Real-time fault diagnosis of nonlinear systems

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This paper concerns the development of a real-time fault detection and diagnosis system for a class of electrical machines. Changes in the system dynamics due to a fault are detected using nonlinear models, namely, nonlinear functions of the measurable variables. At the core of the fault detection and diagnosis system are artificial neural networks and a new neural network structure designed to capture temporal information in the input data. Difficulties such as voltage unbalance, measurement noise, and variable loads, commonly found in practice, are overcome by the system addressed in this paper. Because false alarms are significantly reduced and the system is robust to parameter variations, high detection and diagnosis performance are achieved during both, learning and testing phases. Experimental results using actual data are included to show the effectiveness of the real-time fault detection system developed.

1. Introduction

Fault diagnosis of fast nonlinear dynamic systems in real-time is a major challenge. Learning approaches to fault detection and diagnosis give a wealth of methodologies to detect, identify, and accommodate faults in nonlinear dynamical systems in real-time. The main idea behind the learning approach is to monitor and approximate abnormal behaviors of dynamical systems using real-time approximation structures such as neural networks or adaptive nonlinear models. When faults occur in a system, its dynamics change and the function modeling the faulty behavior through a real-time approximator can be used as an estimate of the corresponding nonlinear fault function, thereby providing a natural framework for fault detection, identification and accommodation.

From a general viewpoint, learning approaches for fault diagnosis fall in the category of model-based redundancy methods. For a detailed overview of the different approaches for fault detection and diagnosis, and the aspects of analytical redundancy methods see the survey papers of Gertler [1], Isermann [2], and Patton [3].

This paper focuses on fault diagnosis of induction motors. Induction motors are highly nonlinear electrical machines and, in most practical and industrial contexts, they are subject to numerous and distinct types of faults and adverse operating conditions. Currently, there is no general theory that provides universal solutions for nonlinear fault diagnosis problems and no methodology is unanimously accepted as the most effective and efficient to solve fault diagnosis of induction motors.
Different applications of induction motors (IMs) require different levels of reliability, security, efficiency and performance. The occurrence of faults in these machines can testify against these requirements. Taking this into account, and considering the industry fast growing level of automation, studies on monitoring and fault diagnosis systems development have been recently emphasized. During the last thirty years, several works on IMs fault diagnosis have been published in the literature such as [4–6], to mention a few. Benbouzid [7] reports 365 works, among books, workshops, conferences and journals, published from the end of the 70s up to 1999 related to this important research topic. Since then there is a continually increasing interest in IMs fault diagnosis and considerable need for methods and procedures.

Diagnosis systems have been developed and improved for condition monitoring and incipient fault detection and diagnosis. Among the several benefits these systems can bring to industry the following are worth to mention: expansion to the motor life, reduction of idling periods, avoidance of unnecessary disconnections and manpower scheduling at the fault instant, minimization of the repair cost, improvement of the human security, reduction of the direct–indirect overtime rewards, reduction of components storage, and minimization of losses (most especially the loss in production). Clearly, even small investments in either data pre-processing or in modeling of diagnosis systems may provide expressive financial profits to industry, in addition to safe and robust operation environment.

A major part of IMs premature faults occurs in the stator windings. The inter-turns short-circuit is a primary fault that happens after insulation breakdowns. Among the main reasons for insulation failures are [8] the high stator core or winding temperatures; slack core lamination, slot wedges, and joints; loose bracing for end winding; contamination due to chemical reactions, moisture, or dirt; electrical discharges due to aging of the insulating material; and leakage in cooling systems. After primary faults the degradation process of the motor increases and more serious, damaging failures, such as phase-to-phase and phase-to-ground short-circuits appear. Usually, these types of faults result in irreversible motor damages. However, if the turn-to-turn fault is detected by diagnosis systems at incipient stage, for example, the faulty phase winding may be substituted, what significantly reduces financial losses and increases operational safety.

In addition to internal faults, IMs are subjected to variable external conditions [9]. Among the most relevant of these conditions is unbalanced voltage supply. Voltage unbalance makes fault detection much more complicated because it induces false alarms harming the diagnosis system performance. Problems caused by voltage unbalance considering healthy the motor internal conditions are reported in [10–12]. The ill effects of voltage unbalance concern line–current unbalance, over heating, derating, torque pulsation, and inefficiency. In general there is a very high risk of erroneous conclusions if a diagnosis system disregards voltage variations and unbalances. Therefore, studies considering this issue are of utmost importance.

This paper develops an extension of the symmetrical deterministic IM model to simulate fault aiming at detecting IMs inter-turns short-circuit under conditions of actual industrial practice. Next, artificial neural networks (ANN) are used to capture temporal information of the nonlinear mapping that models the machine. Comparisons of the performance of the diagnosis system using conventional Multi-Layer Perceptron (MLP), Elman neural network, Time Lagged Feed forward Network (TLFN) [13], and a new recursive version of TLFN we called Time Lagged Feed forward Network with Short-Term memory (ST-TLFN) are pursued to serve as indicators of the most appropriate approach to adopt in practice.

The paper is organized as follows. Section 2 addresses the deterministic nonlinear models of the fault system. Section 3 gives a brief overview of ANN emphasizing its use in fault diagnosis. Next, Section 4 details a methodology to interconnect the deterministic models with the ANNs real-time approximation structures. Section 5 presents experimental results performed with actual data. The paper concludes with Section 6 summarizing its main contributions and suggesting issues for further investigation.

2. Deterministic models of fault systems

2.1. Symmetrical IM model

Without loss of generality, a three-phase squirrel-cage IM with 120° magnetic axis offset, \(N_s\) turns per winding, and resistance \(R_s\) per phase is considered in this work. The IM stator and rotor voltage expressions can be written in the matrix form as:

\[
[V_{abcs}] = [R_{s}] [I_{abcs}] + \frac{d [\lambda_{abcs}]}{dt} ,
\]

\[
[V_{abcr}] = [R_{r}] [I_{abcr}] + \frac{d [\lambda_{abcr}]}{dt} ,
\]

where the subscripts \(s\) and \(r\) mean stator and rotor, respectively; the subscripts \(a, b\) and \(c\) denote the phases in the ABC system; \([R]\) represents the resistance matrix, \([I]\) the current matrix, and \([\lambda]\) the linkage flux matrix determined by:

\[
[\lambda_{abcs}] = \begin{bmatrix} L_{ss} & L_{sr} \\ L_{rs} & L_{rr} \end{bmatrix} [I_{abcs}] ,
\]

\[
[\lambda_{abcr}] = \begin{bmatrix} L_{ss} & L_{sr} \\ L_{rs} & L_{rr} \end{bmatrix} [I_{abcr}] .
\]
where \( L_s, L_r \) and \( L_{sr} \) are inductance matrices given by:

\[
L_s = \begin{bmatrix}
  l_s + l_{ms} & -\frac{1}{2} l_{ms} & -\frac{1}{2} l_{ms} \\
  -\frac{1}{2} l_{ms} & l_s + l_{ms} & -\frac{1}{2} l_{ms} \\
  -\frac{1}{2} l_{ms} & -\frac{1}{2} l_{ms} & l_s + l_{ms}
\end{bmatrix},
\]

\[
L_r = \begin{bmatrix}
  l_r + l_{mr} & -\frac{1}{2} l_{mr} & -\frac{1}{2} l_{mr} \\
  -\frac{1}{2} l_{mr} & l_r + l_{mr} & -\frac{1}{2} l_{mr} \\
  -\frac{1}{2} l_{mr} & -\frac{1}{2} l_{mr} & l_r + l_{mr}
\end{bmatrix},
\]

\[
L_{sr} = \begin{bmatrix}
  l_{sr} \cos(\theta_r) & l_{sr} \cos(\theta_r + \frac{2\pi}{3}) & l_{sr} \cos(\theta_r - \frac{2\pi}{3}) \\
  l_{sr} \cos(\theta_r - \frac{2\pi}{3}) & l_{sr} \cos(\theta_r) & l_{sr} \cos(\theta_r + \frac{2\pi}{3}) \\
  l_{sr} \cos(\theta_r + \frac{2\pi}{3}) & l_{sr} \cos(\theta_r - \frac{2\pi}{3}) & l_{sr} \cos(\theta_r)
\end{bmatrix},
\]

where \( l_s, \ l_{ms}, \ l_r, \ l_{mr} \) and \( l_{sr} \) are the stator leakage and magnetizing inductances, the rotor leakage and magnetizing inductances, and the amplitude of the mutual inductance, respectively.

From expressions (1) and (2), the IM dynamic equation can be written in state-space form as follows:

\[
[I_{abcr}] = [L]^{-1} \left( [V_{abcr}] - \left( [R] + [L] \right) [I_{abcr}] \right),
\]

where \( [I_{abcr}] \) refers to the stator currents [14]. \( [I_{abcr}] \) can be computed using the multi-variable Runge–Kutta algorithm.

The model is complemented by the electromagnetic torque equation, and the rotor speed equation as follows:

\[
T_e = \frac{P}{2} (I_{abcr})^T \frac{\partial}{\partial \theta_r} [U_{sr}^I_{abcr}],
\]

\[
\omega_r = \frac{P}{2} \int \frac{T_e - T_l}{J} dt,
\]

where \( I_{abcr} \) is the rotor currents referred to the stator, \( P \) is the number of poles, \( T_e \) is the electromagnetic torque, \( T_l \) is the load torque, and \( J \) is the inertia.

### 2.2. Fault simulation

A representation of IM stator shorted-turns is illustrated in Fig. 1. In the figure, \( I_s' \) is the current induced in the shorted-turns by the stator and rotor phases [14].

Eq. (3) given below can be used to calculate inductances in either healthy or faulty windings [15]:

\[
L = \frac{\pi N_1 N_2 l r}{4 g} \mu_0,
\]  

(3)

where \( N_m \) is the number of turns of the winding \( m \), \( l \) is the axial size of the magnetic circuit, \( r \) is the medium radium of the air gap magnetic circuit, \( g \) is the length of the air gap, and \( \mu_0 \) is the air permeability.

Assuming that there are no changes in the motor physical dimensions in a condition of shorted-turns, the inductances can be found by [14]:

\[
L_s = (1 - k) \tilde{L},
\]

\[
L_{sk} = k \tilde{L},
\]

\[
L_{s(k)} = k(1 - k) \tilde{L},
\]

\[
L_{m} = (1 - k) \tilde{L},
\]

where \( k \) is the shorted-turns percentage, \( L_s \) is the self-inductance of the winding part without fault, \( L_{sk} \) is the self-inductance of the faulty part of the winding, (6) represents the mutual inductance between the faulty and healthy part of the winding, and (7) is the mutual inductance between the remaining phases and the healthy part of the winding.
From (4)–(7), the inductance matrix can be rewritten as a 7-dimensional matrix

\[ L = \begin{bmatrix}
    L_s & L_{sr} \\
    L_{sr}^t & L_r
\end{bmatrix}, \]

where three lines and columns represent the part of the stator windings without fault, one line and column represent the faulty part of a winding, and three lines and columns represent the rotor phases.

Similarly to the inductance matrix representation, the resistance matrix is rewritten using

\[ R_s = (1 - k)R, \]

\[ R_{sk} = kR, \]

where \( R_s \) and \( R_{sk} \) are the resistances of the healthy and faulty part of the winding, respectively. The resistance matrix is a 7 \( \times \) 7 diagonal matrix.

### 2.3. Voltage unbalances

Usually, voltages in a three-phase system are sinusoidal functions of time, all at the same frequency and magnitude, but offset in time to different phases. The phases are equally spaced, which means a phase separation of one-third cycle. There are certain situations, however, in which these conditions cannot be maintained. Among the causes that provoke unbalanced voltage are open delta transformer connections, transformers and transmission lines asymmetries, unbalanced loads, incomplete transposition of transmission lines, and blown fuses on three-phase capacitor banks.

Three definitions of voltage unbalance are of interest in practice. The line voltage unbalance rate (LVUR) is the NEMA (National Equipment Manufacturer’s Association) definition [16]; the phase voltage unbalance rate (PVUR) is the IEEE definition [17]; and the percentage voltage unbalance factor (%VUF) [18], also known as the true definition, is used often. The %VUF is based on positive- and negative-sequence voltage components, while the first two are based on line and phase voltage, respectively. This study adopts the last two definitions because the proposed diagnosis system, in its conception, deals with phase voltage, sequence components, and phasorial analysis.

Unbalanced voltages can be expressed in eight distinct cases [19]: one, two or three phases under-voltage unbalance \( \rightarrow (1\phi-UV), (2\phi-UV), (3\phi-UV) \), respectively; one, two or three phases over-voltage unbalance \( \rightarrow (1\phi-OV), (2\phi-OV), (3\phi-OV) \), respectively; unequal one- or two-phase angles displacement (different of \( 2\pi/3 \)) \( \rightarrow (1\phi-DD), (2\phi-DD) \), respectively.

The phase voltage unbalance in percent, PVUR, defined in [17], is given by

\[ PVUR = \frac{\Delta V_{\text{max/avg}}}{V_{\text{avg}}} \times 100, \]

where \( \Delta V_{\text{max/avg}} \) corresponds to the maximum deviation of the voltage in relation to the average phase voltage \( V_{\text{avg}} \). This definition considers only amplitude variations.

The definition of voltage unbalance based on [18], %VUF (8), takes into account amplitudes and displacements of the signals since the voltage sequential components depend of both. In (8), \( V_{sp} \) and \( V_{sn} \) are the positive-sequence (9) and negative-sequence (10) voltages, respectively [20].
\[
\%VUF = \frac{|V_{sn}|}{|V_{sp}|} \times 100, \quad (8)
\]
\[
\vec{V}_{sp} = \frac{\vec{V}_{an} + h\vec{V}_{bn} + h^2\vec{V}_{cn}}{3}, \quad (9)
\]
\[
\vec{V}_{sn} = \frac{\vec{V}_{an} + h^2\vec{V}_{bn} + h\vec{V}_{cn}}{3}. \quad (10)
\]

The \( h \) and \( h^2 \) operators rotate a vector anti-clockwise by 120° and 240°, respectively; \( \vec{V}_{mn} \) is the phase \( m \) voltage. In this work, \( \%VUF \) values higher than 3% indicate voltage unbalance.

2.4. Shorted-turns and voltage unbalance effects in the stator currents

The current sequential components of an IM fed with unbalanced voltage can be computed using the IM positive- and negative-sequence equivalent circuits \([21,12]\) as follows
\[
\vec{I}_{sp,vu} = \frac{|V_{sp}|}{|Z_{sp}|} \sin(\beta_{sp} - \phi_{sp}), \quad (11)
\]
\[
\vec{I}_{sn,vu} = \frac{|V_{sn}|}{|Z_{sn}|} \sin(\beta_{sn} - \phi_{sn}), \quad (12)
\]
where \( Z_{sp} \phi_{sp} \) and \( Z_{sn} \phi_{sn} \) are the equivalent impedances of the positive- and negative-sequence circuits, respectively; \( \beta_{sp} \) and \( \beta_{sn} \) are the angles of the sequential voltages.

Stator inter-turns short-circuit is another factor that affects IM currents that cause their unbalance. The sequential components of the currents due to this fault can be obtained from
\[
\vec{I}_{sp,vu} = \frac{\vec{I}_{an} + h\vec{I}_{bn} + h^2\vec{I}_{cn}}{3}, \quad (13)
\]
\[
\vec{I}_{sn,vu} = \frac{\vec{I}_{an} + h^2\vec{I}_{bn} + h\vec{I}_{cn}}{3}, \quad (14)
\]
where \( \vec{I}_{mn} \) is phase \( m \) current.

Assuming the same rotation frequency of the reference frames in expressions (11–14), the superposition principle applies and the resultant sequential components of the currents are
\[
\vec{I}_{sp} = \vec{I}_{sp} + \Delta\vec{I}_{sp,vu} + \Delta\vec{I}_{sp,vu},
\]
\[
\vec{I}_{sn} = \vec{0} + \vec{I}_{sn,vu} + \vec{I}_{sn,vu},
\]
where \( \Delta\vec{I}_{sp,vu} \) and \( \Delta\vec{I}_{sn,vu} \) are the variations related to the condition of balanced voltage and to the condition of symmetric windings, respectively. Note that these “healthy” conditions are represented by the first term of the equations.

The level of unbalance of the stator currents can be evaluated through the percentage current unbalance factor (\( \%CUF \)) whose definition is similar to that of the \( \%VUF \), namely:
\[
\%CUF = \frac{|I_{sn,vu}|}{|I_{sp,vu}|} \times 100.
\]

3. Neural networks for fault diagnosis

3.1. Brief contextualization

A key for the fault diagnosis technology advancement is brought by ANN-based approaches. Many papers have been written outlining this issue, e.g. \([22–24]\). ANNs can learn how to perform IM fault diagnosis based solely on input–output examples, what reduces the complexity of analytical modeling. For the next years, it is expected that ANN usage will increase in the context of fault diagnosis because it is hard to formulate and solve fault diagnosis problems using only conventional analytical techniques. This is mainly due to several breakthroughs in this research field and also to the limitations of the currently available problem solving techniques. Results to date have demonstrated that ANN performs significantly better than the conventional techniques \([22]\).
Actually, the dynamics of induction machines cannot be modeled or accurately approximated by linear approaches because the motor is a highly nonlinear system. Thus, even if an operation point is known, the linearized model, e.g. obtained via first-order Taylor series expansion, may not be satisfactory. ANNs are nonlinear in nature and can approximate complex dynamical systems behaviors more easily because activation functions of neurons in one or more layers of the network are nonlinear functions. Therefore ANNs become especially appropriate for IM fault diagnosis. Once ANN is trained appropriately, the network parameters will contain the knowledge needed to perform fault diagnosis.

3.2. Capturing temporal information in data with ANNs

The vast majority of real-world engineering application data contains distinct levels of noise. Noise is known to decrease the overall performance of fault diagnosis systems [25,22]. Because such a system is to be used in real-time, where measurement noise is anticipated, a method to suppress the effects of noise and enhance the accuracy of ANNs is needed.

The original ANN can be modified to capture temporal information in data, improve robustness, and operate in noisy environments [22]. A possibility is to increase the number of input neurons while keeping the hidden and output layers structures the same. Measurements, coming from IM condition monitoring, are fed to the ANN input neurons through tapped delay lines. The input layer of the network model is basically an expansion from the input measurements at time $t_1$ to $n$ consecutive measures at times $t_1, t_{n-1}, \ldots, t_{n-n+1}$. This scheme can be seen as a nonlinear filter coupled to the ANN input neurons. Tapped delay lines, therefore, help to suppress noise and to enhance ANN robustness.

The above-described ANN is called TLFN [13]. A possible variation of TLFN network is to insert recurrent connections from the output of the hidden layer neurons to their own input (similarly to the context layer of the Elman neural network). Because of the existence of local recurrent connections, the recurrent networks have some dynamical advantages over TLFN. Delay lines and memory turn a MLP network in a network we called time lagged feed forward network with short-term memory, or ST-TLFN. They resemble the effect of short-term memory on human brain. Short-term memory can be described as the capacity for holding a small amount of active information in mind, and in a readily available state. We use both of the above-mentioned networks in our study.

4. Methodology

The procedures and assumptions underlying this study are summarized in this section. We consider an experimental IM properly designed to simulate stator shorted-turns such that faults in all phases and in different operating conditions could be evaluated, and mathematical models validated. Fig. 2 shows the instrumental set up and the prototype external connections. Refer to [26,14,27], for more details about the experimental setup.

A general view of the learning and adaptation mode of the diagnosis system is given in Fig. 3(a). Notice that the deterministic models introduced in Section 2 are fundamental to construct a database whose data are intended to train ANNs. In the figure, the input code refers to a condition of fault (Table 1), and voltage supply (Table 2). The IM rotor slip, s, is considered in the ANNs supervised training scheme to incorporate information about the motor load condition in the network parameters. Although only the suggested ST-TLFN is shown in Fig. 3(a), we compare the overall system performance using alternative nonlinear modeling techniques, namely MLP, Elman and TLFN neural networks, for the same purpose.

We assume 4-layer ANNs employing a structure with $[6(p + 1), 18, 18, 4]$ neurons per layer, where $p$ is the order of the nonlinear filter coupled to the ANNs — note that $p$ must be 1 to characterize conventional MLP and Elman network structures.
Table 1
Incipient faults in the stator windings.

<table>
<thead>
<tr>
<th>Code</th>
<th>$N'_a$ [turns]</th>
<th>$N'_b$ [turns]</th>
<th>$N'_c$ [turns]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
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<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>11</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
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<td>5</td>
<td>0</td>
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</tr>
<tr>
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</tr>
<tr>
<td>16</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
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</table>

Table 2
Supply voltage conditions.

<table>
<thead>
<tr>
<th>Code</th>
<th>Case</th>
<th>$V_a$ (V)</th>
<th>$\theta_a$ (°)</th>
<th>$V_b$ (V)</th>
<th>$\theta_b$ (°)</th>
<th>$V_c$ (V)</th>
<th>$\theta_c$ (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>(1φ-UV)</td>
<td>116</td>
<td>0</td>
<td>116</td>
<td>240</td>
<td>116</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>(1φ-UV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>4</td>
<td>(1φ-UV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>5</td>
<td>(2φ-UV)</td>
<td>116</td>
<td>0</td>
<td>116</td>
<td>240</td>
<td>116</td>
<td>120</td>
</tr>
<tr>
<td>6</td>
<td>(2φ-UV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>7</td>
<td>(2φ-UV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>8</td>
<td>(3φ-UV)</td>
<td>116</td>
<td>0</td>
<td>116</td>
<td>240</td>
<td>116</td>
<td>120</td>
</tr>
<tr>
<td>9</td>
<td>(1φ-OV)</td>
<td>140</td>
<td>0</td>
<td>140</td>
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<td>120</td>
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<td>127</td>
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<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>11</td>
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<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>12</td>
<td>(2φ-OV)</td>
<td>140</td>
<td>0</td>
<td>140</td>
<td>240</td>
<td>140</td>
<td>120</td>
</tr>
<tr>
<td>13</td>
<td>(2φ-OV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>14</td>
<td>(2φ-OV)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240</td>
<td>127</td>
<td>120</td>
</tr>
<tr>
<td>15</td>
<td>(3φ-OV)</td>
<td>140</td>
<td>0</td>
<td>140</td>
<td>240</td>
<td>140</td>
<td>120</td>
</tr>
<tr>
<td>16–17</td>
<td>(1φ-DD)</td>
<td>127</td>
<td>0 ± 8</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
<tr>
<td>18–19</td>
<td>(1φ-DD)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
<tr>
<td>20–21</td>
<td>(1φ-DD)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
<tr>
<td>22–25</td>
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<td>127</td>
<td>0 ± 8</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
<tr>
<td>26–29</td>
<td>(2φ-DD)</td>
<td>127</td>
<td>0 ± 8</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
<tr>
<td>30–33</td>
<td>(2φ-DD)</td>
<td>127</td>
<td>0</td>
<td>127</td>
<td>240 ± 8</td>
<td>127</td>
<td>120 ± 8</td>
</tr>
</tbody>
</table>

The activation function of all neurons are sigmoidal, and the learning is carried out by the backpropagation algorithm with momentum.

Fig. 3(b) illustrates the scheme of the diagnosis system in monitoring mode. During the experiments, Gaussian white noise $v(k)$ models measurement noise with maximum magnitude $\sigma$ for voltages and $\varsigma$ for currents. In Fig. 3(b), the Acquisition Block basically sends chunks of data to the Processing Block while the Holder Block aims at synchronizing the transmission frequency of data chunks with the ANNs processing time.

5. Experimental results

An example of the overall performance of the system operating with the TLFN model is shown in Fig. 4. The following measurement noise levels, $\sigma \in [-1 \text{ V}, 1 \text{ V}]$ and $\varsigma \in [-0.1 \text{ A}, 0.1 \text{ A}]$, were considered in accordance with the error range of sensors currently found in the industry. We define a variable $\tau = 10 \varsigma$, and linguistic descriptions about the quality of the sensors: high quality ($\tau \in [-0.33, 0.33]$), good quality ($\tau \in [-0.66, 0.66]$), and fair quality ($\tau \in [-1, 1]$). Different orders $p$ of the coupled filter were chosen as illustrated in the figure.

In Fig. 4, * means the system’s ideal operating point. It corresponds to the adoption of a filter of order $p = 23$ and to the use of high quality sensors. These conditions have led the system to online detect 96.58% of the faults occurring. Clearly, worse instruments sensibility and worse measurement reliability worsen the performance of the diagnosis system. In Fig. 4, vector 1 means sensor precision ranges not available in practice (optimistic) while vector 2 means a condition of excessive filtering. Increasing the order of the filter contributes significantly to increase the performance of the system. However, after a certain order, the remaining detection errors are not attributed to noises only.
Experiments with MLP, Elman, and ST-TLFN showed similar surfaces. Table 3 summarizes the results obtained with the different ANNs. We notice that ST-TLFN presented a slightly superior surface in all operating points, the best maximum and average performance in correct fault detection, and has shown to be more robust to noisy environments due to its higher dynamical characteristics.
6. Conclusion

This paper has suggested a real-time fault diagnosis system to detect and approximate faulty states of induction motors. Changes in the system dynamics due to a fault were modeled as nonlinear functions of the measurable variables. The nonlinear models have succeeded to provide consistent data bases with fault indicators. Artificial neural networks have successfully mapped the fault indicators space into the corresponding motor condition space. Difficulties including voltage unbalances, measurement noises, and variable loads were overcome using a new neural architecture with tapped delay lines and recurrency called ST-TLFN. High correct detection rate was achieved with ST-TLFN. Further work shall consider the development of evolving intelligent systems for fault detection, and extensions of the diagnosis system to capture the occurrence of broken rotor bars and air-gap eccentricity. The use of static and dynamic logic fuzzy neural networks is also an issue to be pursued in the future.

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