Induction Motors Stator Fault Analysis based on Artificial Intelligence

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Abstract
This article presents a method for fault detection and diagnosis of stator inter-turn short circuit in three phase induction machines. The technique is based on the stator current and modelling in the dq frame using an Adaptive Neuro-Fuzzy artificial intelligence approach. The developed fault analysis method is illustrated using MATLAB simulations. The obtained results are promising based on the new fault detection approach.

Keywords: Fault diagnosis, induction motor, turn-to-turn stator fault, dqmodelling, Neuro-Fuzzy, ANFIS

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1 Introduction
The induction machine is commonly used in all the industries. It is utilized in 90% of electrical motor applications [1]. The merits of the induction machine are its low price, ease of control and reliability. Investigating induction machines faults is crucial to minimize downtime and the cost of damages [1, 2].

The induction machine faults are classified as winding faults, unbalanced stator and rotor, broken rotor bars, Eccentricity and bearing faults. The failure due to stator winding breakdown is about 30~40% of total induction faults [3]. The predictions of stator faults will save the high maintenance cost [3, 4]. There are a lot of approaches to diagnose the stator turns fault. Some methods are based on the stator currents and fast Fourier transforms (FFT) while other methods use the torque profile analysis and vibration study [4, 5]. Recent research work investigated the use of intelligent control, Fuzzy logic (FL), Neural Network (NN), combination of FL and NN and adaptive control in fault analysis [6-8]. This article is organized as follows: Modelling of the three phase induction motor for both the healthy and faulty cases is presented in section II. An overview of the Adaptive Neuro-Fuzzy Inference System (ANFIS) is discussed in section III. The proposed fault analysis technique is investigated in section IV through MATLAB simulations of induction machines with inter-turn stator faults. The results and conclusion are discussed in section V.

2 Modelling of A Three Phase Induction Motor
A dq frame is used to reduce the complexity of differential equations. The original stator and rotor frames of reference are transformed to a common frame that rotates with arbitrary angular velocity [9].

3 Healthy Case
The three phases of a healthy motor are symmetrical. Thus, all the phases have the same number of turns [8-12]. The rotor is balanced star connection cage rotor...
The voltage equations of the motor can be written as below:

\[ V_{abc}^{s} = r_{abc}^{s} i_{abc}^{s} + p \lambda_{abc}^{s} \]
\[ 0 = r_{abc}^{'} i_{abc}^{'} + p \lambda_{abc}^{'} \] (1)

\[ \lambda_{abc}^{s} = \begin{bmatrix} \lambda_{a}^{s} \\ \lambda_{b}^{s} \\ \lambda_{c}^{s} \end{bmatrix} = L \begin{bmatrix} i_{a} \\ i_{b} \\ i_{c} \end{bmatrix} \]

Where \( P = \frac{d}{dt} \)

Converting to dq stationary frame

\[ X_{dq0}^{s} = K X_{abc}^{s} = \frac{2}{3} \begin{bmatrix} 1 & -0.5 & -0.5 \\ 0 & -\sqrt{3} & \sqrt{3} \\ 0.5 & 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} X_{abc} \end{bmatrix} \] (2)

The voltage equations of stator and rotor are derived as:

\[ V_{dq0}^{s} = r_{dq0}^{s} i_{dq0}^{s} + p \lambda_{dq0}^{s} \]
\[ 0 = r_{dq0}^{'} i_{dq0}^{'} - \omega_{r} \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \lambda_{dq0}^{s} + p \lambda_{dq0}^{'} \] (3)

The stator resistances in the dq frame depend on the stator resistance values for each phase.

\[ R_{dq0}^{s} = \begin{bmatrix} r_{11}^{s} & r_{12}^{s} & r_{13}^{s} \\ r_{21}^{s} & r_{22}^{s} & r_{23}^{s} \\ r_{31}^{s} & r_{32}^{s} & r_{33}^{s} \end{bmatrix} \] (4)

The Rotor resistance

\[ R_{dq0}^{r} = r_{13} \] (5)

The Motor flux equation
The developed torque and speed are given by:

\[ T_d = \frac{3}{2} (P) (\lambda_s^q \lambda_s^d - \lambda_s^q \lambda_s^d) \]  

Where \( P \) is number of pair poles

\[ P_{w_m} = \frac{P}{(2J)} (T_d - T_L - T_{damp}) \]  

### 4 Inter-Turn Fault Case

Under “a” phase inter-turn fault, the motor parameters (stator resistance, inductance and the mutual inductance between all phases and the faulty phase) change as shown in Figure (1).

\[ X(\text{fault %}) = N_{a2} / N_a \]  

\[ r_{sh} = X r_a \]  

\[ L_{a1a1} = (1-X)^2 L_{asas} \]  

\[ L_{a2a2} = X^2 L_{shash} \]  

\[ L_{asr} = (1-X)L_{m} \]  

\[ L_{asr} = L_{m} + L_{shar} \]  

\[ L_{as} = L_{m} + L_{shar} \]  

\[ L_{as} = L_{shar} + L_{m} \]  

\[ L_{as} = L_{shar} + L_{m} + L_{asr} \]  

\[ L_{as} = L_{shar} + L_{m} + L_{asr} \]
The flux equation in the dq frame after taking the shorted turns in consideration is:

\[
\begin{bmatrix}
\lambda_{sh} \\
\lambda_{sq} \\
\lambda_{sd}
\end{bmatrix} =
\begin{bmatrix}
L_{sh} & L_{sh} & 0 \\
L_{sh} & L_{sq} & 0 \\
0 & 0 & L_{sd}
\end{bmatrix}
\begin{bmatrix}
I_{sh} \\
I_{sq} \\
I_{sd}
\end{bmatrix} +
\begin{bmatrix}
0 \\
0 \\
L_{sr}
\end{bmatrix} I_{r}
\]

(13)

The stator resistance is given by:

\[
\begin{bmatrix}
R_{sh} \\
R_{sq} \\
R_{sd}
\end{bmatrix} =
\begin{bmatrix}
2 R_{sh} & 0 & 0 \\
0 & R_{sq} & 0 \\
0 & R_{sd} & 0
\end{bmatrix}
\]

(14)

The flux linkage derived from equation (3) is:

\[
p\lambda_{sh} = V_{q}^{sh} - r_{sh} i_{sh}^{q},
\]

\[
p\lambda_{sq} = V_{q}^{sq} - r_{sq} i_{sq}^{q} - r_{11} i_{q}^{d} - r_{12} i_{d}^{d},
\]

\[
p\lambda_{sd} = V_{d}^{sq} - r_{21} i_{q}^{d} - r_{22} i_{d}^{d},
\]

\[
p\lambda_{q} = -r_{1} i_{q}^{q} + w_{s} \lambda_{q}^{d}, p\lambda_{d}^{r} = -r_{1} i_{d}^{d} + w_{s} \lambda_{d}^{r}
\]

(15)

The equations (10-14) show the induction motor dq modeling with fault conditions and the effect of fault severity on the motor parameters.
5 Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy inference system (ANFIS) depends on two main systems fuzzy logic (FL) and artificial neural networks (ANN). The fuzzy logic acts as the human logic thinking and the neural network acts as human brain [13]. Both the FL and ANN increase the system efficiency and decrease the mathematical equations compared to other detection methods [14]. The system is widely used for many applications of systems modelling, control systems and forecasting predictions [15]. The ANFIS consists of IF-then rules, training and learning algorithms [13].

For the Fuzzy inference system, consider a system with two inputs \((X,Y)\) and one output \((Z)\). The fuzzy rules based on 1st order Sugeno type [16] are:

**Rule1:** IF \(X\) is \(A_1\) and \(Y\) is \(B_1\) Then \(f_1=p_1X+q_1Y+r_1\),

**Rule2:** IF \(X\) is \(A_2\) and \(Y\) is \(B_2\) Then \(f_2=p_2X+q_2Y+r_2\),

\(A_i, B_i\) are the Fuzzy set, \(f_i\) is the system outputs within the specified fuzzy rules and the \(p_i, q_i\) and \(r_i\) are the design parameters based on the ANFIS training [7], [17-20].

The adaptive neuro-fuzzy inference (ANFIS) network consists of five layers. A normalization layer more than the neuro-fuzzy network [21-34].

**Layer 1** is the fuzzification layer adaptive nodes with bell membership function with equation of:

\[
\mu_{A_i}(X) = \frac{1}{1 + \left(\frac{X - m_i}{b_i}\right)^{2b_i}},
\]

\[
\mu_{B_i}(Y) = \frac{1}{1 + \left(\frac{Y - m_i}{b_i}\right)^{2b_i}}
\]

Where the \(m_A, m_B, 6A, 6B, b_A\) and \(b_B\) are the bell function parameters = 1, 2, 3 [20]

\[
MF_{1,i} = \mu_{A_i}(X) \& \mu_{B_i}(Y), \text{ for } i=1,2,3
\]

The \(A_i\) and \(B_i\) are the linguistic variable of \(X\) and \(Y\).
Layer 2 is the rules layer where its output is considered as fire strength of each node
\[ W_i = \mu_A(X) \times \mu_B(Y), \quad i=1, 2, 3 \] (18)

Layer 3 is the normalization layer and its output is the normalized fire strength
\[ W_i^\prime = \frac{W_i}{(W_1 + W_2 + \ldots + W_9)} \] (19)

Layer 4 is the consequent layer where each node is an adaptive node and its output is the product of the consequent polynomial of fuzzy rules and normalized firing strength
\[ \overline{W}_i f_i = \overline{W}_i (p_i X + q_i Y + r_i), \quad i=1, 2, 3...9 \] (20)

Layer 5 is the defuzzification layer which has only one node (output node) and its output is the overall ANFIS output, summation of the layer 4 output
\[ f = \sum \overline{W}_i f_1 + \overline{W}_2 f_2 + \ldots + \overline{W}_i f_i \] (21)

6 Simulation and Results
The developed fault analysis technique is investigated through MATLAB simulations. An induction motor with inter-turn stator faults is modelled in SIMULINK based on the equations presented in section II. Figure (4) illustrates the fault analysis system procedure.

Figure 4. The fault analysis system for induction motor with dq modeling

The qd current indicate better resolution for fault detection. It increase as the fault percentage increases as per Figure (5)
The fault detection technique uses an ANFIS network to estimate the inter turn fault percentage. Training and testing data are generated from the SIMULINK induction motor model. The motor loading condition was varied to simulate no-load, 25%, 50%, 75%, full-load and 110% loading. The inter turn fault percentage was varied to span the range of 0~16% with steps of 0.005. The total points are 199.

The ANFIS network was trained with 66% of the total data and checked/tested with the remaining 34%. The design is based on three input fuzzy membership functions. It was noticed that the learning phase was completed in the first 120 Epochs out of 300 iterations.

Figure (6) views the ANFIS error for the different loading cases and fault percentages estimating.

The fault percentage at the 25% loading case gives the highest error as the ANFIS network was not trained with this fault data. The maximum % error is 6.83% at 25% loading and 16% fault. The results illustrate the ANFIS accuracy for fault detection even for cases that were not included in the training data.
The network initial configuration has an effect on the performance and accuracy of the fault diagnosis system. Table (1) shows the errors for a two input and three input membership functions. The three input membership function has lower error for testing and checking data.

<table>
<thead>
<tr>
<th>Table 1. The error comparison for the two and three membership</th>
<th>Error</th>
<th>Two MMF</th>
<th>Three MMF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training data</td>
<td>9*10^-4</td>
<td>6*10^-4</td>
<td></td>
</tr>
<tr>
<td>Testing (75%)</td>
<td>6*10^-3</td>
<td>4*10^-3</td>
<td></td>
</tr>
<tr>
<td>Checking (25%)</td>
<td>9*10^-3</td>
<td>3*10^-2</td>
<td></td>
</tr>
</tbody>
</table>

The fault severity was varied from 0% till 16%. However, an actual fault will be limited to 10% fault only at 110% loading based on the induction motor over load protection setting $I_{o,l}=1.5*I_{rated}$.

7 Conclusion

This paper shows the fault diagnosis of inter-turn fault of induction motor based on an artificial network system using the stator dq currents. The dq stator currents give better resolution for inter-turn fault diagnosis. The ANFIS network detects the inter-turn stator faults with high accuracy even for low fault percentages. The average ANFIS error is 1% among all the data training, testing and checking. The ANFIS initial structure has an effect on the fault detection system accuracy.

APPENDIX

The motor parameters are given in Table 2.

<table>
<thead>
<tr>
<th>Table 2. Motor Parameters</th>
</tr>
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<tbody>
<tr>
<td>parameter</td>
</tr>
<tr>
<td>power</td>
</tr>
<tr>
<td>no. poles</td>
</tr>
<tr>
<td>$R_s$</td>
</tr>
<tr>
<td>$L_{ls}$</td>
</tr>
<tr>
<td>$R_r$</td>
</tr>
<tr>
<td>$L_{lr}$</td>
</tr>
<tr>
<td>$L_{m}$</td>
</tr>
<tr>
<td>$I_{rated}$</td>
</tr>
</tbody>
</table>

References


Induction Motors Stator Fault Analysis based on Artificial Intelligence (Hussein Taha Hussein)

