A Diagnosis System for the Rotor Cage of Induction Motor Using Fuzzy Reasoning Method

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In this paper, a diagnosis system, using fuzzy logic, for rotor bar defects in the squirrel cage induction motor is proposed. In the iron and steel industry, induction motors are widely used for various facilities. Recently induction motors have been used in rolling mills. Accordingly the requirement for stabilization in their operations has become very stringent. Various methods are used to diagnose the rotor bar defects of the induction motor, such as the frequency analysis method, the neural network method and so on. However it is difficult to quantitatively determine the degree of deterioration by conventional diagnosis methods. To overcome the difficulty, a new identification method using fuzzy logic is proposed for the diagnosis of rotors in the squirrel cage induction motor. Due to a lot of non-linear elements in the induction motor model, conventional identification methods, such as the least squares method, are not applied to the identification of the induction motor parameters. Our proposed method utilizes the simulator based on the mathematical model and the actual data. The rotor bars resistance in the simulator is modified reflecting the difference between the calculated current and the measured current. After iteration of these modification steps, the rotor bars resistance in the simulator converges to its real value. Using our proposed method, the trend of the rotor deterioration can be managed quantitatively, enabling the appropriate condition-based maintenance of the induction motors.

Keywords: fuzzy reasoning rules, diagnosis, maintenance, modeling, identification, simulation

1. Introduction

Squirrel cage induction motors are widely used for the driving facilities of various plants because of their high reliability and ease of maintenance. In the iron and steel industry, induction motors are used for various facilities, such as conveyors, pumps, roll driving actuators and so on. Recently, induction motors have been used for rolling mills with the advance of power-electronics. Therefore, the requirement for stabilization in their operation has become very stringent.

Because of their simple structure, squirrel cage induction motors are more resistant to breakdown than other types of motors. However, after using the motors under severe conditions for a long time, the rotor bar deteriorates. Eventually, the deterioration leads to a broken rotor bar. Once this trouble occurs, the performance of facilities is heavily damaged.

Numerous methods are used to diagnose the rotor bar defects of the induction motor, such as the frequency analysis method, the neural network method and so on.1-7) When the frequency analysis method is used, the stator current can be measured without special sensors, and hence, this method is quite popular for the diagnosis.1-3) However, it is impossible to accurately diagnose the rotor deterioration by this method, because this method cannot quantitatively recognize the degree of deterioration. Recently, papers proposing the use of neural networks for the diagnosis have been published.4,5) From the practical viewpoint, a major drawback of using the neural network is that it needs a substantial amount of data both in the non-defect case and those in the case of a broken rotor bar. The occurrence of a broken rotor bar is rather rare, and therefore, it is difficult to collect both types of data sufficiently in the actual plant. The air gap monitoring method uses the air-gap flux density.4,6) The faults of the induction motor can be detected appropriately by the search coil output. However, this method is difficult to be applied to all of the induc-
tion motors in the plant considering the cost required to install a search coil on the stator. The leakage flux monitoring method does not require any pre-installation of a search coil to the motor. But, instead, this method needs to install some sensors to measure the leakage flux waveforms.

If the rotor bars resistance can be measured without special sensors, the above problems concerning the installation cost can be avoided. However, it is still impossible to quantitatively estimate the rotor bars resistance by the least square method or the sensitivity function method. This is because the rotor bars current cannot be directly measured and there are a lot of non-linear elements involved in the induction motor model. Based on the above consideration, the goal of our work is the quantitative estimation of the rotor bar resistance to diagnose the degree of deterioration. To achieve this, we propose a method that utilizes the simulator based on the mathematical model and the actual data. The rotor bars resistance in the simulator is modified reflecting the difference between the calculated current and the measured current from the actual machine. We show that, after the iteration of these modification steps, the rotor bars resistance in the simulator converges to its actual value. Furthermore, in order to shorten the convergence time, we propose the use of a fuzzy reasoning method. In this paper, the mathematical models for the induction motor, the identification method of the rotor bars resistance and its application to the diagnosis system are explained. The trend of the rotor deterioration can be managed by the proposed method, allowing the induction motors to be repaired at the most suitable time.

2. Mathematical Model for the Induction Motor

Figure 1 shows the parameters of the induction motor and the geometrical position between the stator and the rotor. Notations used in our paper are summarized as follows; $V_s$ : voltage vector of stator, $I_s$ : current vector of stator, $I_r$ : current vector of rotor, $p$ : differentiation operator, $R_s$ : resistance of each stator, $R_r$ : resistance of each rotor bar, $R_e$ : end resistance of rotor, $L_s$ : inductance of each stator, $L_e$ : leakage inductance of rotor, $L_m$ : mutual inductance between each stator and rotor, $L_s$ : mutual inductance between stators, $M_r$ : mutual inductance between rotor bars, $\alpha$ : phase angle of stator and $\beta$ : electric phase angle of rotor bar.

2.1 Equilibrium Equation for Voltages

The equilibrium equations for voltages of the induction motor is described by:

$$
\begin{bmatrix}
V_s \\
0
\end{bmatrix} = \begin{bmatrix}
Z_{ss} & Z_{sr} \\
Z_{rs} & Z_{rr}
\end{bmatrix} \begin{bmatrix}
I_s \\
I_r
\end{bmatrix} = Z \begin{bmatrix}
I_s \\
I_r
\end{bmatrix}
$$

(1)

As for the variables in equation (1), $Z_{ss}$ is a $3 \times 3$ matrix whose diagonal elements are $R_s + pL_s$ and the others are $pM_s$, $Z_{sr}$ is a $3 \times k_a$ matrix whose $(i,j)$ element is $pM \cos[\theta - (i-1) \alpha + (i-1) \beta]$ and $Z_{ss}$ is a matrix which is the transpose of matrix $Z_{ss}$. Here, $k_a$ is the number of rotor slots, $Z_r$ is a $k_a \times k_a$ matrix whose $(i,i)$ element is $R_e + R_{ri} + R_b(i+1) + R_e + p [2(L_s + L_e) + (n-1)M_r]$, $(i,i+1)$ and $(i+1,i)$ elements are $-R_e(i+1) - p(L_s + M_r)$, and the other elements are $-pM_r$. (See Appendix A)

The accuracy of the model in the equilibrium equation (1) is guaranteed even if the rotor bars resistance goes to infinity.

2.2 Equilibrium Equation for Torque

The equilibrium equation for the torque of the induction motor is described by:

$$
Jp\omega_m + TL = PM_m(I_{sa} \times IT_1 - I_{ra} \times IT_2)
$$

(2)
where \( M_m = \sqrt{\frac{3k_rM}{2P}} \)

As for the variables in equation (2), \( I_{f0} \) and \( I_{00} \) are the current components of stator current in the direction of phase angle \( \alpha \) and its orthogonal direction respectively, \( fT_1 \) and \( fT_2 \) are the current components of rotor current in the direction of phase angle \( \alpha \) and its orthogonal direction respectively, \( \omega_m \) is the rotating speed, \( J \) is the rotating inertia, \( TL \) is the loading torque, \( P \) is the number of the pair of poles.

The proposed diagnosis algorithm uses this equilibrium equation (2) in the stationary state.

By moving the terms involving differential operators \( p \) in eq. (1) to the left-hand side, eq.(1) is written as:

\[
ApX = BX + U
\]

where \( X = \begin{bmatrix} I_f & I_r \end{bmatrix} \), \( U = \begin{bmatrix} V_s \end{bmatrix} \)

Here, \( X \) is the current vector, the size of which is \((3+k_r) \times 1\) and \( U \) is the voltage vector, the size of which is \(3 \times 1\). The matrix \( A \) is the differentiation clause of matrix \( Z \), which is defined in the equation (1) and \( B \) is the other clause.

Multiply the inverse of matrix \( A \) to both sides of equation (3), we obtain equation (4):

\[
pX = A^{-1}BX + A^{-1}U
\]

Equations (2) and (4) are the fundamental equations used in the motor simulator describing the characteristics of the induction motor.

### 3. Simulator of Induction Motor

The simultaneous numerical solution of the equations (2) and (4) is calculated by the Runge-Kutta & Gill method. Here, a simplified induction motor with a single pair of poles and six rotating slots is simulated. We simulate the following two kinds of deterioration: the case where one rotor bar resistance changes to three values from the initial value, and the case in which the resistance of two rotor bars are changed. In the following, the simulated results of the rotating speed are shown. The values of the parameters for simulations are listed in Table 1. Here, the time interval used in the calculation of the Runge-Kutta & Gill method is 0.2msec.

#### 3.1 Simulation Results I (changing one rotor bar resistance)

Figure 2 shows the rotating speed under three different values of one rotor bar resistance with a constant load. Here, the initial rotor bar resistance \( R_b \) is 33.5Ω as in Table 1. As shown in the figure 2, the rotating speed fluctuates due to the rotor bar deterioration. It should be noted that the amplitude of vibration is not in proportion to the rotor bar resistance. Therefore, it is impossible to estimate the degree of the deterioration by the amplitude.

<table>
<thead>
<tr>
<th>Table 1 : Value of parameter of the motor</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L_s )</td>
</tr>
<tr>
<td>( L_a )</td>
</tr>
<tr>
<td>( L_r )</td>
</tr>
<tr>
<td>( M )</td>
</tr>
<tr>
<td>( M_r )</td>
</tr>
<tr>
<td>( M_e )</td>
</tr>
<tr>
<td>frequency</td>
</tr>
</tbody>
</table>

[Figure 2: Simulation result 1 (changing one rotor bar resistance)]

#### 3.2 Simulation Results II (changing two rotor bars resistance)

Figure 3 shows the rotating speed under the three different conditions of two rotor bars resistance with a constant load. Here, the initial rotor bars resistance is 33.5Ω, and the deterioration is simulated by changing the resistance values of the two
rotor bars to 335Ω. As shown in this figure 3, the rotating speed fluctuates according to the rotor bars deterioration, similar to the first case.

4. Conventional Method for Diagnosis (Data Analysis by Fourier Transform)

In order to analyze the simulated data, the Fourier Transform method is used. Figure 4 shows the analyzed result by the Fourier Transform method for the deteriorated data under the changed rotor bars resistance values. There exist sub peaks which occur by the unbalance rotor bars current. These sub peaks are related to the power source frequency and the slips frequency. However, these sub peaks are not related to the change of the rotor bar resistance. Therefore, though the occurrence of the deterioration can be detected from the existence of such sub peaks by the Fourier transform method, it is impossible to detect the change in rotor bars resistance. The difficulty in recognizing the degree of the deterioration is revealed from this results. For more precise analysis, it is necessary to develop a new method to analyze deterioration.

5. The Basic Principle of the Identification Method

To overcome the problem stated above, we propose a new diagnosis system using the identification method of motor parameters. In our proposed system, the value of rotor bar resistance is identified by using the stator currents and the input power voltages.

The identification is carried out by the procedure shown in Figure 5. As shown in Figure 5, the input voltage $V_s$ is used to calculate the stator current $I_s^*$ by the mathematical model of the induction motor, assuming the value of rotor bars resistance $R_b$. Then, the calculated stator current $I_s^*$ is compared with the measured stator current $I_s$. If a difference exists between $I_s^*$ and $I_s$, the rotor bars resistance is modified reflecting the difference in the estimation of the stator current. After iteration of these steps, the value of $R_b^*$ converges to its real value $R_b$.

$$V_s$$

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Figure 3: Simulation result II (changing two rotor bars resistance)

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Figure 4: Fourier transform of stator current changing a rotor bar resistance

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Figure 5: Identification method of rotor bar resistance

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5.1 Basic Algorithm

Our proposed identification method is based on Ohm’s law. If the same input $V_s$ is given to the real machine and to the simulator in Figure 5, the following equation (5) can be obtained.

$$R_b = R_b^* \times \left( \frac{I_s^*}{I_s} \right)$$

(5)
Therefore, if the following equation (6) holds, $R'_t$ of the real machine can be estimated from equation (7).

$$I'_t = I_0$$  \hspace{1cm} (6)

$$R'_t = R_0$$  \hspace{1cm} (7)

Next, new variable $E$ is defined as follows.

$$E = \frac{I'_t}{I_s}$$  \hspace{1cm} (8)

In our algorithm, estimated value of $R'_t$ at the sampling time $m+1$ is calculated from $R'_t$ and $E$ at the previous sampling time as given in equation (9).

$$R'_t(m+1) = R'_t(m) \times E(m)$$  \hspace{1cm} (9)

Here, $u(m)$ is the enforced factor for fast convergence as given in equation (10).

$$u(m) = \begin{cases} -k(k > 0) & \text{if } E(m) < E(m-1) \\ 1 & 1 < E(m-1) < E(m) \\ k & \text{else} \end{cases}$$  \hspace{1cm} (10)

5.2 Stability Analysis

The stability analysis of proposed algorithm is discussed.

When the natural logarithm of both sides of equation (9) is taken, we have:

$$\ln R'_t(m+1) = \ln R'_t(m) + u(m) \times \ln E(m)$$  \hspace{1cm} (11)

We define $X(m)$ and $Y(m)$ as follows:

$$X(m) = \ln E(m)$$  \hspace{1cm} (12)

$$Y(m) = \ln R'_t(m)$$  \hspace{1cm} (13)

Using equations (12) and (13), equation (11) can be rewritten as follows:

$$Y(m+1) = Y(m) + u(m) \times X(m)$$  \hspace{1cm} (14)

Equation (10) can be expressed as follows:

$$u(m) = k \cdot \text{sign}(-AX(m) \times X(m))$$  \hspace{1cm} (15)

$$\text{Sign}(input) = \begin{cases} -1 & \text{input < 0} \\ 1 & \text{else} \end{cases}$$  \hspace{1cm} (16)

We employ an additional condition $X(m) \times X(m-1) > 0$ for the sign function to exclude the case such as $E(m) < 1 < E(m-1) \text{ or } E(m-1) < 1 < E(m)$ even if $(X(m) - X(m-1)) \times X(m) > 0$.

Using

$$\Delta Y(m) = Y(m+1) - Y(m)$$  \hspace{1cm} (17)

$$\Delta X(m) = X(m) - X(m-1)$$  \hspace{1cm} (18)

Equation (14), (15) are written as (19) and (20), respectively:

$$\Delta Y(m) = k \cdot \text{sign}(-AX(m) \times X(m)) \times X(m)$$  \hspace{1cm} (19)

$$u(m) = k \cdot \text{sign}(-AX(m) \times X(m))$$  \hspace{1cm} (20)

If $\Delta X(m) \times X(m) < 0$ holds, $(X(m), \Delta X(m))$ exists in II and IV domain as shown in Figure 6, i.e., the second quadrant, or the fourth quadrant. In these domains, variable $X(m)$ tends to zero with time.

However, if it is $\Delta X(m) \times X(m) > 0$, $(X(m), \Delta X(m))$ exists in the first quadrant, or the third quadrant in Figure 6. At this time, $X(m)$ goes away from zero with time.

\[ \text{Figure 6: } X \text{ and } \Delta X \]

It can assume as follows form equation (5) and equation (19).

$$\Delta X(m) = f(-AX(m) \times X(m)) \times X(m)$$  \hspace{1cm} (21)

Where,

$$f(w) = k \cdot \text{sign}(-w)$$  \hspace{1cm} (22)

Here, $X(m)$ is multiplied to both sides of equation...
A diagnosis system for the rotor cage of induction motor using fuzzy reasoning method

These characteristics are shown as trajectories in Figure 7.

Thus, $X(m)$ converges to zero, $Y(m)$ converges to a constant value by equation (14).

6. Identification Method of Motor Bar Resistance

6.1 Identification of One Unknown Rotor Bar Resistance

Based on equations (9) and (10), in the case of one unknown $R_{bi}$ value, the algorithm for identification is described as follows:

$$R_{bi}(m+1) = R_{bi}(m) \times E(m)^{\frac{1}{n}} (i = 1, \ldots, 6)$$  \hspace{1cm} (26)

$$E(m) = \frac{i_a(m)}{I_{sa}(m)}$$  \hspace{1cm} (27)

$$u(m) = \begin{cases} -u(m-1) & \text{if} \ E(m) < E(m-1) \\ <1 \text{ or } 1 < E(m-1) < E(m) & u(m-1) \\ \text{else} \end{cases}$$  \hspace{1cm} (28)

where $u(m)$ is the control factor to stabilize the convergence of the identification algorithm, $m$ is the number of calculation.

The identification processes by this algorithm are shown in Figure 8 and Figure 9. Figure 8 shows the convergence processes for different initial values. As shown in these figures, the values of $R_{bi}$ and $R_{a}$ successfully converge to their real values (335Ω) after several hundred iterations. Starting from sufficiently large rotor resistance, it approaches to its real value smoothly.
6.2 Identification of Two Unknown Rotor Bars Resistance

In the case of two unknown \( R_b \) values, it is necessary to use current data from two stators. Similar to one unknown \( R_b \) case, we define two ratios \( E_1 \) and \( E_2 \) as follows.

\[
E_1 = \frac{I_{sb}}{I_{sa}} \quad (29)
\]

\[
E_2 = \frac{I_{sb}^*}{I_{sa}} \quad (30)
\]

In the case of two unknown \( R_b \)s, both \( E_1 \) and \( E_2 \) are used for the estimations of \( R_{b1} \) and \( R_{b2} \) simultaneously.

The estimation is done by the following equations:

\[
R_{b1}(m+1) = R_{b1}(m) \times E_1(m)^{z_1 \times u_1(m)} \\
\times E_2(m)^{z_2 \times u_2(m)} \quad (31)
\]

\[
R_{b2}(m+1) = R_{b2}(m) \times E_1(m)^{z_1 \times u_1(m)} \\
\times E_2(m)^{z_2 \times u_2(m)} \quad (32)
\]

\[
u_1(m) = \begin{cases} 
-u_1(m-1) & \text{if } E(m) < E(m-1) \\
< 1 \text{ or } 1 < E(m-1) < E(m) & u_1(m-1)
\end{cases} \quad (33)
\]

\[
u_2(m) = \begin{cases} 
-u_2(m-1) & \text{if } E(m) < E(m-1) \\
< 1 \text{ or } 1 < E(m-1) < E(m) & u_2(m-1)
\end{cases} \quad (34)
\]

where \( u_1(m) \) and \( u_2(m) \) are the control factors stabilizing the convergence of the estimation algorithm, \( z_1 \) and \( z_2 \) are reflecting factors of \( E_1 \) and \( E_2 \) for iterative modification.

The values of \( u_1(0), u_2(0), z_1 \) and \( z_2 \) are chosen by try and error.

The identification process by this algorithm is shown in Figure 10. As shown in the figure, the \( R_{b1} \) and \( R_{b2} \) values successfully converge to their real values (\( R_{b1} = 335 \Omega \), \( R_{b2} = 670 \Omega \)) after several hundred iterations.

7. Stabilization of the Identification by Fuzzy Logic

7.1 Identification by Fuzzy Logic

If the parameter \( k \) of equation (10) is positive, the proposed identification method has its stability (see chapter 5). The parameter \( k \) has an effect on the trend of convergence. We empirically know that it is effective to change the parameter \( k \) depending on the value of ratio \( E \).

One drawback of asymptotic convergence is that the convergence speed becomes slower as it approaches to the target. In our case, as easily seen from eq. (14), as \( X(m) \) converges to \( 0 \), the amount of update for \( Y(m) \) decreases under a constant \( k \), and this leads to the slower convergence. Another problem to consider is rooted in the non-linearity of the system; the convergence speed is not uniform due to the non-linearity. To deal with these problems, we use fuzzy reasoning approach as described below to optimize the learning gain depending on the situation, in stead of the straight-forward use of a globally constant gain.
A diagnosis system for the rotor cage of induction motor using fuzzy reasoning method

To design the control factor $u$, $X$ and $\Delta X$ are defined as follows:

$$X_j(m) = \ln E_j(m)$$  \hspace{1cm} (35)

$$\Delta X (m) \ln E_j(m) - \ln E_j(m-1)$$  \hspace{1cm} (36)

The control factor is defined as follows:

$$u_j(m) = k \cdot \text{sign}(u_j(m-1))$$  \hspace{1cm} (37)

$$\text{sign}(\text{input}) = \begin{cases} -1 & \text{if input} < 0 \\ 1 & \text{else} \end{cases}$$

Fuzzy rules that we use to determine the parameter value of $k$ are represented by 5x5 cells as shown in Table 2.

As shown in Table 2, the value of $k$ is changed its sign according to the fuzzy rules. Where, P, M, N, S, B means positive, medium, negative, small and big. The stability of the algorithm is attained from the existence of dead band for both variables and the control of the modification factor $z$. In case of estimating the values of two $R_6$, $R_{6x}$ and $R_{6y}$, the identification is carried out as follows:

$$E_j(m) = \frac{I_j^2(m)}{I_{jy}(m)}$$  \hspace{1cm} (38)

$$R_{6x}(m+1) = R_{6x}(m) \times E_a(m)^{2x \times u_j(m)}$$
$$\times E_b(m)^{2y \times u_j(m)}$$  \hspace{1cm} (39)

$$R_{6y}(m+1) = R_{6y}(m) \times E_a(m)^{2y \times u_j(m)}$$
$$\times E_b(m)^{2x \times u_j(m)}$$  \hspace{1cm} (40)

where $x, y \in \{1, 2, \ldots, 6\}$, $x \neq y$, $\bar{E}$ means the average of $E$.

As for the variables in equation (39), (40), $m$ is the number of calculation. And, $u_i(m)$ $u_f(m)$ are the control factors stabilizing the convergence of the estimation algorithm determined by the fuzzy reasoning. The parameter $z_1$ and $z_2$ are reflecting factors of $E_a$ and $E_b$ for iterative modification and are determined by try and error.

The flow chart of this estimation method is shown Figure 11.

7.2 Numerical Simulation Results

Numerical Simulations are executed to evaluate the proposed estimation method in the case where two of the rotor bars resistance values are unknown.

In this case, Table 3 shows the fuzzy rules by which the parameter $k$ is given. As shown in the

![Flow Chart of this identification method](image)

Table 2: Fuzzy logic parameter $k$

<table>
<thead>
<tr>
<th>$X_j$</th>
<th>NB</th>
<th>NS</th>
<th>M</th>
<th>PS</th>
<th>PB</th>
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<tr>
<td>$\Delta X_j$</td>
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<td>$-k_{j2}$</td>
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<td>$k_{j4}$</td>
<td>$k_{j5}$</td>
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<tr>
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<td>$k_{j3}$</td>
<td>$k_{j4}$</td>
<td>$k_{j5}$</td>
</tr>
<tr>
<td>$M$</td>
<td>$k_{j1}$</td>
<td>$k_{j2}$</td>
<td>$k_{j3}$</td>
<td>$k_{j4}$</td>
<td>$k_{j5}$</td>
</tr>
<tr>
<td>$P$</td>
<td>$k_{j1}$</td>
<td>$k_{j2}$</td>
<td>$k_{j3}$</td>
<td>$-k_{j4}$</td>
<td>$-k_{j5}$</td>
</tr>
<tr>
<td>$B$</td>
<td>$k_{j1}$</td>
<td>$k_{j2}$</td>
<td>$k_{j3}$</td>
<td>$-k_{j4}$</td>
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Table 3: Value of $k$

<table>
<thead>
<tr>
<th>$\Delta X_i$</th>
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</tr>
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<td>PB</td>
<td>1.0</td>
<td>1.5</td>
<td>1.0</td>
<td>−1.5</td>
<td>−1.0</td>
</tr>
</tbody>
</table>

Table, parameters $k$ are determined symmetrical patterns, therefore it's not difficult to give the value to parameters $k$. Here, $X$ and $\Delta X$ are defined as Figure 12.

The identification process by this algorithm is shown in Figure 13. As shown in the figure, the $R_{a1}$ and $R_{a2}$ values successfully converge to their true values (335Ω) after three hundred iterations.

It approaches its real value by the half of calculation number of Figure 10, which the resistance is estimated by the fixed parameter $k$.

We discuss the appropriateness of using fuzzy rules as in Table 3. By rewriting eq.(25), we have;

$$\Delta V(m) = \frac{k}{(2X(m)\Delta X(m) - \Delta X^2(m))}$$

Thus,

$$\Delta V(m) = -2kX^2(m) - \chi\Delta X^2(m)$$

Now let us consider maintaining the ratio $\Delta V(m)/X^2(m)$ at the constant level, i.e.,

$$\Delta V(m)/X^2(m) = -2kX^2(m)/X^2(m) = -C.$$ 

By rearranging the formula, we have

$$k = \frac{(1/2C - (1/2)(\Delta X(m)/X(m))^2)}{X(m)}.$$ 

This implies that $k_{ij}$ can be tuned based on the ratio of the magnitude of $X(m)$ and $\Delta X(m)$ to maintain $\Delta V(m)$ at $O(X^2(m))$. More concretely, the gain $k_{ij}$ becomes higher when $|\Delta X(m)/X(m)| < 1$ in comparison with the case when $|\Delta X(m)/X(m)| > 1$.

Based on the above discussion, we investigate the appropriateness of Table 3. Fuzzy rules work as a normalization method, by mapping absolute values.
A diagnosis system for the rotor cage of induction motor using fuzzy reasoning method

Figure 13: Identification result using fuzzy logic such as 0.003 to categorical values such as NB. We compare the magnitude of $X(m)$ and $\Delta X(m)$ based on the categorical values. Then, in Table 3, when $X=NB$ and $\Delta X=NS$, we have $|\Delta X(m)/X(m)|<1$, resulting in a higher gain 1.5. In contrast, when $X=NS$ and $\Delta X=NB$, we have $|\Delta X(m)/X(m)|>1$, resulting in a smaller gain, 0.75. In the other cells where the magnitude is considered as to be the same, the gain is chosen to be 1. Another point worth noting is that when $X=\Delta X=M$, the gain is the largest, 2. This aims at the high-gain around the target where the convergence slows down.

8. On-line Diagnosis System

Our proposed identification algorithm is applied to the on-line system. Figure 14 shows the structure of the on-line diagnosis system. The system consists of a Personal Computer (PC) and the sensors that measure the voltages and the currents of the stator. These data, such as the initial value of motor parameters, the warning threshold value, the repair boundary value and the past repair information, are set before the diagnosis. The algorithm of identification for the diagnosis is carried out in the PC, then the degree of the deterioration of rotor bars, the warning, the trends of rotor bars resistance and the measured voltages and currents are indicated on the display.

The estimated values of the two rotor bars resistance are shown in Figure 15. The vertical axis shows the ratio between the initial resistance and the present resistance. The horizontal axis shows the number of the diagnosis, which is periodically carried out.

As shown in the figure, $R_{oe}$ exceeds the boundary value at the eighth diagnosis occasion. Therefore this result shows the induction motor should be repaired.

Once this on-line diagnosis system is constructed, the rotor deterioration is automatically recognized before the occurrence of a serious trouble.

9. Conclusions

The identification algorithm, using fuzzy logic, for the rotor bar resistance has been developed. And in order to improve the trend of convergence, we
adopted fuzzy reasoning rules. The proposed method enables us to quantitatively monitor the progress of the rotor deterioration. The usability of the method was demonstrated using the simulated data based on the actual motor specifications. Compared with conventional methods, such as Fourier analysis, this method has the following advantages.

1) Special sensors are not necessary to diagnose the rotor bar defects.
2) Our proposed identification algorithm can be applied to the on-line system. By monitoring the deterioration of rotor bars resistance continuously, the trend of the rotor deterioration can be managed and the induction motors can be repaired appropriately.

References
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Appendix A

The equation (1) is described by equation (A-1) if the number of rotor slots are six \((k_s=6)\)

\[
\begin{pmatrix}
V_s \\
0
\end{pmatrix} =
\begin{pmatrix}
Z_{as} & Z_{ar} \\
Z_{re} & Z_{rr}
\end{pmatrix}
\begin{pmatrix}
I_s \\
I_r
\end{pmatrix}
\]

where \(Z_{as} = \begin{pmatrix}
R_s + pL_s & pM_s & pM_s \\
pM_s & R_s + pL_s & pM_s \\
pM_s & pM_s & R_s + pL_s
\end{pmatrix}\)

\(Z_{ar} = \begin{pmatrix}
pM \cos \theta & pM \cos(\theta + \beta) & pM \cos(\theta + 2\beta) & \cdots & pM \cos(\theta + 5\beta) \\
pM \cos(\theta - \alpha) & pM \cos(\theta - \alpha + \beta) & pM \cos(\theta - \alpha + 2\beta) & \cdots & pM \cos(\theta - \alpha + 5\beta) \\
pM \cos(\theta - 2\alpha) & pM \cos(\theta - 2\alpha + \beta) & pM \cos(\theta - 2\alpha + 2\beta) & \cdots & pM \cos(\theta - 2\alpha + 5\beta)
\end{pmatrix}\)

\(Z_{re} = Z_{ar}^T\) (the transpose of matrix \(Z_{ar}\)) : a \(6 \times 3\) matrix

\(Z_{rr}\) is a \(6 \times 6\) matrix.

\[
Z_{rr} = \begin{pmatrix}
R_{s1} + R_{s2} + R_{s3} + R_{s4} + R_{s5} + R_{s6} + 5M_r & -R_{s2} - p(L_o + M_r) & -pM_r & \cdots & -R_{s5} - p(L_o + M_r) \\
-R_{s2} - p(L_o + M_r) & R_{s2} + R_{s3} + R_{s4} + R_{s5} + R_{s6} + 5M_r & -R_{s3} - p(L_o + M_r) & \cdots & -pM_r \\
-pM_r & -R_{s3} - p(L_o + M_r) & R_{s3} + R_{s4} + R_{s5} + R_{s6} + 5M_r & \cdots & -M_r \\
-pM_r & -pM_r & -R_{s4} - p(L_o + M_r) & \cdots & -R_{s5} - p(L_o + M_r) \\
-R_{s5} - p(L_o + M_r) & -pM_r & -pM_r & \cdots & R_{s6} + R_{s6} + R_{s6} + R_{s1} + 5M_r \\
-pM_r & -pM_r & -pM_r & \cdots & p[2(L_o + L_o) + 5M_r]
\end{pmatrix}
\]

[連結先]

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