development of an experimental setup that includes both hardware and software components. The complete relaying scheme is shown in Fig. 6. The hardware includes the dSPACE DSP board model ds1102 with the 32-bit floating point processor TMS320C31. The software loads the values of filter coefficients of the selected mother wavelet ‘db3’ and the values of weights and biases of the network for extracting features of fault currents using WPT algorithm and processing of the tripping decision using WNN algorithm, respectively.

The proposed hybrid algorithm is written in the turbo C language. It used a set of initialization and input/output (I/O) functions in order to initialize the 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 line currents at the rate of 4 kHz. The samples of line 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 WNN algorithm.

The proposed hybrid algorithm is tested on a three-phase squirrel-cage induction motor of ratings: 1hp, 208V, 1670 rpm, 1.2A, 60Hz. A sinusoidal pulse width modulated voltage source inverter (PWM-VSI) is used to drive the induction motor. The PWM pulses are generated from digital I/O channels of the DSP board with the help of pulse width modulation closed loop control technique. Two types of fault currents are investigated to test the hybrid algorithm on the inverter-fed induction motor: (a) inverter single phasing and (b) inverter shot through fault. These fault conditions are tested on phase-a of the induction motor and initiated by connecting the points involved in faults. The on-line test results in Figs. 7(a)-7(c) show that the proposed algorithm identified every disturbance properly and initiated a trip signal almost at the instant or within one cycle of the fault occurrence in all cases.

VI. CONCLUSION

In this work, a hybrid WPT and WNN based algorithm is developed and implemented in real-time using a DSP board for fault diagnostics in PWM inverter fed induction motor drives. Faults such as inverter shoot through fault and single phasing are tested successfully using this novel hybrid WPT and WNN algorithm based diagnosis scheme. The WPT feature coefficients of three-phase line currents are used as inputs to a two-layer WNN. Both off-line and on-line test results show that the proposed scheme is able to quickly discriminate between fault and normal (unfaulted) currents with high accuracy. The proposed algorithm identified every disturbance properly and initiated a trip signal almost at the instant or within one cycle of the fault occurrence. It is also to be noted that the algorithm did not cause any false trip with the presence of harmonics in phase currents during the healthy operation. The proposed technique is quite fast and easy to implement. It also requires less computational memory for on-line implementation.
REFERENCES


