Vibration for detection and diagnosis bearing faults using adaptive neuro-fuzzy inference system

The fault diagnosis of electrical machines is a primordial and necessary task in industry. The failure is unbearable because it causes, incontestably, decrease in production and increases cost repair. Induction motors are the most important equipment in industry, where reliability and safe operation is desirable, for maintenance, such as detection, and diagnosis of mechanical and electrical defects of electric drives. The several techniques are adopted and frequency analysis is the most widely used. Artificial intelligence techniques was gained popularity last decay’s in numerous applications. The presented results show the detected and diagnosed, of the bearing faults of the induction motor, based on Adaptive Neuro-Fuzzy Inference System. The vibrations analysis of the induction machine using the Artificial Intelligence Techniques, combining neural networks and fuzzy logic has been applied successfully. The designed ANFIS network shows about 99% accurate results as validated by Mat lab / Simulink simulation.

Keywords: Diagnosis, fault, vibration; bearing, ANFIS

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1. Introduction

The diagnosis of Induction Motor (IM) faults was studied under various approaches by many researchers duo to its widely application in industry, to obtain more efficient and reliable electric drive system and to guarantee continuity of its duty.

Electric drive systems must be equipped with reliable monitoring technology, to avoid risks of the drive system components damage [1, 2]. The early detection of the defect makes it possible to minimize faults, also reduce the maintenance costs and overall system breakdown while aiming to meet specific requirement [3, 4].

Induction motor has several types of faults: faults of the stator windings, open phase’s circuits, bearings, air-gap [5, 6]. Roller bearings are very commonly used in rotating machines which are easy to deteriorate. The investigations show that 30% of the faults of rotating machines are caused by bearing faults. Bearing faults diagnosis is to reflect bearing’s working state by collecting and analyzing signals relevant to bearing faults [7-9].

In literature several techniques of diagnosis are based on the analysis of electrical signatures: stator or rotor current, neutral voltage, and the analysis of electromagnetic size such that the magnetic flux or vibration signal [10, 11].

In this case, by measuring accessible and easily quantifiable sizes, the vibration data is gathered using accelerometers which are placed on the bearing’s housings by their magnetic plates. Accelerometers are placed on many positions at both sides fan and end bearings. Data is collected using a channel DAT and pre-processed using MatLab [12, 13].

Neural network and fuzzy logic techniques, combination of these two techniques known as Adaptive Neuro-Fuzzy Inference System (ANFIS) have developed as a better alternative [14-16]. The ANFIS technique offers the best training feature of neural network and heuristic interpretation of the process results similar to fuzzy logic theory thus providing a...
powerful tool that can be employed in conjunction with the condition monitoring and fault diagnostic applications.

Mechanical fault diagnosis using ANFIS is also discussed in for induction motor drive system [17]. Example of bearing fault, inter-turn insulation windings faults, stator current, rotor speed, motor winding temperature, bearing temperature and noise of the motor are used as inputs to the ANFIS [18,19]. The suggested approach in present work uses the vibration signal analysis based on wavelet packet decomposition to diagnosis the bearing faults in induction motor. Additionally noise sensors used for data recording as they are very reliable and more accurate. The bearings are installed in a motor driven mechanical system, as shown in Figure 1.

The three-phase induction motor is connected to a dynamometer and a torque sensor using a self-aligning coupling method. The dynamometer is controlled so that desired load torque levels can be achieved. An accelerometer is mounted on the motor housing at the driven-end of the motor to acquire the vibration signals from the bearing. The data collection system consists of a high bandwidth amplifier particularly designed for the vibration signals and a data recorder with a specific sampling frequency [20, 21].

The present work, interested particularly in the mechanical faults such as the bearing faults (Outer race, Inner race and ball fault) of the induction motor as show by Figure 2. Therefore, the propose approach is based on adaptive Neuro-Fuzzy inference system, in order to increase the effectiveness and the reliability of the diagnosis of the IM [22, 23].

2. Wavelet packet method

The wavelet method requires the use of time-frequency basis functions with different time supports to analyze signal structures of different sizes. The wavelet transforms an extension of the Short-time Fourier Transform, projects the original signal down on to
wavelet basis functions and provides a mapping from the time domain to the time-scale plane. The wavelet $\psi(t)$ is a zero mean function [24-27].

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0$$  \hspace{1cm} (1)

Latter is dilated with a scale parameter $s$, and translated by $u$.

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}} \psi \left( t - \frac{u}{s} \right)$$  \hspace{1cm} (2)

The wavelet transform of a function $f$ at the scale $s$ and position $u$ is computed by correlating $f$ with a wavelet atom:

$$W_f(u,s) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \psi \left( t - \frac{u}{s} \right) dt$$  \hspace{1cm} (3)

A real wavelet transform is complete and conserves energy as long as it satisfies a weak admissibility condition:

$$\int_0^{+\infty} \frac{|\phi(\omega)|^2}{|\omega|} d\omega = \int_{-\infty}^{0} \frac{|\phi(\omega)|^2}{|\omega|} d\omega = C_\phi < +\infty$$  \hspace{1cm} (4)

The discrete wavelet transform (DWT) is based on the continuous version, unlike the latter. The DWT uses a scaling factor and a translation discretized. We called discrete wavelet transform any dyadic wavelet basis working with a scale factor $s = i/2$. The multi-resolution analysis can analyze a signal into different frequency bands. Either $\phi$ the scale function. It must be in $L2$ and having a non-zero mean. Base scaling functions are formed for all $i \in Z$ as follows:

$$\phi_{i,j}(t) = 2^{-i/2} \phi(2^{-i} t - j)$$  \hspace{1cm} (5)

In the same manner, the wavelet base is:

$$\psi_{i,j}(t) = 2^{-i/2} \psi(2^{-i} t - j)$$  \hspace{1cm} (6)

The following equations represent the decomposition of the scaling function and the wavelet linear combinations of the scale function to the full resolution directly. The dyadic scaling factor leads to:

$$\phi(t) = \sum_j 2h(j) \phi(2t - j)$$  \hspace{1cm} (7)

$$\psi(t) = \sum_j 2g(j) \psi(2t - j)$$  \hspace{1cm} (8)

The terms $h(j)$ and $g(j)$ are the low-pass filters and high pass respectively in wavelet decomposition. The Mallat algorithm allows decomposing the signal $f(n)$ in several decomposition levels as shown in Figure 3.

![Fig. 3: Decomposition of wavelet packet](image-url)
We obtain $2^i$ frequency bands each with the same bandwidth as:

$$\left[ \frac{(i-1)f_n}{2}, \frac{if_n}{2} \right]$$

(9)

With, $i = 1, 2 \ldots 2^l$.

Such that $f_n$ is the Nyquist frequency in the frequency bands $i$. When, $h(n)$ and $g(n)$ are $f(n)$ decomposition filters in D1 and A1 respectively. The next level of decomposition is based on A1 and coefficients are expressed as follows:

$$A_2(n) = \sum_j h(k - 2n)A_1(k)$$

(10)

$$D_2(n) = \sum_j h(k - 2n)A_1(k)$$

(11)

When the bearing fault, of the IM occurs, the fault information of the vibration signal is included in each frequency band resulting from the wavelet decomposition or wavelet packet.

By calculating the energy associated with each level or each decomposition, one can build a very effective diagnostic tool. The clean energy value of each frequency band is defined:

$$E_j = \sum_{k=1}^{k=m} \left| D_{jk}(n) \right|^2$$

(12)

Where, $j$ is the decomposition level. Based on the value of clean energy, the vector is given by:

$$T = \left[ \frac{E_0}{E}, \frac{E_1}{E}, \frac{E_2}{E}, \ldots, \frac{E_{2^m-1}}{E} \right]$$

(13)

Such as:

$$E = \sum_{j=0}^{2^m-1} \left| E_j \right|^2$$

(14)

3. Adaptive Neuro-Fuzzy Inference System

ANFIS is a hybrid controller structure using fuzzy logic inference system and the architecture of a neural network having five-layer feed-forward structure. Thus, the ANFIS offers the advantages of learning capability of neural networks and inference mechanism of fuzzy logic. A typical architecture of ANFIS having $n$ inputs, one output, and $m$ rules is illustrated in Figure 4 [28-30].

Fig. 4: Typical ANFIS structure
Here \( x, y \) are inputs, \( f \) is output, the circle represent fixed node functions and the square represent adaptive node functions. This is a Sugeno type fuzzy system, where the fuzzy \textbf{if-then} rules have the following form:

- Rule 1: \textbf{if} \( x \) is \( A_1 \), \( y \) is \( B_1 \), \ldots, \( n \) is \( k_1 \) \textbf{then} \( f_1 = (p_{11}x + q_{11}y + r_{11}z + \ldots + v_{11}) \)

- Rule 2: \textbf{if} \( x \) is \( A_2 \), \( y \) is \( B_2 \), \ldots, \( n \) is \( k_2 \) \textbf{then} \( f_2 = (p_{21}x + q_{21}y + r_{21}z + \ldots + v_{21}) \)

- Rule \( m \): \textbf{if} \( x \) is \( A_m \), \( y \) is \( B_m \), \ldots, \( n \) is \( k_m \) \textbf{then} \( f_m = (p_{m1}x + q_{m1}y + r_{m1}z + \ldots + v_{m1}) \)

4. Bearing fault detection using ANFIS

Adaptive Neuro-Fuzzy inference system is one of the most powerful approaches for off-line diagnostic of electrical machines and has been successfully applied in recent years [31]. The structure thus created is depicted in Figure 5.

![Fig.5: ANFIS structure for bearing fault detection](image-url)

This paper uses vibration signals collected in two positions (Fan End and Drive End show Figure 2), as the input nodes, and the output is the estimated bearing friction. The friction conditions are classified (Outer race fault, Inner race and ball fault). The ANFIS model provides the friction crisp value which can be used for further decision making, either to go for preventive maintenance or to schedule the maintenance.

The MatLab/Simulink model is developed for the proposed diagnostic system. Data collected from off-line is used for the training of the ANFIS structure. The inputs are designated in the figure by "x" and "y". In fact, they represent the energy of the vibratory signal in Fan End and Drive End, respectively. However, the wavelet decomposition is done for sixteen (16) energy bands. Among them the seventh (7th) band is richer in information and more significant. Therefore, this band of energy has been retained as inputs (acquisition signals at Fan End and Drive End) for to be analyzed by the ANFIS system. They are designated by "x" for the energy vector band in Fan End and by "y" for the energy vector band of Drive End. These inputs are translated into Gaussian membership functions. Moreover, for each of the inputs "x" and "y" the ANFIS model generates eight (8) inputs membership functions of Gaussian structure with the help of subtractive clustering method as shown in Figure 6. It should be noted that the structure comprises the layers leading, ultimately, to the system output ANFIS. Therefore, the eight
input functions $8^2=64$ rules are generated, allowing to have a decision on the condition of the bearing and mainly defects: No fault, Ball fault, Inner fault and outer fault. The model is run for 500 Epochs and the post training input membership functions are displayed in Figure 6a and Figure 6b, where, respectively, the membership function for input "x" are designed by the Gaussian membership inputs: in1mf1, in1mf2, in1mf3,......and in1mf8, and those for the input "y" by in2mf with i=1:8.

5. Simulation results and discussion

Recall that the data of vibratory signals analyzed for the healthy case and faults cases are downloading by the web site: [http://www.eecs.cwru.edu/laboratory/bearing/download.htm].

These tests are carried out according to the data in Table 1:

Table 1: Drive End Bearing Fault Data.

<table>
<thead>
<tr>
<th>Fault Diameter</th>
<th>Motor Load (HP)</th>
<th>Motor Speed (rpm)</th>
<th>Inner Race</th>
<th>Ball</th>
<th>Outer Race entered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>0</td>
<td>1796</td>
<td>No Data</td>
<td>No Data</td>
<td>No Data</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1725</td>
<td>No Data</td>
<td>No Data</td>
<td>No Data</td>
</tr>
<tr>
<td>0.007&quot;</td>
<td>0</td>
<td>1797</td>
<td>IR007_0</td>
<td>B007_0</td>
<td>OR007_0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1772</td>
<td>IR007_1</td>
<td>B007_1</td>
<td>OR007_1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1750</td>
<td>IR007_2</td>
<td>B007_2</td>
<td>OR007_2</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1730</td>
<td>IR007_3</td>
<td>B007_3</td>
<td>OR007_3</td>
</tr>
</tbody>
</table>

For each case, the analyzed vibratory signal is subdivided into four parts and for each interval of the recording, the energy is calculated and at the end of which we obtains 16
elements of each input vector. The operation is repeated for all cases of defects considered.

Moreover, for each subclass, one assigns a number that actually represents the elements of the output vector "f" (Decision), particular, the healthy case "0", the ball fault case "1", the Inner fault "2" and Outer fault "3". Then, one proceeds to the learning of each class of defect and we introduce the checking vector whose the dimensions are reduced compared to that of learning. However, if the learning and verification classes are superimposed, we validate the ANFIS and consequently its effectiveness.

The trained and checked ANFIS output for different types of fault diagnosis are shown in Figure 7, with the result that a non-significant dispersion. Indeed, the error is about 1%. Both the error curves are plotted in Figure 8. The root mean square error for the training output is found to be 0.25 %. The real fresh data are checked with the developed ANFIS model.

The ANFIS performance is found to be excellent. The efficiency of developed ANFIS is about 99% which can be shown from Figure 8. The input relationships or dependencies of the ANFIS output are also analyzed. These are the unique characteristics of adaptive Neuro-Fuzzy inference system. Unlike neural network, the input-output mapping in ANFIS is not a black box.
To validate the investigated network shown in Figure 9, test of recognition is carried out and the results are consigned in the following table (Tab.2).

**Table 2:** Numerical input-output values of the validate ANFIS.

<table>
<thead>
<tr>
<th>Input</th>
<th>Estimated Output</th>
<th>Desired Output</th>
<th>Observations of the Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.8779</td>
<td>0.7801</td>
<td>0.3562</td>
<td>0.0000</td>
</tr>
<tr>
<td>1.1690</td>
<td>7.3476</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>0.4117</td>
<td>1.0479</td>
<td>0.9842</td>
<td>1.0000</td>
</tr>
<tr>
<td>0.3128</td>
<td>1.8131</td>
<td>1.0628</td>
<td>1.0000</td>
</tr>
<tr>
<td>0.1583</td>
<td>0.1583</td>
<td>2.0002</td>
<td>2.0000</td>
</tr>
<tr>
<td>0.1692</td>
<td>0.1692</td>
<td>2.0004</td>
<td>2.0000</td>
</tr>
<tr>
<td>0.0121</td>
<td>0.0121</td>
<td>2.9994</td>
<td>3.0000</td>
</tr>
<tr>
<td>0.0178</td>
<td>0.0178</td>
<td>2.9997</td>
<td>3.0000</td>
</tr>
</tbody>
</table>

The mapping is optimized by neuro adaptive learning techniques by fuzzy modeling procedure to learn information about the data set. The surface thus created Input 1, Input 2 and Output is show in Figure 10.

**Fig. 9:** Testing Data and Output

**Fig. 10:** Surface views between Input 1, Input 2 and Output (bearing stat)
6. Conclusion

This paper presents the diagnostic technique of bearing faults in induction motor. The diagnostic approach was based on the use of Adaptive Neuro-Fuzzy Inference System aiming for the estimation of bearing state of induction motor. The crisp value of the motor bearing friction obtained from ANFIS model. ANFIS can be used as a reliable tool for monitoring the wear and tear of the bearing. The vibration signal will be used as an indicator of the bearing incipient fault which can be used as on-line diagnostic purposes. The designed ANFIS network shows about 99% accurate results as validated by Matlab/Simulink simulation. Further experimental validation of the fault investigation will be carried out using the proposed techniques.

References


